Drivers of Innovation, Dynamics of Innovation Persistence and Performance: The Case of Small Food Industry Businesses in Australia

FRANKLIN ARCIA SORIANO

BScStats (UPLB) MStats (UPD) GDipEmet MEcon (UNE)

Dissertation submitted for the Degree of Doctor of Philosophy

UNE Business School

University of New England

Armidale NSW 2351

Australia

November 2019

Certification

I certify that this dissertation has not already been submitted for any other degree and is not currently being submitted for any degree.

I confirm that, to the best of my knowledge, any form of support received in preparing this dissertation and all cited sources used have been appropriately acknowledged.

[redacted]

Franklin Arcia Soriano

Abstract

There is strong evidence that innovation is the primary driver of the economic growth of small businesses in the Australian food industry. As Australia continues to compete and grow the share of the Australian food industry in the global market, it is imperative that food and non-food businesses be innovative to improve performance. With the small food businesses playing a significant role in the Australian economy by creating jobs and economic growth, and offering service opportunities to the regional economies, this dissertation investigates the dynamic relationships among the key drivers of innovation, innovation persistence and business performance within small businesses in the food industry in Australia.

Using a panel of business-level data collected through the ABS Business Characteristics Survey (2006/07 to 2010/11 Australian Bureau of Statistics' Business Longitudinal Database Confidential Unit Record File), this dissertation provides evidence on: (1) the factors driving small food businesses to innovate in any of the four innovation dimensions—goods and services, organisational and managerial processes, operational processes and marketing methods; (2) the degree and dynamics of innovation persistence; and (3) their impacts on four business performance measures—gross output, gross value-added, labour productivity and productivity dispersion. The author employs several complex dynamic panel data modelling techniques with bootstrapping and other econometric procedures in the empirical analyses.

The empirical findings show that engaging in collaboration; using science, technology, engineering and mathematics (STEM) skills; having higher information and communication technology (ICT) intensity; implementing flexible working arrangements; having exporting capability; seeking finance through debt and equity; and facing some degree of market competition are significant factors influencing the small food businesses' innovation behaviour. The relative importance of these factors varies in the different aspects of innovation—the propensity to innovate, innovation dimensions, innovation intensity and innovation persistence—and between agricultural and non-agricultural food subsectors. Persistent innovation-active small food businesses are shown to introduce more than one type of innovation, and the degree of persistence in business' innovation behaviour was strong for new products, new operational processes and new marketing methods whereas new organisational and managerial processes exhibited weak persistence of innovative behaviour. Results evidently confirm the hypotheses of: true state-dependence; the variation in the degree of innovation persistency among the innovation dimensions; and the important role of

unobserved heterogeneity in explaining the persistence of innovation behaviour. Moreover, it is observed that innovation-active small food businesses, particularly persistent innovators, tended to have higher contributions to growth in gross output, value-added and labour productivity, with the impacts being different for the different types of innovation. Further, the dissertation reveals significant, positive and direct associations among the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion within small food businesses in Australia.

This dissertation provides important contributions in the literature. Empirical studies on the determinants of innovation in the Australian food sector are non-existent. No Australian food industry study to date has simultaneously observed whether different types of business performance growth and changes in productivity dispersion are supported by persistence in different types of innovation, and by their innovation determinants. Providing empirical evidence that connects innovation behaviour and productivity dispersion in the food businesses is also a novelty to the growing body of empirical literature on productivity dynamics. In addition, establishing the role of work flexibility and STEM skills as key determinants of innovation in the food industry is a pioneering work.

The empirical results support the Australian government's innovation agenda and initiatives which would motivate and trigger the small food businesses in Australia to start and/or continue to engage in innovation through development of new products or services, new operational processes, new marketing strategies and methods, and new organisational and managerial processes, for job creation, global competitiveness, and income growth. The fact that the overall innovation behaviour of small food businesses in the Australian food industry is characterised by true state-dependence in the new marketing methods and new operational processes implies that innovation-stimulating policy programmes for these types of innovations will potentially have long-lasting effects in the industry. For the food subsectors, government assistance should be provided to agricultural small food businesses engaged in products and marketing methods innovations whereas for non-agricultural small food businesses, government should provide stimulus for organisational and managerial processes, operational processes and marketing methods innovation activities. Most importantly, the empirical results of this research provide useful inputs to the current research undertaking of the Department of Industry, Innovation and Science on assessing the impact of the Industry Growth Centres programme, particularly in the Food and Agribusiness Growth Sector in Australia.

Acknowledgements

I want to express my deepest gratitude to my principal supervisor Professor Renato A. Villano for his expert guidance throughout my research work. He has been an inspiration to fulfil my dream to complete this PhD research on business innovation and performance. He has been an excellent mentor and a kind and caring colleague who has given me his golden time and tireless effort. My sincere appreciation also goes to Emeritus Professor Euan M. Fleming and Adjunct Professor George E. Battese who have heartily accepted to become my co-supervisors. They brought with them their professionalism, empathy and compassion, generous support and encouragement, and excellent collaboration and advice. It has been an honour and great pleasure to partner with them in this remarkable PhD journey.

This dissertation will not come to a reality without the support of the Australian Bureau of Statistics (ABS). To Ruel Abello, Sybille McKeown and Dr Siu-Ming Tam, thank you for the encouragement and approval of my study support programme. The ABS-UNE Agreement and the ABS Innovation and Technology Section provided access and use of the confidentialised business microdata in the analysis. Barry Tynan, Talei Parker and Kim McCosker of the ABS Customised and Microdata Delivery facilitated my ABS DataLab account and output clearance in timely fashion. My fellow economists at the ABS Methodology Division Cristian Rotaru, Dr Kay Cao and Dr Thai Nguyen, provided assistance and analytical advice.

I am grateful to the UNE Business School for accepting me to the PhD programme. My appreciation goes to Sharon Styles and Robert Webster for providing a conducive working environment during my visits to UNE, to the Library Staff for facilitating inter-library loans and metadata repository, and to Pauline Fleming and the rest of UNE Business School Staff and other PhD students for the camaraderie, support, comments and feedback during my study visits and seminar presentations.

Special thanks are also due to Professor D.S. Prasada Rao, Professor Bert Balk, and Professor Tim Coelli for introducing me to the realm of index number, efficiency and productivity analysis. To all of my other former mentors and colleagues at the University of Queensland Centre for Efficiency and Productivity Analysis, the postgraduate research and teaching experiences I acquired while working with you all are greatly appreciated.

To all my friends who have always given me company, moral and spiritual support, thank you very much—to Rene, Precy, Kyanna, Kyle, Ninang Alice, Ninong Winch for always taking good care of me in Armidale; to my brothers and sisters in the Canberra Couples for Christ community, Tita Nancy and Naomi, Angie and the ABS Pinoys for the prayers; to Ric, Ressie, Jericho, Patrisha and Patrick for providing company to my family whenever I go on interstate travel and conferences in relation to my study.

Finally, I am very grateful to my loving wife Menchie for her unconditional love, care, trust, understanding, patience and confidence in me to finish this very long battle but successful PhD journey. My son Franko is the Lord's gift and my inspiration in completing this research work. To my dearest Nanay and my late Tatay, thank you for your loving support, and for bringing and giving me good life and education on earth. To my siblings, Fatti, Filoy and Kuya Ferdi and their families thank you for your unconditional care and affection.

And most importantly, above all, to the Lord our God—for giving me this wonderful life, for always giving me the wisdom and capacity to grasp and do things correctly, for always giving me hope when I am down, for always giving me strength when I am weak, for shining me the light of the Holy Spirit to continue this educational journey, and for always giving me and my family—love, hope, happiness, peace and protection. In the name of Jesus, Mama Mary, I pray with much thanksgiving. Amen.

I humbly dedicate this dissertation to Menchie, Franko, Nanay and to my late Tatay.

Table of Contents

List of Tables

List of Figures

List of Appendices

Appendix Page

List of Acronyms

ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABN	Australian Business Number
ABS	Australian Bureau of Statistics
AgriFF	Agriculture, Forestry and Fishing Industry
AIC	Akaike Information Criterion
AIS	Australian Innovation System
ANOVA	Analysis of Variance
ANZSIC	Australian and New Zealand Standard Industrial Classification
APE	Average Partial Effects
ASIC	Australian Securities and Investment Commission
ATT	Average Treatment effects on the Treated
ATO	Australian Taxation Office
BAS	Business Activity Statements
BCS	Business Characteristics Survey
BIC	Bayesian Information Criterion
BLADE	Business Longitudinal Analysis Data Environment
BLD	Business Longitudinal Database
CDM	Crépon, Duguet and Mairesse
CIA	Conditional Independence Assumption
CIS	Community Innovation Survey
CRC	Cooperative Research Centres
CRCP	Cooperative Research Centres Program
CRE	Correlated Random Effects
CURF	Confidentialised Unit Record File
DA	Department of Agriculture
DAFF	Department of Agriculture, Fisheries and Forestry
DAWR	Department of Agriculture and Water Resources
DIIS	Department of Industry, Innovation and Science
DIISR	Department of Industry, Innovation, Science and Research

DIISRTE	Department of Industry, Innovation, Science, Research and Tertiary Education
DiSP	Dispersion Statistics on Productivity
DPMC	Department of the Prime Minister and Cabinet
FIAL	Food Innovation Australia Ltd
GFC	Global Financial Crisis
GO	Gross Output
GST	Goods and Services Tax
HHG	Hausman, Hall and Griliches
ICT	Information and Communication Technology
IICA	Industry Innovation and Competitiveness Agenda
IQR	Interquartile Range
LP	Labour Productivity
MFG	Manufacturing
NISA	National Innovation and Science Agenda
OCS	Office of the Chief Scientist
OECD	Organisation for Economic Co-operation and Development
OI	Open Innovation
PAYG	Pay as you go
PC	Productivity Commission
PSM	Propensity Score Matching
R&D	Research and Development
RFPIPP	Regional Food Producers' Innovation and Productivity Program
SE	Standard Errors
SME	Small and Medium Enterprise
SMLE	Simulated Maximum Likelihood Estimation
STEM	Science, Technology, Engineering and Mathematics
TPM	Transition Probability Matrix
USD	Unconditional State Dependence
VA	Value Added
WT	Wholesale Trade

Chapter 1: Introduction

1.1 Preface

There is strong evidence that innovation is a primary driver of a nation's economic growth. As Australia continues to compete and grow the share of the Australian food industry in the global market, it is imperative that food and non-food businesses be innovative to improve performance—this is the main thrust of the government's *Industry Innovation and Competitiveness Agenda (IICA)* (Department of the Prime Minister and Cabinet [DPMC], 2014). Innovation takes place through development of new products or services, operational processes, marketing strategies and organisational methods (i.e., innovation dimensions), both within the workplace and through their external relations. There are significant improvements on this front, but the main challenge remains—why do some firms innovate, but others don't?

This dissertation provides empirical evidence on the main drivers of innovation of small food industry businesses in Australia; investigates the dynamics of innovation dimensions, persistence of innovation, and impact of innovation on business growth performance (using gross output, gross value added and labour productivity) and productivity dispersion; and discusses the implications of the findings for the government's innovation agenda and initiatives. Exploring these implications, in return, will benefit the small food businesses in Australia through the formulation of more effective policies that can lead to continued innovation, job creation, global competitiveness, and income growth. We apply complex dynamic panel data and econometric modelling procedures to firm-level data contained in the Australian Bureau of Statistics (ABS) Business Longitudinal Data Confidential Unit Record file (BLD CURF).[1]

The novel contribution of this work is that no study to date has look at innovation by Australian small food businesses as well as simultaneously observed whether different types of business performance growth and changes in productivity dispersion are supported by persistence in different types of innovation (product, operational process, organisational and marketing methods), and by their innovation determinants. The findings also underscore the

[1] The ABS BLD CURF is discussed thoroughly in Chapter 5.

importance of understanding the key drivers of innovation; enabling environment; and an appropriate platform for policy design, support and development, all of which are essential for small food businesses to collaborate, innovate and contribute to a productive and progressive Australian economy.

1.2 Rationale

The Australian Government is strongly committed to developing an internationally competitive and productive environment for small businesses. Small businesses[2] play a significant role in the Australian economy, accounting for almost half of the employment in the private nonfinancial sector and over one third of production (ABS, 2015b). They account for most Australian businesses (97.5 per cent in 2017–2018) (ABS, 2019a) and are believed to be the critical players in Australia's economy, underpinning growth and innovation, and providing jobs for millions of Australians (Department of Industry, Innovation and Science [DIIS], 2015a). A recent study by Hendrickson, Bucifal, Balaguer, and Hansell (2015) established that young small and medium enterprises (SMEs) made the highest contribution (40 per cent) to net job creation in Australia over the period 2006 to 2011.

Along with these small businesses, the Australian Government considers the food and agribusiness industry an important part of the Australian economy because it makes significant contributions to the economies of regional areas in employment, business and service opportunities (DIIS, 2017a). Australia's food and agribusiness industry outputs were around AU$54 billion of industry value added in 2014/15 which is equivalent to 3.3 per cent of the total GDP. Its labour productivity increased at an annual rate of 2.4 per cent over the five years 2010/11–2014/15. The industry's exports were worth AU$40.8 billion in 2015 (Chaustowski & Dolman, 2016). With this industry spending nearly AU$728 million on research and development (R&D) related to food, beverage and agricultural machinery manufacturing, an important question is: Have the small food businesses been engaging in any form of innovation activities that are useful in improving their performance?

This study uses the Organisation for Economic Co-operation and Development (OECD) definition of *innovation* as provided in the Oslo Manual:

[2] The concept of a *small business* is discussed in the next chapter.

'*...the implementation of a new and significantly improved product (good or service); or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations.'* (OECD, 2005a, p. 46)

A business is called *innovation-active* if it engages in any innovation activities that were implemented, ongoing or abandoned during a period. A business is called an *innovator* if it successfully developed and implemented an innovation, which may have taken many years to complete (OECD, 2005a). The current investigation is conducted for innovation-active businesses using an output-based measure of innovation obtained from the ABS Business Characteristics Survey (BCS) data; hence, in the rest of the chapters, the terms innovator and noninnovator businesses are equivalent to innovation-active and non-innovation-active businesses, respectively. Four types of innovation (also known as innovation dimensions) are scoped and are the focus in this analysis: product innovation, organisational or managerial innovation, process innovation, and marketing innovation (OECD, 2005a). Product innovation is any good or service or combination of these that is new (or significantly improved) to a business. New or significantly improved strategies, structures or routines of a business that aim to improve performance belong to organisational or managerial process innovation. Process innovation refers to new methods of producing or delivering the products including significant changes in techniques, equipment and/or software. And new design, packaging and sales methods to increase the appeal of goods or services of a business or to enter new markets are classified as marketing innovations. Of course, a business could undertake more than one type of innovation in a given period.

Innovation remains vital to the expansion and international competitiveness of Australia's economy. As Australia continues to compete in the global economy, Australian businesses such as the small food businesses need to be innovative for job creation and income growth (Department of Industry, Innovation, Science and Research [DIISR], 2009; DIIS, 2018a). Innovation statistics in selected growth sectors[3] in Australia show that only 32.7 per cent of all businesses in the food and agribusiness sectors were engaged in any innovative activity in 2013/14, of which 28.2 per cent successfully introduced and implemented innovation (ABS, 2015d). This was lower than the overall proportion of business innovators in Australia, which

[3] The food and agribusiness growth sector includes food-related production, food processing and the major inputs into these sectors, but not the wholesale and retail sale of these goods (ABS, 2015d). It is important to note that the scope and coverage of the food industry (or food sector) in this dissertation is different from the food and agribusiness growth sector. Also, the terms 'industry' and 'sector' are used interchangeably.

was 48.3 per cent in that period. In addition, the innovation rate for Australian small businesses employing 5–19 persons was 59.9 per cent in 2013/14 (ABS, 2015c). Evidently, there is a need to encourage small businesses in the food and agribusiness sector to innovate to become more competitive and productive. To unleash the potential of small food businesses to innovate, grow and create more jobs, it is imperative to examine more closely what drives their innovation activities. This is one of the goals the current dissertation seeks to achieve.

Central to the vision of providing the right economic incentives to enable businesses—big and small—to grow, the Australian Government, through the IICA,[4] has identified food and agribusiness as an area of competitive strength and prioritised it as a growth sector (DPMC, 2014). A key initiative in the agenda was establishing Industry Growth Centres and, in the case of the Australian food and agribusiness sector, the Food and Agribusiness Growth Centre, known as Food Innovation Australia Ltd (FIAL). FIAL was established to build capability and encourage collaboration and innovation in the industry involved (DIIS, 2017a). For the growth centre's plans, activities or strategies to drive innovation, productivity and competitiveness and help food and agribusiness businesses build stronger futures for themselves, it is essential to provide empirical evidence of factors that drive these businesses to innovate.

Analysing the determinants of innovation in the Australian industries using microdata is not new in the national public arena (e.g., Rogers, 2004; Bhattacharya & Bloch, 2004; ABS, 2008; Griffiths & Webster, 2009; Todhunter & Abello, 2011; Rotaru, Dzhumasheva, & Soriano, 2013; Rotaru & Soriano, 2013; Soriano & Abello, 2015; Palangkaraya, Spurling, & Webster, 2016; Tuhin, 2016; Smith & Hedrickson, 2016; Tuhin & Swanepoel, 2017), nor is analysis of the relationship between innovation and business performance in an Australian setting (e.g., Phillips, 1997; Storey, 2004; Shanks & Zheng, 2006; Wong, Page, Abello, & Pang, 2007; ABS, 2008; Nossal, 2011; Nossal & Lim, 2011; Soames, Brunker, & Talgaswatta, 2011; Sheng, Mullen, & Zhao, 2011; Elnasri & Fox, 2015, 2017; Palangkaraya, Spurling, & Webster, 2015; Smith & Hendrickson, 2016; Khan, Salim, Bloch, & Islam, 2017; Rafi, 2017; Hendrickson et al., 2018). However, no Australian food industry study to date has simultaneously observed whether different types of business performance growth and changes in productivity dispersion are supported by persistence in different types of innovation, and by their innovation determinants. Not only is the current study a significant addition to the empirical literature, but

[4] More information regarding the IICA and Growth Centres can be found at the DIIS website: www.industry.gov.au.

a study on small food businesses in Australia using firm-level data is desirable to support the earlier above-mentioned agenda as well as an encouragement for these businesses to persist in innovating. Evidence drawn from this study may have implication to the government policies in growing the Australian food industry. Providing empirical evidence that connects innovation behaviour and productivity dispersion in the small food businesses is also a novelty to the growing body of literature on productivity dynamics. What is compelling in this work is the use of the food industry sample in five waves (2006/07 to 2010/11) of the ABS BLD CURF, a unique extract of longitudinal microdata that have never been used by any previous researcher to analyse business innovation or performance in small businesses in the Australian food industry using panel data. The data also allowed us to go deeper and analyse the food industry subsectors. These data are discussed in Chapter 5.

Another remarkable contribution of our study is the estimation of robust standard errors for the impact measures called *average partial effects* via simulation using modern bootstrapping procedures as well as analysing their distributions. This empirical study also adds to the literature on the analytical use of the ABS confidentialised business survey microdata.

1.3 Objectives and research questions of the study

Considering the above rationale, this dissertation aims to provide empirical evidence and policy implications on the dynamic relationships between the key drivers of innovation, innovation persistence and productivity in small businesses in the food industry in Australia using some simple to complex dynamic panel data modelling and other econometric procedures.

Specifically, the study addresses the following key themes:

- Four aspects of innovation—the propensity of businesses to innovate; innovation dimensions (and/or diversity); innovation intensity; and innovation persistence;
- Food industry subsectors—the small food businesses belonging to the agriculture, forestry and fishing industry, and manufacturing and wholesale trade industries;[5]
- Five important potential drivers (or business characteristics)—collaboration; use of science, technology, engineering and mathematics (STEM) skills; use of

[5] These are the only Australian and New Zealand Standard Industrial Classification (ANZSIC) division 1 industries covered in the ABS BLD CURF used in this study. Businesses sampled for the food industry are predominantly associated with food for human consumption in the above three industry divisions (ABS, 2013).

information and communication technology (ICT); labour market flexibility; and degree of market competition;

- Four business growth performance indicators—gross output growth; value added growth; labour productivity growth; and productivity dispersion.

In exploring the linkages between these key themes, we: examine the impacts of the potential drivers on the four aspects of business innovation; evaluate the dynamics of innovation persistence; investigate how the degree of innovation persistence affects the business performance indicators; and establish the implications of the findings for the government's innovation agenda and initiatives. The dissertation assesses other drivers of innovation such as business size, exporting capability and financial assistance which are also covered in the ABS BCS results.

To achieve the above objectives, we formulate the following general research questions:

1. What are the key drivers of innovation in small food industry businesses in Australia?
2. How large are the impacts of these key drivers on the overall and each dimension of innovation for businesses belonging to the food industry agribusiness and non-agribusiness subsectors?[6]
3. Does innovation persist among small food industry businesses in Australia?
4. Does the degree of innovation persistence vary among the different types of innovation?
5. Do the Australian small food industry businesses sustain productivity growth if they engaged in any form of innovation?
6. What is the relationship between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia?
7. Do the empirical findings support the government's innovation initiatives and agenda for growing the Australian food industry sector?

[6] The food industry agribusiness and non-agribusiness subsectors are defined in the conceptual framework in Chapter 4.

1.4 Structure of the dissertation

To address the above research questions, this dissertation is organised in a standard manuscript format. Chapter 2 establishes our definition of a small business and provides a brief overview of the small businesses in Australia focusing on the food industry and its growing role in the Australian economy. It also contains discussion of the relevant current government initiatives, agendas and policies on innovation and productivity growth. Chapter 3 presents a review of the relevant theoretical and empirical literature that forms the basis for the hypotheses and conceptual framework contained in Chapter 4. The methodologies used in the empirical analyses are also formulated in the same chapter whereas Chapter 5 describes the ABS business microdata employed in the investigation of the food industry. Chapter 5 also includes data visualisation of the actual panels of sampled small food businesses.

Chapters 6, 7 and 8 present all the empirical findings and discussions that answer the first six research questions. Chapter 6 presents the empirical models and findings for evaluating the status and main drivers of innovation in small businesses in the food sector in Australia (i.e., addressing research questions 1 and 2). The dynamics of innovation dimensions and persistence (i.e., addressing research questions 3 and 4) are examined in Chapter 7. Empirical evidence is presented in Chapter 8 on the sustained business performance growth for innovation-active businesses as well as on the existing relationships between the identified key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses (i.e., addressing research questions 5 and 6).

Chapter 9 synthesises all the findings and offers policy implications. The chapter concludes with recommendations and potential areas for future research.

Chapter 2: Small Food Businesses in Australia

2.1 Introduction

Small businesses in the food and agribusiness industry have a significant role in the Australian economy in that they create jobs and business and service opportunities to regional economies. They are critical players in underpinning growth and innovation, and providing jobs for Australians (DIIS, 2015a). Currently, the national government has a strategic economic plan to help food businesses grow and create stronger employment growth (DIIS, 2017b). The government is committed to create an improved conditions for these businesses by: lifting competitiveness and productivity; providing advice and support through the various innovation and science programmes; providing R&D tax incentives; developing workplace skills; and building capabilities in trade and innovation. It is therefore important to examine the connection between innovation, productivity growth and the characteristics of small businesses in the Australian food industry, and to provide empirical evidence to support the government's agenda.

Section 2.2 presents the definition of small businesses and how the current study operationally uses it, followed by a discussion of the role of small businesses in the Australian economy in section 2.3. Section 2.4 describes the Australian food industry whereas section 2.5 provides a comprehensive assessment of the food and agribusiness growth sector, focusing on selected characteristics of innovating small businesses. The current government initiatives relating to innovation and productivity growth, as well as the challenges being faced by the small food businesses, are outlined in sections 2.6 and 2.7, respectively. The chapter concludes in section 2.8.

2.2 Definition of a small business

The concept of a *small business* is quite intuitive, but there is no single definition that is consistently used or agreed upon among OECD countries, national statistical agencies, academics and researchers. YourDictonary defines a small business as an independently owned and operated company that is limited in size and in revenue depending on the industry; where the owners or managers tend to have close control of operations, undertake principal decision making and contribute most of the operating capital (Small-business, 2018).

The OECD refers to a small business as one with 10–49 employees whereas a microbusiness has less than 10 employees (OECD, 2005b). Financial assets are also used by the OECD to define small enterprises, i.e., the turnover (or balance sheet) of small enterprises should not exceed 10 million *EUR* whereas that of microbusinesses should not exceed two million *EUR*. The same definition is being used by the member countries of the European Union (see European Commission (2016) for more details) as well as in the Eurostat Community Innovation Survey (CIS) where most innovation research studies in European countries are based. The United States (US) Census Bureau provides various business statistics and economic indicators using 12 business size categories (1–4, 5–9, 10–19, 20–49, etc.). The variety of business sizes in the US allows any organisation or researcher flexibility in defining small businesses according to their purpose, and it also varies by industry. Statistics Canada defines small enterprises size with operating revenue of less than CA$25 million, but, when using employment sizes, it follows the same categories as the US Census Bureau but with only eight size categories, ending with 500+ employees.

In Australia, a small business is defined differently by regulators, depending on the laws they administer. For example, the Australian Securities and Investment Commission (ASIC) regulates small proprietary companies having at least two of the following characteristics: an annual revenue of less than AU$25 million; fewer than 50 employees; or having gross assets of less than AU$12.5 million at the end of the financial year (ASIC, 2013). The Australian Taxation Office (ATO) defines a small business as an individual, partnership, company or trust having an aggregated annual turnover (excluding GST) of less than AU$2 million, whereas Fair Work Australia uses the definition of less than 15 employees. Despite these differences, many Australian regulators and academic researchers adopt the ABS definition of a business employing less than 20 staff because most statistics used in their regulation policy and analysis come from the ABS. In New Zealand, Statistics New Zealand defines a small business as a firm having between two and 20 rolling mean employment.[7]

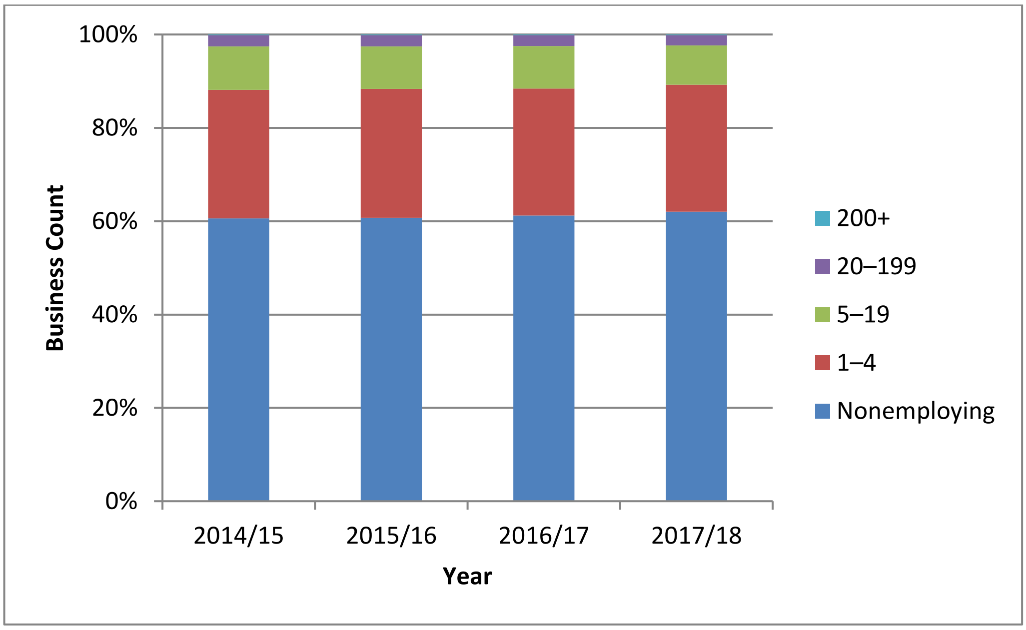
In this dissertation, and for all empirical applications in Chapters 6, 7 and 8, we employ the ABS definition of an actively trading food business with less than 20 employees as our working definition for small food businesses. Categories of these businesses include: nonemploying business–sole proprietorships without employees; microbusinesses (businesses employing

[7] Rolling mean employment is the twelve-month moving average of the monthly employment count, derived from employer monthly schedule data provided by New Zealand Inland Revenue (Statistics New Zealand, 2015).

fewer than five people), including nonemploying businesses; and small businesses (businesses employing five or more, but fewer than 20, people) (ABS, 2002). The details on how we actually derived the small business information from the ABS BLD CURF are discussed in Chapter 5. We caution the reader that when we use or refer to small business data and results/analysis coming from other sources and/or international literature or research works, the definition of small businesses in the current study may not be exactly the same, though the concept is similar.

2.3 Role of small businesses in the economy

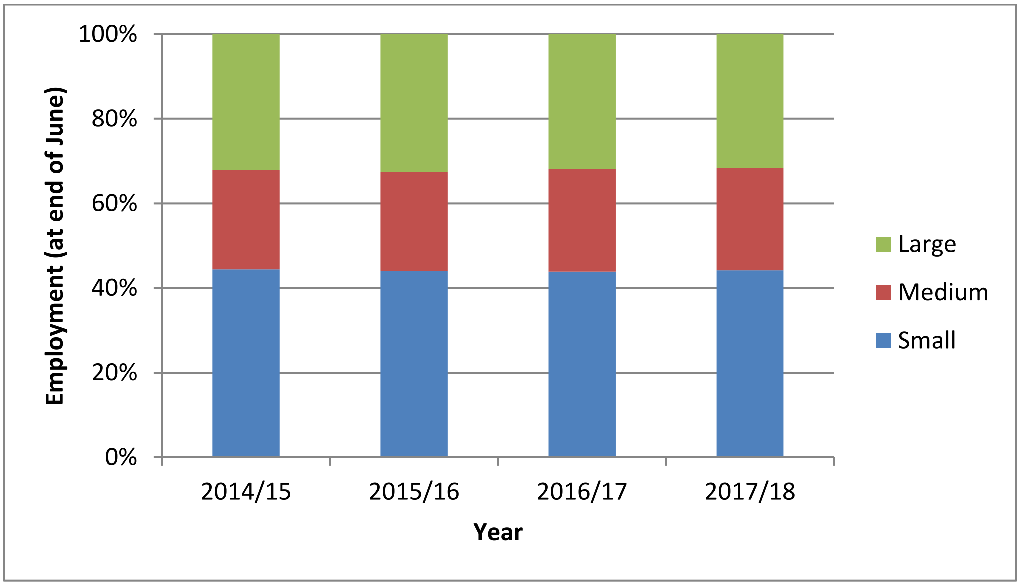
Small businesses play an important role in the Australian economy. They account for the majority of the Australian business counts (see Figure 2.1 below). The proportion of business counts by employment size in Australia has remained stable over the past decade, with nonemploying businesses accounting for around 61 per cent of the total business counts, followed by microenterprises (1–4 employees), representing around 27 per cent of total business counts, and businesses with 5–19 employees, representing around nine per cent of the total business counts. Medium and larger businesses also play an important role, given their comparative advantages through economies of scale. They are more likely to innovate and export and attract more skilled workers.



Source: ABS (2019a)

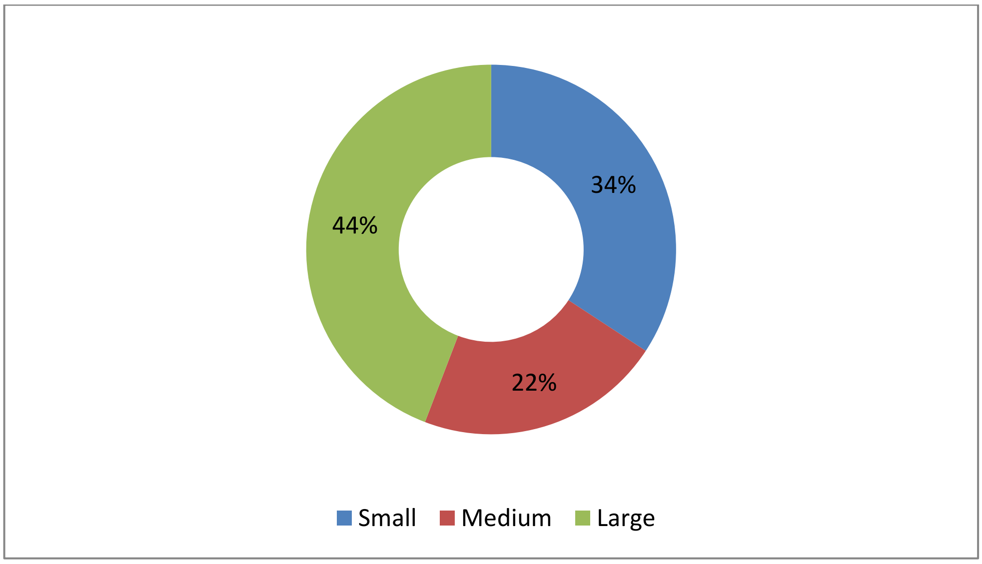
Figure 2.1. Australian business counts, by employment size, 2014/15–2017/18.

Small businesses contribute significantly to the Australian economy, accounting for nearly one-half of the private sector industry employment (see Figure 2.2) and contributing approximately one-third of private sector industry value added (see Figure 2.3) in 2017/18.



Source: ABS (2019a)

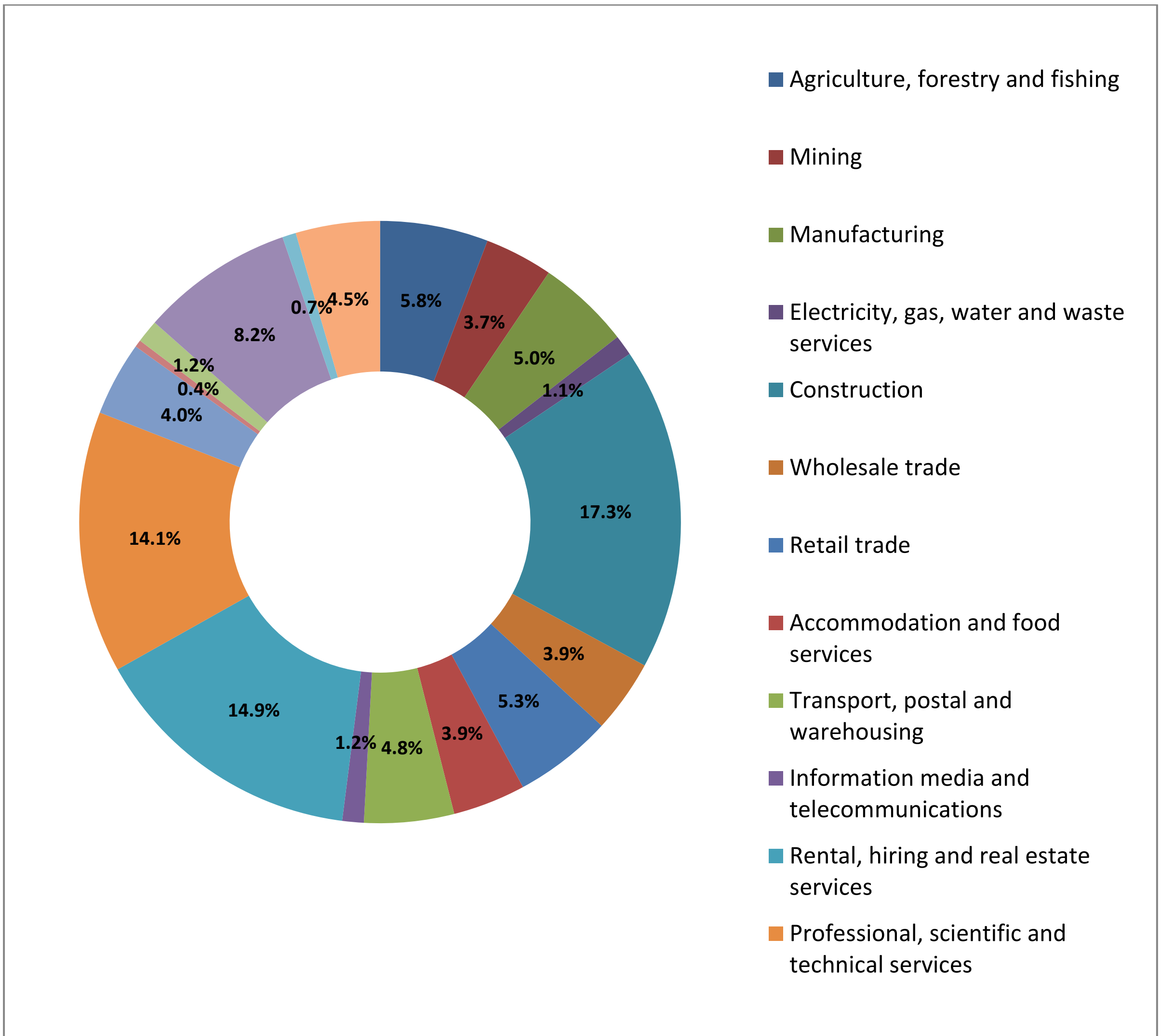
Figure 2.2. Business employment, by size classes, 2014/15–2017/18.



Source: ABS (2019a)

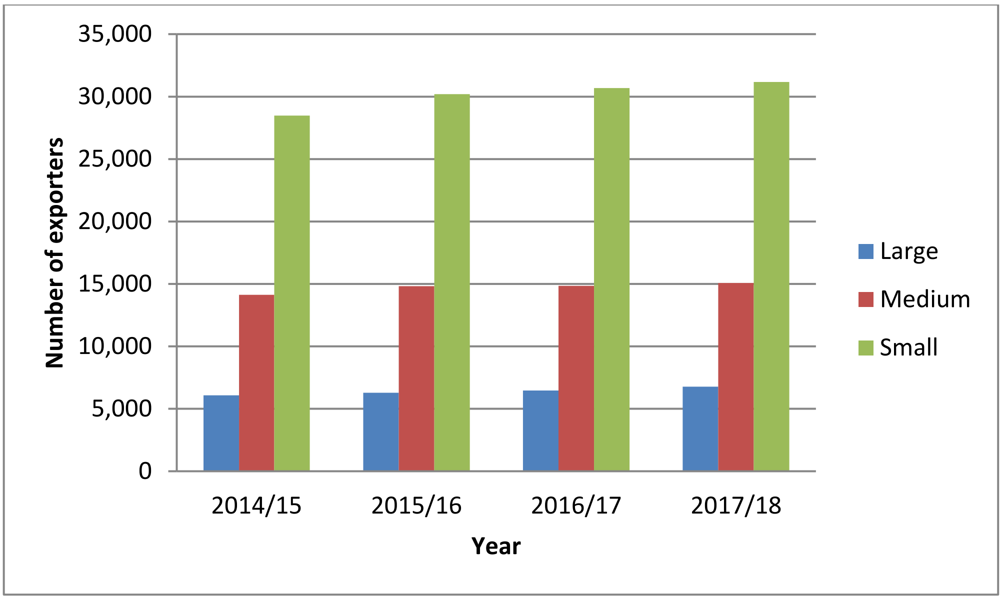
Figure 2.3. Private sector industry value added, by size classes, 2017/18.

The contributions of small, medium and large businesses vary from industry to industry, and, in some industries, businesses may tend to have large turnovers but not employ any staff. Agriculture, forestry and fishing, construction, accommodation and food services and rental hiring and real estate services are the industries dominated by small businesses (ABS, 2019b). However, the top three industry sectors where small businesses contribute significantly in terms of industry value added (see ABS (2019a) for the actual values in AU$) are: construction (17.3 per cent); rental, hiring and real estate services (14.9 per cent); and professional, scientific and technical services (14.1 per cent). The agriculture, forestry and fishing industry contributes around 5.8 per cent. These can be seen from Figure 2.4 below.



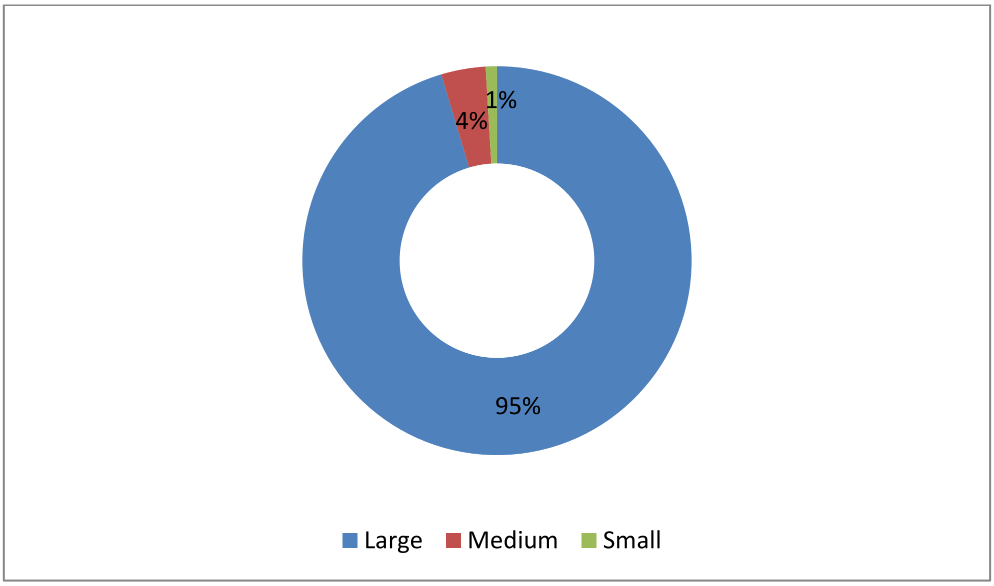
Source: ABS (2019a)

Figure 2.4. Small businesses industry value added, by industry division, 2017/18.



Source: ABS (2019c)

Figure 2.5. Number of goods exporters, by size classes, 2014/15–2017/18.



Source: ABS (2019c)

Figure 2.6. Mean value of goods exports (% to total), by size classes, 2014/15–2017/18.

With regard to export contribution, Figure 2.5 shows that 31,177 small businesses exported goods in 2017/18 (up by 1.6 per cent from the previous year).[8] This represents 59.0 per cent of

[8] The ABS defines an exporter as an Australian resident owner of exported goods where the value of export consignments is not less than AU$2,000 and export statistics are compiled from merchandise trade statistics (ABS, 2019c).

all businesses exporting goods (still an increase from 58.5 per cent reported in 2014/15). Although the number of small business goods exporters increased, their economic contribution, in terms of value of goods exported, was only about one per cent, on average, between 2014 and 2017 (see Figure 2.6).

2.4 The Australian food industry

The food industry is integral to Australia's economic and social prosperity, accounting for around 20 per cent of domestic manufacturing sales and service income (Department of Agriculture and Water Resources [DAWR], 2016). The majority of food businesses are Australian owned (ABS, 2015f); hence, most of the food sold in Australia is grown and supplied by Australian farmers. More than 90 per cent of the fresh fruit and vegetables, meat, milk and eggs sold in Australian supermarkets are domestically produced (DAWR, 2016).

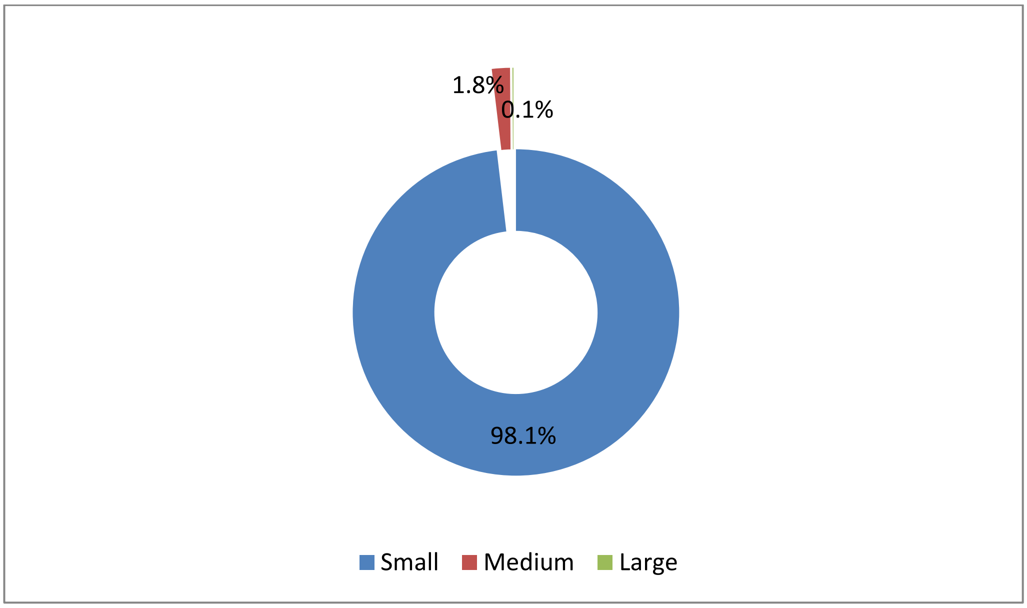
The latest edition of the Australian Food Statistics (Department of Agriculture [DA], 2014) provides a statistical overview of the major aspects of the Australian food industry[9] as of 2012/13. The value of farm and fishing food production is about AU$42.8 billion (a 10.3 per cent increase from 2007/08). The industry value added share of food, beverages and tobacco processing was around 1.6 per cent of the total GDP in that year whereas the contribution of the food and liquor retailing is about AU$141.4 billion. The Australian food and beverage industry in 2012/13 benefited from favourable production conditions in most of Australia and strong world demand for food. The value of food exports increased by 35.9 per cent from 2007/08 to 2012/13 (i.e., AU$31.8 billion from AU$23.4 billion). The food industry in Australia–ranging from farm production to food services–employed around 1.6 million persons in 2012/13, around 14.0 per cent of total employment in Australia. It is an important growing industry in the Australian economy.

Chaustowski and Dolman (2016) profiled the Australian food and agribusiness sector[10] and reported that the sector employed around 552,000 employees in 2015/16 (a decline of 1.1 per cent since 2014/15). Sadly, an average annual decline of 1.2 per cent since 2010/11 is also evident from the report. The two highest subsector employments in 2015/16 are recorded for agriculture (251,200) and food product manufacturing (206,700). On the positive side, the

[9] The scope and coverage of the food industry here is different from the current study.

[10] The food and agribusiness sector is defined in ABS (2015e, 2015f). The specific lists of the four-digit ANZSIC industries and subdivisions are contained in Appendix A. These four-digit ANZSIC are identified following the DIIS' conceptual definition of the food and agribusiness growth sector.

gross value added for the food and agribusiness sector (amounting to AU$53.9 billion in 2014/15) increased, on average, by 1.0 per cent per annum from 2010/11 to 2014/15. This also translated to a five-year annual average change of 2.4 per cent in labour productivity (which is around AU$55.1 billion per employee).



Source: Chaustowski and Dolman (2016)

Figure 2.7. Business counts for food and agribusiness sector, by size classes, 2014/15.

Figure 2.7 shows that, as of June 2015, the majority of actively trading businesses in the food and agribusiness sector were small food businesses (i.e., 98.1 per cent of the total business counts). In terms of contribution to exports, the value of the sector's exports grew by 6.1 per cent per annum over the 10 years to December 2015. The five years from 2010 saw both a positive growth rate in food and agribusiness exports and an increase in its share of the economy's total exports. This trend of increasing exports is similar to what is happening in all small businesses in Australia, as shown in the previous section. The sector's imports grew, on average, by 8.9 per cent per annum over the 10 years to December 2015.

2.5 A profile of the food and agribusiness growth sector

As part of the IICA, a number of sectors have been identified as having potential to contribute to the future economic growth in Australia. These industry sectors are referred to as *growth* *sectors*[11] to align with the DIIS' policy and programme initiatives. One of the growth sectors being prioritised for potential growth and competitive strength is the food and agribusiness sector.[12] The DIIS, in collaboration with the ABS, funded an additional sample in the 2013/14 BCS to collect a range of characteristics and indicators that would provide a greater understanding of the innovation status as well as the performance of the businesses in this sector.

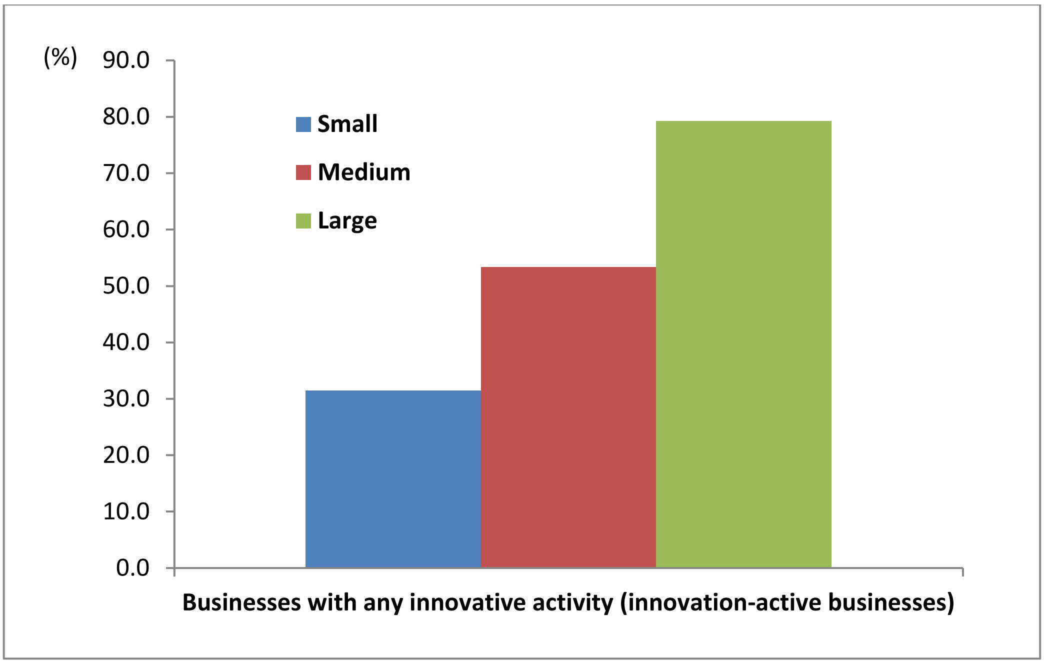
In this section, we present selected summary statistics on the small businesses derived by the author from the downloaded ABS data in ABS (2015d, 2015f). The summary statistics cover innovation and its dimension, collaborative arrangements, business use of information and communication technology (ICT), skills and shortages, barriers to innovation and some performance measures. A comparison between the large, medium and small businesses, as well as innovators versus noninnovators in the food and agribusiness sector, is also provided.

2.5.1 Small food businesses innovation

Nearly one third of all businesses in the food and agribusiness sector were innovation-active during 2013/14 (32.7 per cent). The percentage of businesses with innovative activity was similar for the small businesses (31.4 per cent) but higher for medium and large businesses (53.3 and 79.2 per cent, respectively) (see Figure 2.8).

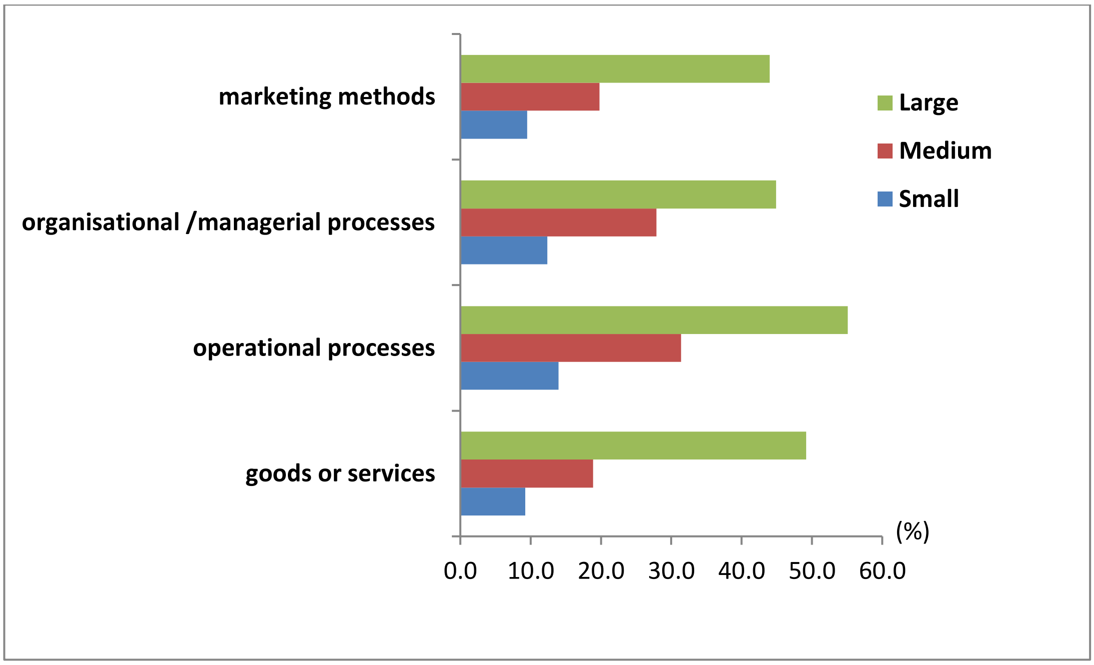
A relatively large number of food and agribusiness businesses introduced new or significantly improved operational processes. This is evident in Figure 2.9 and applies for all the business sizes. For both small and medium businesses, marketing methods and goods or services exhibited almost similar numbers of innovative-active firms. The case was different for large food businesses where goods or services innovation received the second highest number of innovators.

[11] See DIIS (2018c) for more details about the six industry growth centres initiative.
[12] The food and agribusiness growth sector includes food-related production, food processing and the major inputs into these economic activities but excludes the wholesale or retail sale of these goods. This is the same sector used by Chaustowski and Dolman (2016) (see Footnote 3).



Source: ABS (2015d)

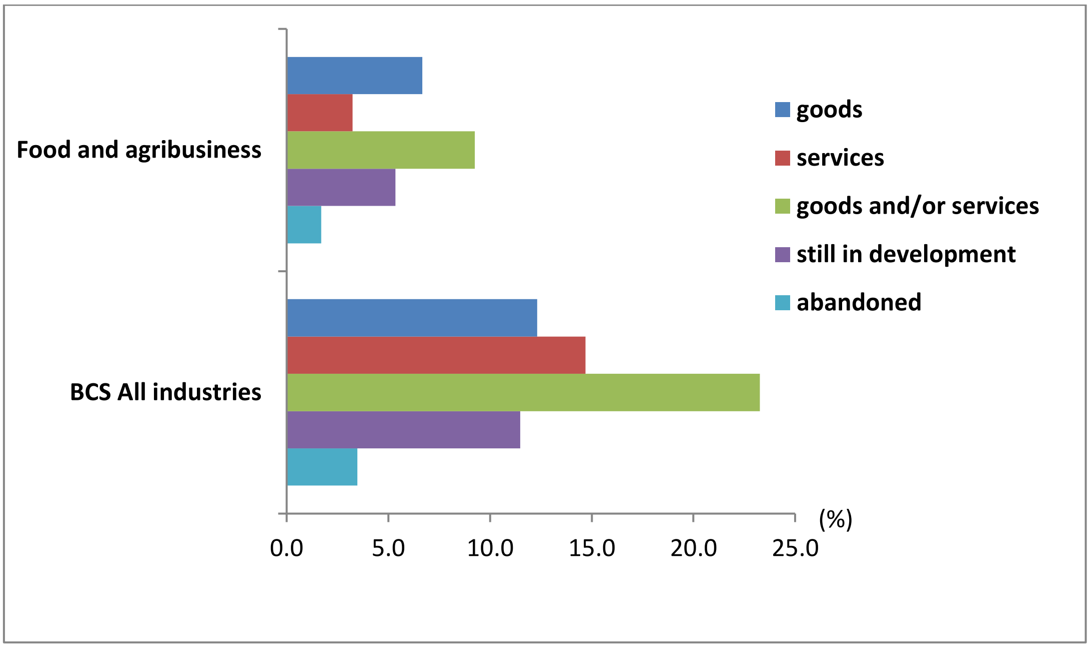
Figure 2.8. Innovation-active businesses in the food and agribusiness sector, by size classes, 2013/14.



Source: ABS (2015d)

Figure 2.9. Innovation-active businesses in the food and agribusiness sector, by type of innovation, by size classes, 2013/14.

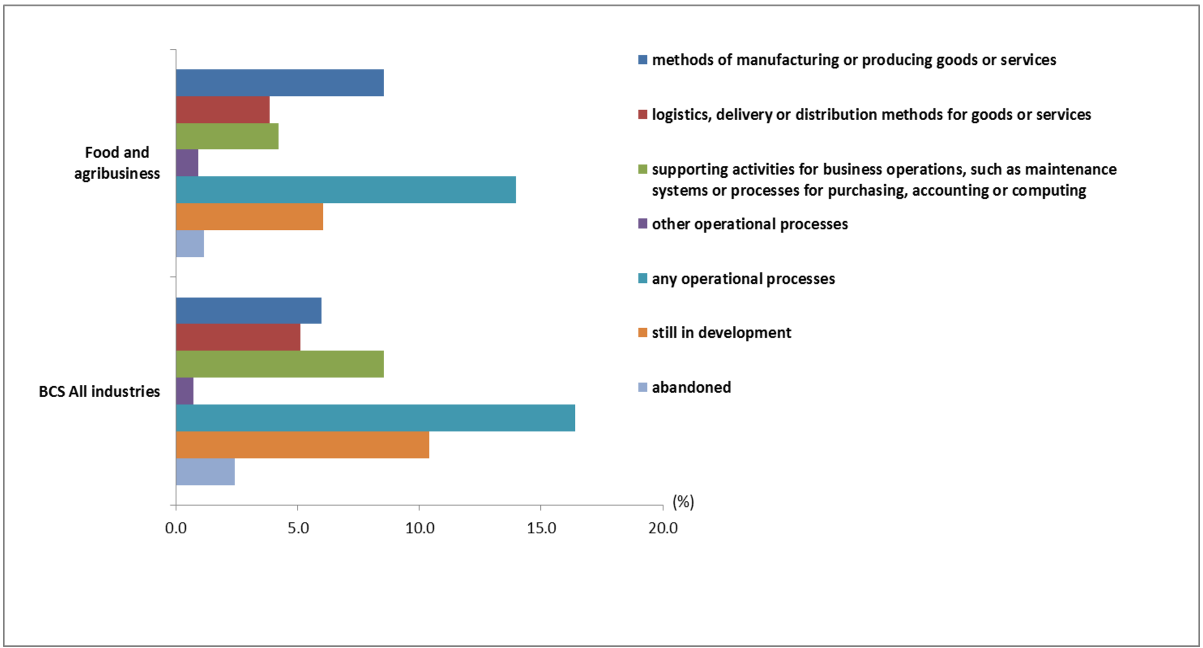
We now look more closely at the rate of innovation in each type of innovative activity focusing on the small businesses. The summary statistics for the BCS all industries are also presented for comparison purposes, particularly to assess how the food and agribusiness businesses are doing relative to all businesses in the Australian economy. Firstly, on product innovation, the proportion of small businesses engaging in goods and/or services innovation in the food and agribusiness sector was lower than all BCS small businesses during the year 2013/14. Goods innovation rate for small food businesses was double that of services innovation and there was around 5.5 per cent of product innovation still in development (see Figure 2.10).



Source: Derived by author from ABS (2015f)

Figure 2.10. Goods and services innovation in small businesses, by sector group, 2013/14.

Figure 2.11 shows that the overall behaviour of engaging in any operational process innovation was similar for small businesses in the food and agribusiness sector and the BCS all industries during the year 2013/14. Nearly one in ten small food and agribusiness businesses introduced operational processes innovation for new methods of manufacturing or producing goods or services (8.6 percent). This was higher by more than two percentage points than all BCS small businesses. On the other hand, one in 12 small food and agribusiness businesses implemented processes innovation for supporting activities for business operations, such as maintenance systems or processes for purchasing, accounting or computing (4.2 per cent) and for logistics, delivery or distribution methods for products (3.8 per cent).

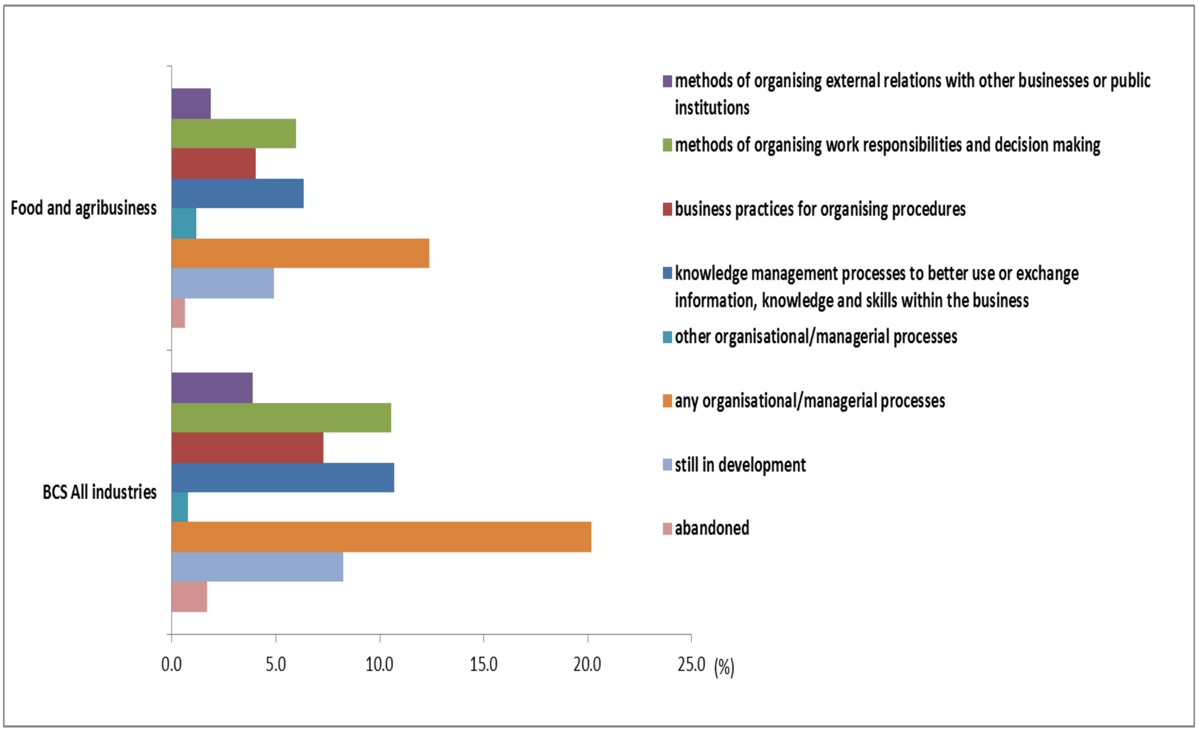


Source: Derived by author from ABS (2015f)

Figure 2.11. Operational processes innovation in small businesses, by sector group, 2013/14.

During the year 2013/14, new or significantly improved organisational/managerial processes were introduced by slightly more than one in 10 small food and agribusiness businesses. This proportion is nearly one-half of what was reported for small businesses in all Australian industries.The most commonly introduced and implemented processes were knowledge management processes to better use or exchange information, knowledge and skills within the businesses, and methods for organising work responsibilities and decision making (6.3 and 6.0 per cent, respectively). The process least likely to be introduced by the small food businesses was methods for organising external relations with other businesses or public institutions, at 1.9 per cent. The same organisational/managerial innovation behaviours can be seen in the case of small businesses in all Australian industries (see Figure 2.12).

As at 30 June 2014, just like in the operational process innovation, almost one in 10 small food and agribusiness businesses introduced at least one type of new or significantly improved marketing method (9.5 per cent), with the most common being media or techniques for product promotion (5.2 per cent) (see Figure 2.12). This proportion is nearly one-third of what was reported for small businesses in all Australian industries.

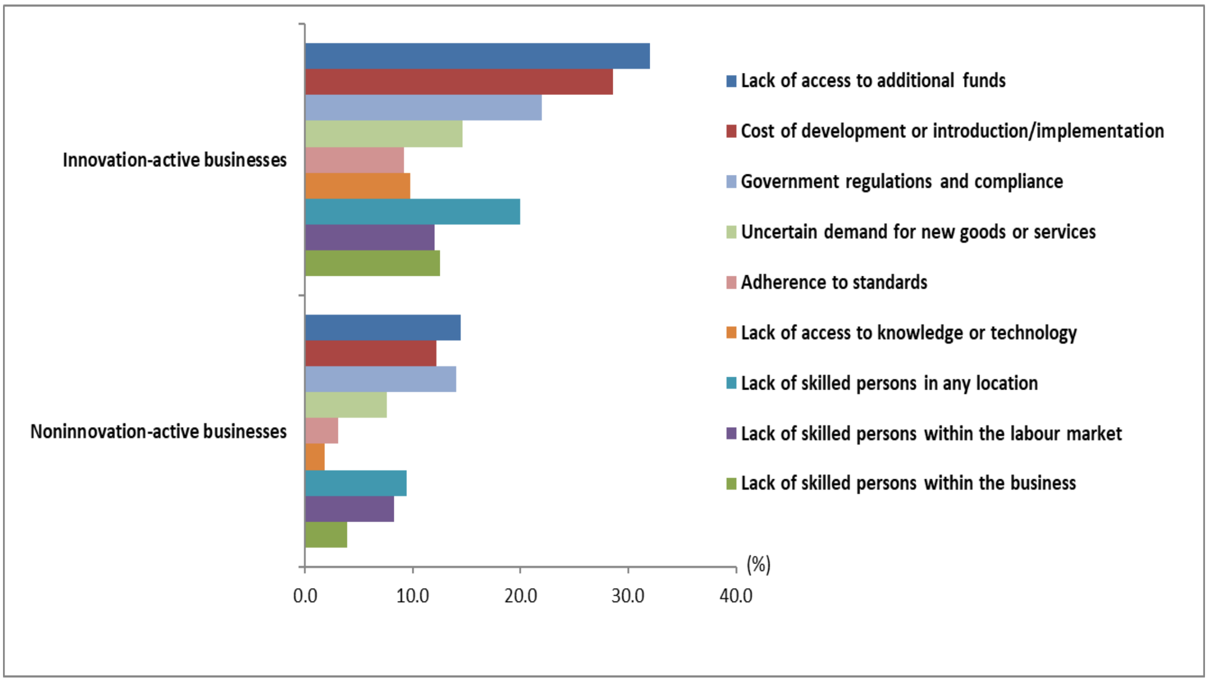


Source: Derived by author from ABS (2015f)

Figure 2.12. Organisational and/or managerial process innovations in small businesses, by sector group, 2013/14.

The development, introduction or implementation of new or significantly improved goods, services, processes or methods are seen in the small businesses of the food and agribusinesses sector; however, the reported proportions are still lower than the all industry results. Although there are underlying reasons that continuously encourage them to perform innovation, there are also barriers that we need to look at that are important for this study. These are barriers that significantly hampered the development or introduction of any type of innovation. Figure 2.13 reveals the factors perceived by the innovating and noninnovating small food and agribusiness businesses that have affected their ability to undertake or continually perform innovation.

In 2014, the small food and agribusiness innovation-active businesses were more likely to report facing any of the identified barriers to innovation than noninnovation-active businesses. Among small food and agribusiness innovators, lack of access to additional funds was the most frequently identified barrier to innovative activity (32.0 per cent), followed by cost of development or introduction or implementation of innovation (28.6 per cent) and government regulations and compliance (22.0 per cent). Lack of skilled persons in any location was also prevalent at 20.0 per cent for innovation-active small food and agribusiness businesses. For noninnovators, lack of access to additional funds and government regulations and compliance were the two most likely barriers (both approximately 14.0 per cent).



Source: Derived by author from ABS (2015f)

Figure 2.13. Barriers to innovation in small food and agribusiness businesses, by innovation status, 2013/14.

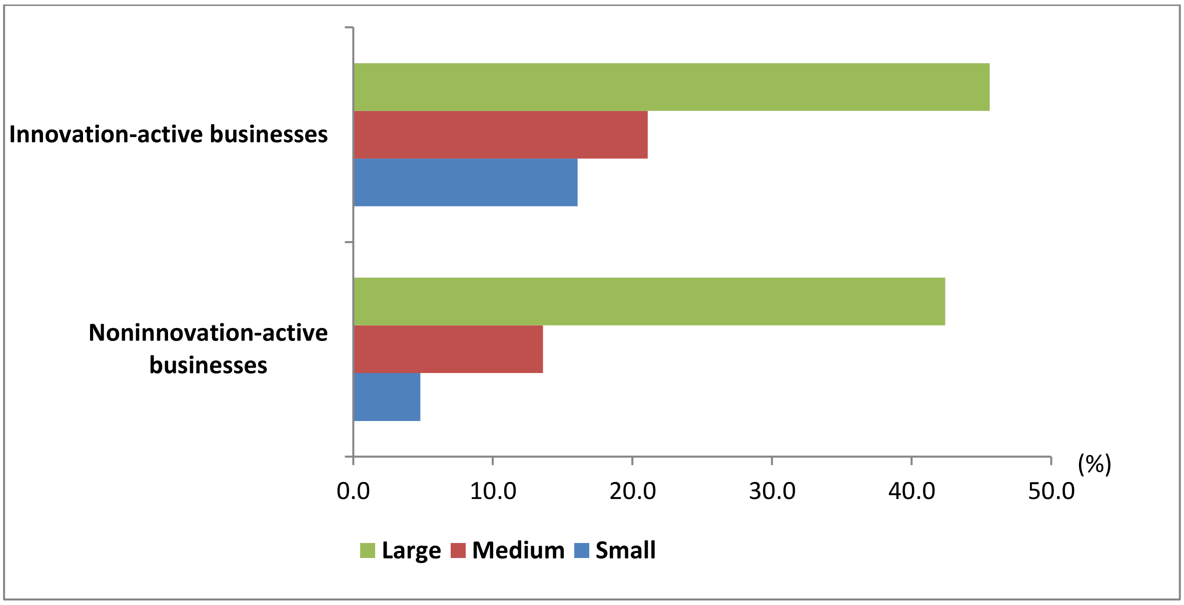
2.5.2 Business collaboration

Statistics on collaboration[13] provide insight into the degree of linkages between businesses, particularly innovation-active businesses and other organisations. Nearly half of the large businesses—innovating or noninnovating—in the food and agribusiness sector had at least one type of collaborative arrangement during the year 2013/14. The likelihood of an innovation-active business having any collaborative arrangements increased with each successive employment size, from 16.1 per cent of small businesses, 21.1 per cent of medium businesses to 45.6 per cent for large businesses (see Figure 2.14).

Collaboration for the purpose of innovation is more likely among large businesses in the food and agribusiness sector compared with all large businesses from the BCS results (42.0 per cent compared with 25.2 per cent). But the likelihoods of collaboration for innovation among

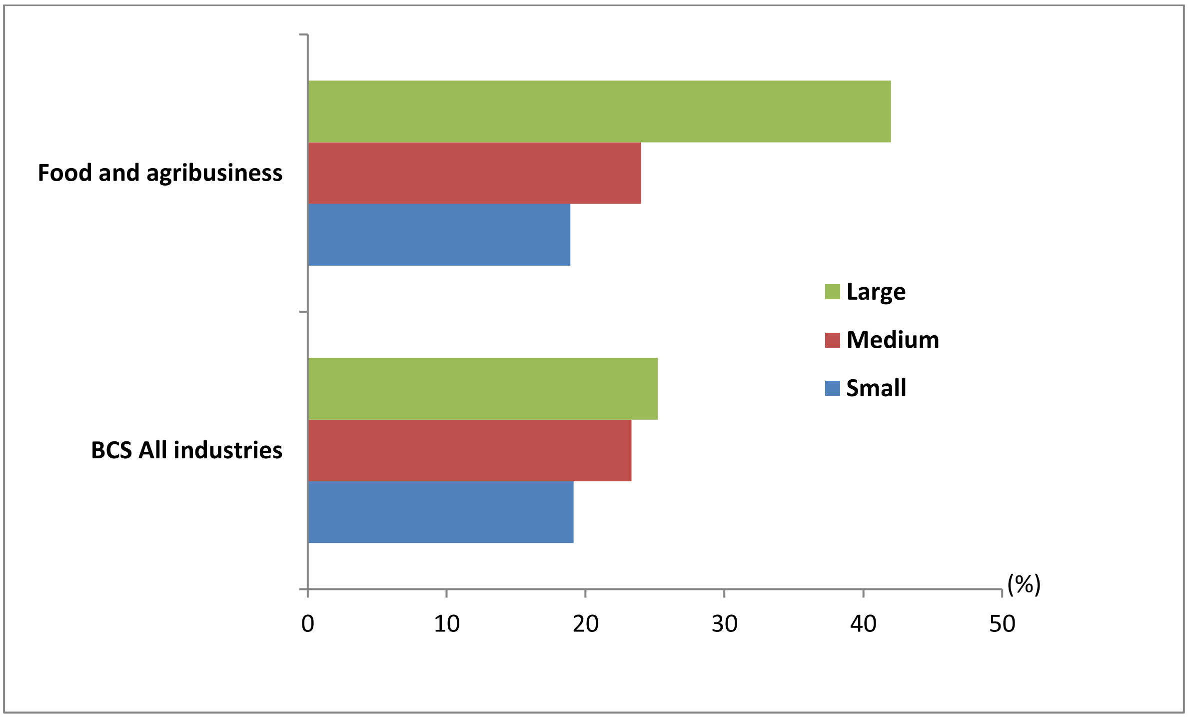
[13] The BCS defined collaboration as the arrangement where businesses work together for mutual benefit, including some sharing of technical and commercial risk. The BCS collects information from all businesses on the type of collaborative arrangement businesses were involved in; and for innovation-active businesses, whether that collaboration was for innovation purposes or not (ABS, 2015a).

small and medium businesses were equivalent for the two sectoral groups. These are clearly exhibited in Figure 2.15.



Source: Derived by author from ABS (2015f)

Figure 2.14. Collaborative arrangements in food and agribusiness businesses, by innovation status, by size classes, 2013/14.

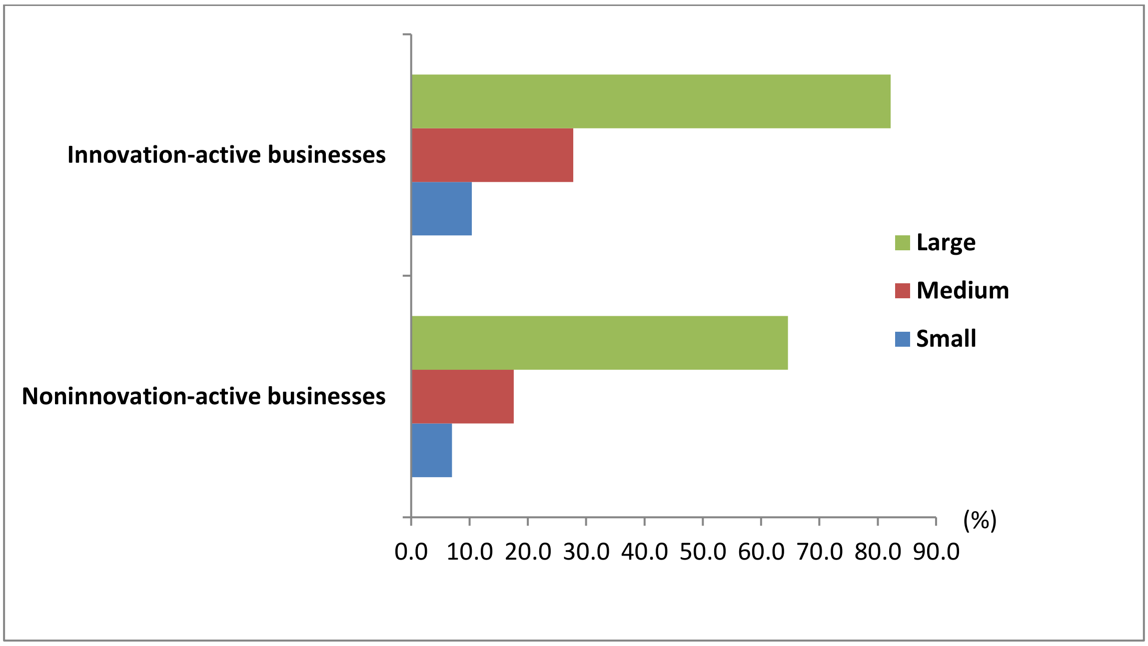


Source: Derived by author from ABS (2015f)

Figure 2.15. Collaboration for the purpose of innovation in food and agribusiness, innovation-active businesses, by sector group, by size classes, 2013/14.

2.5.3 Exporting capability for food businesses

The BCS also asked the businesses if they have received income from exporting goods and/or services. Results presented in Figure 2.16 indicate that 82.2 per cent of large businesses engaging in any form of innovation activity received income from exporting products whereas only one in 10 small businesses received income from exports. Though smaller, the likelihood indicators behave similarly for the noninnovation-active small food businesses.



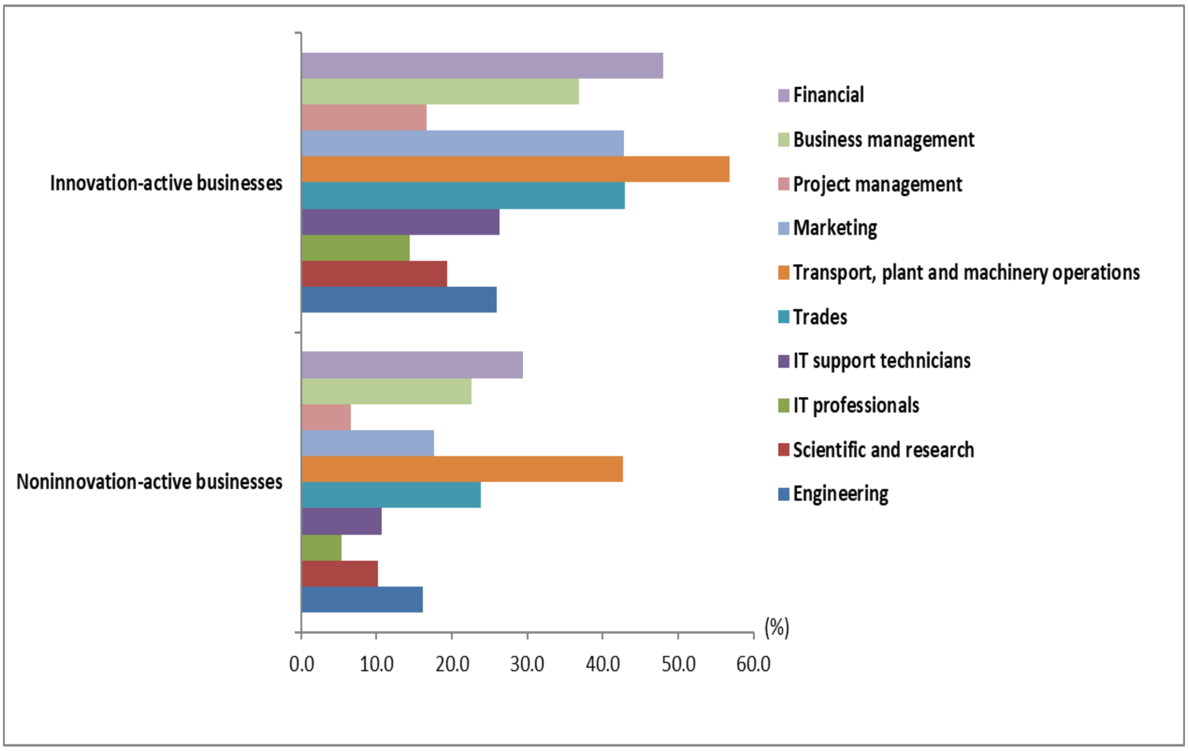
Source: Derived by author from ABS (2015f)

Figure 2.16. Exporting indicator in food and agribusiness, by innovation status, by size classes, 2013/14.

2.5.4 Small Businesses Skills

All food and agribusiness businesses were also asked to indicate the types of skills they used in undertaking core business activities during the year 2013/14. Businesses can choose to identify more than one type of skill in the list provided in the BCS but were not required to provide any other skills not on the list. They were also asked if there was a shortage or deficiency in types of skills needed to undertake core business activities, irrespective of whether they had been able to address the shortage or deficiency.

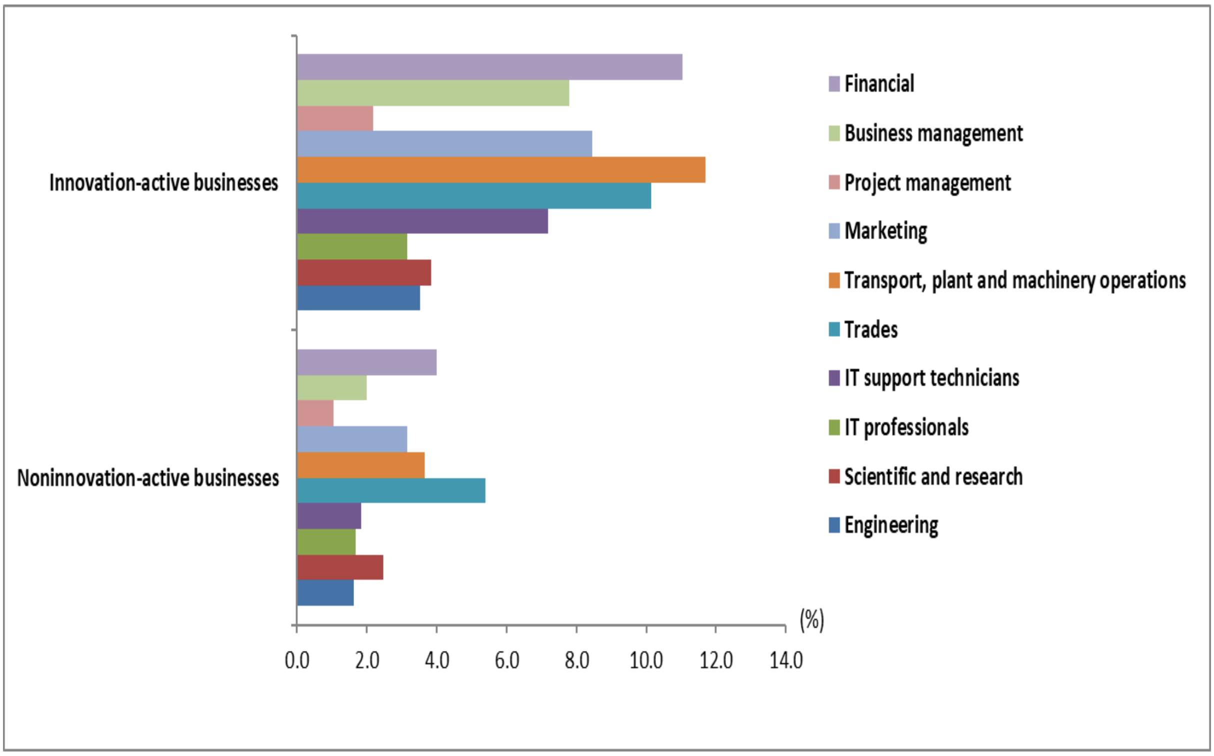
Overall, transport, plant and machinery operations skills topped the list for innovation-active small businesses in the food and agribusiness sector with 56.8 per cent. Financial skills (48.0 per cent) were also more likely to be used to undertake core business activities for both innovators and noninnovators. Trades (43.0 per cent), marketing (42.9 per cent) and business management (36.9 per cent) skills were also commonly used whereas IT professional skills (14.4 percent) were less used by the small businesses in the sector (see Figure 2.17).



Source: Derived by author from ABS (2015f)

Figure 2.17. Skills used in undertaking core business activities by small businesses in the food and agribusiness sector, by innovation status, 2013/14.

Figure 2.18 presents the skills shortage or deficiency in undertaking core business activities during the year 2013/14. For small food and agribusiness businesses, the three most common types of skill shortage or deficiency were transport, plant and machinery operational skills (11.7 per cent), trades skills (10.1 per cent) and financial skills (11.0 per cent). These were also the top three skills that the food sector most commonly used in their activities and operations. From the graph, we see that innovation-active small food and agribusiness businesses experienced more skill shortages in all the types of skills than noninnovation-active businesses.



Source: Derived by author from ABS (2015f)

Figure 2.18. Skills shortage in undertaking core business activities by small businesses in the food and agribusiness sector, by innovation status, 2013/14.

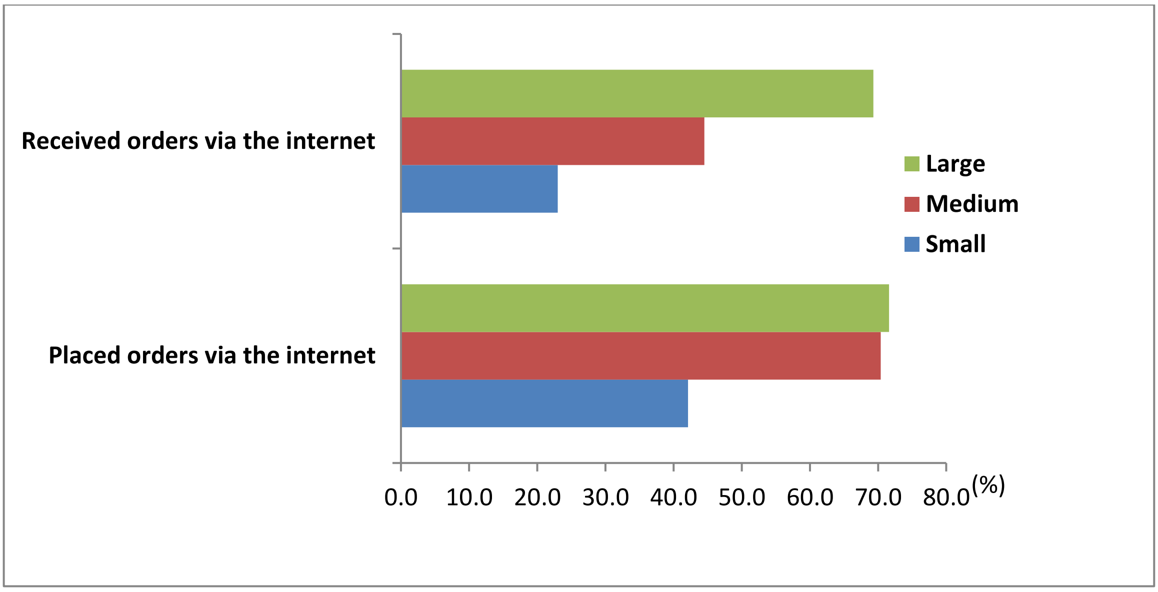
2.5.5 Business use of information technology

Another key indicator about the business use of information technology, the Internet commerce (i.e., the placing and receiving of orders via the Internet) is compiled for the food and agribusiness sector. The ABS defines an order via the Internet as a transaction where the commitment to purchase goods or services is made via the Internet (ABS, 2015c). The commitment[14] to purchase is the agreement to purchase whether or not the payment is made via the Internet.

During the year 2013/14, results in Figure 2.19 show that over half of the large and medium food and agribusiness businesses placed orders via the Internet (71.6 and 70.4 per cent, respectively) with 42.1 per cent in small businesses. By comparison, the proportion of businesses that received orders via the Internet during 2013/14 was also over half for larger businesses (69.3 per cent) but lower for small businesses (23.0 per cent).

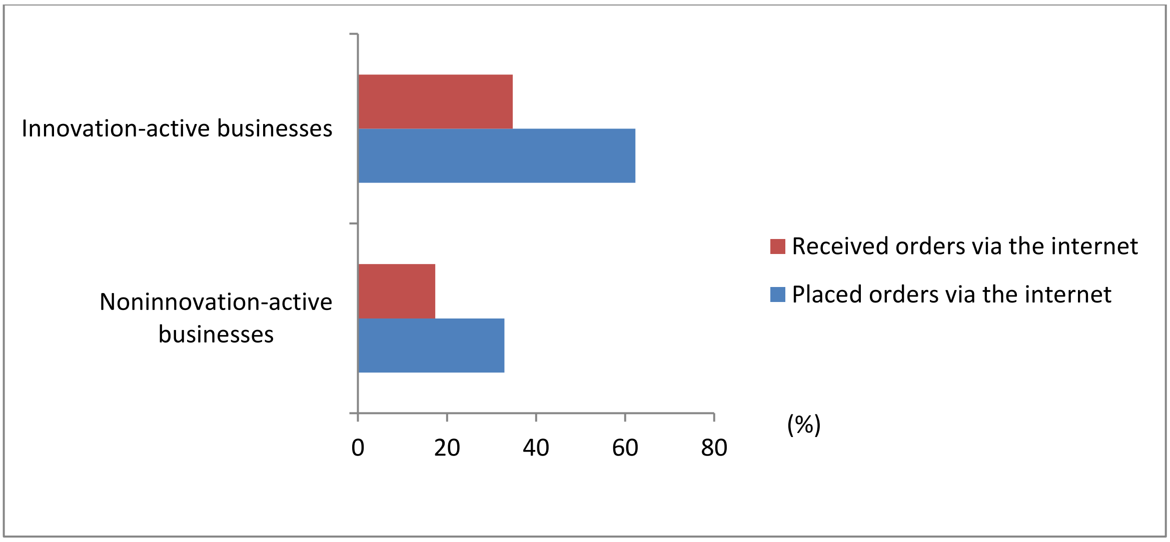
[14] The scope of receiving orders is not limited to orders solely received from Australian households, businesses or government but also includes orders received from overseas customers.

For innovation-active small food and agribusiness businesses in Figure 2.20, 62.3 per cent of orders were placed via the Internet, higher than for all small businesses. Noninnovators were not really much engaging in Internet commerce.



Source: Derived by author from ABS (2015f)

Figure 2.19. Internet commerce in the food and agribusiness sector, by size classes, 2013/14.

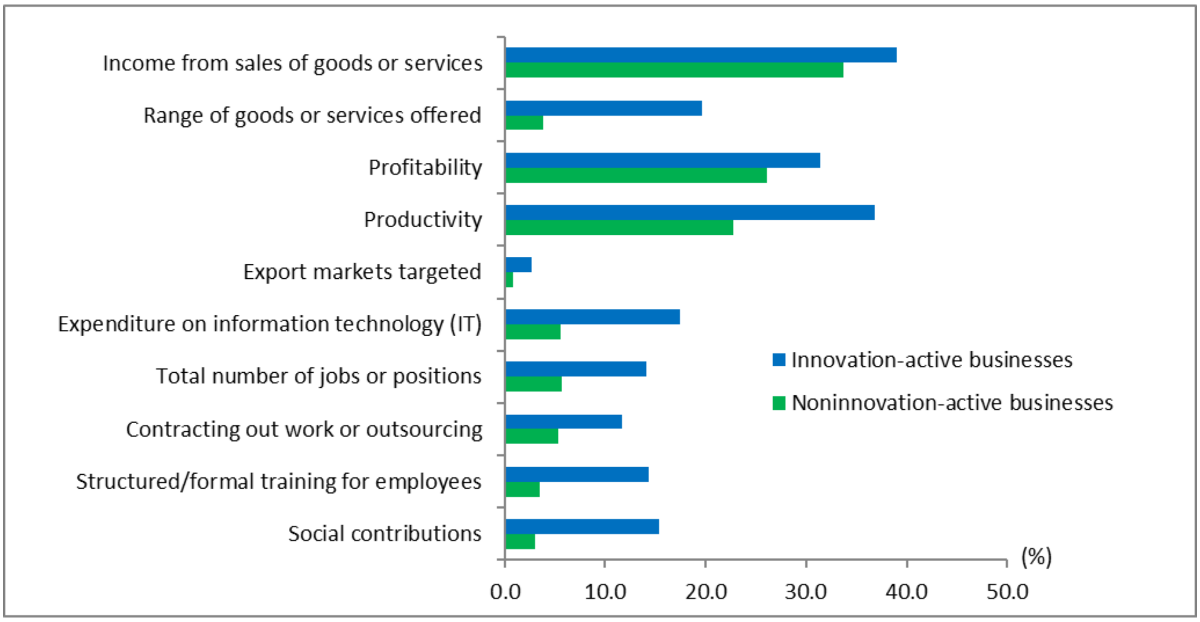


Source: Derived by author from ABS (2015f)

Figure 2.20. Internet commerce in the food and agribusiness sector, small business by innovation status, 2013/14.

2.5.6 Business performance and barriers

Detailed statistics on business performance and barriers to general performance were also collected in the 2013/14 BCS. Businesses were asked to assess the changes in various business performance indicators and activities (i.e., whether they decreased, stayed the same, or increased compared with the previous year). Businesses were also asked if any factor significantly hampered[15] them in their general business activities or performance during the year 2013/14. The increases in small business performance indicators from the previous year in the food and agribusiness sector are summarised in Figure 2.21.



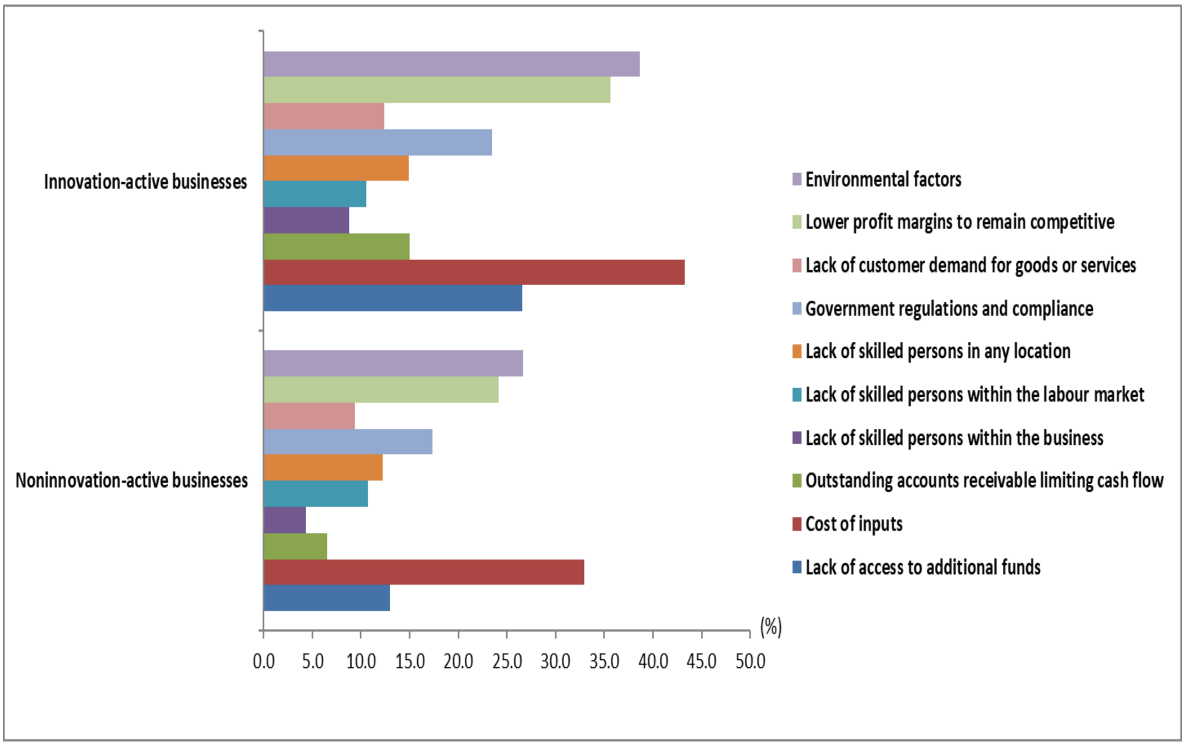
Source: Derived by author from ABS (2015f)

Figure 2.21. Increase in small business performance or activity from the previous year in the food and agribusiness sector, by innovation status, 2013/14.

In 2013/14, for each of the performance indicators, innovation-active small food and agribusiness businesses were more likely to have had an increase in an indicator or activity from the previous year than noninnovation-active businesses. For example, profitability in the innovation-active businesses increased by 5.3 per cent higher than noninnovators and the

[15] It is noted that businesses were not provided with a definition of what constituted a significant level of hampering and were not asked to rank barriers in order of significance (ABS, 2015a).

growth nearly tripled in terms of productivity with a 14.1 per cent difference between the two groups. An increase in income from sales of goods or services compared with the previous year was reported by 39.1 per cent of innovation-active businesses, which was 5.4 per cent higher than the proportion of noninnovating businesses. One in five innovating small food businesses (19.6 per cent) reported an increase in the diversity of products or services being offered by them compared with the previous year. Similarly, this was higher than the increase for noninnovators (3.9 per cent). Moreover, innovation-active businesses were more than twice as likely to increase in export markets targeted (2.7 percent), expenditure on information technology (17.4 per cent), total number of jobs or positions (14.1 per cent) and outsourcing (11.7 per cent) than noninnovation-active businesses (0.9, 5.6, 5.7 and 5.3 per cent, respectively).



Source: Derived by author from ABS (2015f)

Figure 2.22. Barriers to general business activities or performance in small food and agribusiness businesses, by innovation status, 2013/14.

Figure 2.22 presents the factors that significantly hampered small food and agribusiness businesses in their general business activities or performance during the year 2013/14. The three most common barriers for innovative-active businesses were cost of inputs (43.3 per cent), environmental factors (38.7 per cent) and lower profit margins to remain competitive

(35.6 per cent). The results were similar for noninnovating small food and agribusiness businesses.

2.6 Government initiatives relating to innovation and small businesses

The Australian Government's vision is for an agile economy, capitalising on Australia's commercial and scientific strengths, and central to this vision is the need for strong, self-reliant and innovative businesses. The DIIS contributes to this vision by facilitating the performance of globally competitive industries that are important contributors to the nation's economic growth and productivity. The programmes include: supporting businesses, big and small, to collaborate and engage with scientists and researchers and other institutions (both domestic and international); improving workforce skills and capabilities; supporting regional businesses to innovate, expand and invest in new technology; and promoting the growth of internationally competitive industries (DIIS, 2018d).

Innovation is the core driver of business competitiveness and productivity. It supports economic growth, exports and job creation (DIIS, 2015a). Counting on small businesses to play a significant role as a driver of Australia's economy, underpinning growth and innovation, and providing employment for millions of Australians, the government is providing economic plans to help them grow and become more competitive. In this section, we examine more closely the current government programmes and initiatives to drive small businesses to innovate, grow, and create more jobs for the future.

2.6.1 The national innovation and science agenda

On 7th December 2015, the Australian Government launched the *National Innovation and Science Agenda (NISA)* (DIIS, 2015b). The agenda is a comprehensive suite of initiatives to enable Australia to seize future prosperity by embracing new ideas through innovation and science. The NISA focuses on four key pillars:

- *Culture and capital:* backing Australian entrepreneurs by opening new sources of finance, embracing risk, taking on innovative ideas, and making more of our public research;
- *Collaboration:* increasing collaboration between industry and researchers to find solutions to real world problems and to create jobs and growth;
- *Talent and skills:* developing and attracting world-class talent for the jobs of the future; and

- *Government as an exemplar:* the Australian Government will lead by example; embracing innovation and agility in the way we do business.

Together, these pillars provide a framework for Australian innovation policy with initiatives worth AU$1.1 billion during the period, 2015/16 to 2019/20.

In delivering the NISA, various programmes are to be put in place that encourage investment in technological capability, collaboration between industry and researchers, and more innovation and entrepreneurship. In addition, the government supports strong STEM skills as one of the critical requirements for productivity and economic growth. When government supports small businesses to collaborate with scientists and researchers in universities and other institutions, they expect that it will contribute to: growth in the proportions of small firms engaging in innovative activity; increased investment in knowledge capital; and growth in the value-added of knowledge-intensive industries.

In relation to small businesses, the NISA builds on measures that the Australian Government had already put in place like: establishing regional growth centres; delivering tax cuts through the AU$5.0 billion small business and jobs package; delivering the small business entrepreneurs' programme to help small entrepreneurs get their businesses off the ground; reforming the Australian curriculum and putting priority on STEM subjects to secure skills needed by small businesses' future workforces; and backing up small businesses and startups to help them establish and grow—ensuring small businesses have access to the resources, knowledge and networks necessary to transform their ideas into globally competitive new businesses.

2.6.2 The industry innovation and competitiveness agenda

To increase the economic strength and competitiveness of Australia, the government also announced the IICA on 14th October 2014. It focuses on providing the right economic incentives to enable businesses, big and small, to grow. It contains immediate reforms to boost competitiveness, and a range of proposals for public consultation. Through the IICA, the government aims to achieve four goals:

- Industry policy that fosters innovation and entrepreneurship (e.g., key initiatives include establishing Industry Growth Centres to improve collaboration between industry and researchers, and the provision of tax incentives for R&D);
- A more skilled labour force (e.g., promoting STEM skills in schools and reforming vocational education and the training sector);

- Better economic infrastructure (e.g., recalibrating the National Broadband Network and providing good transport infrastructures); and
- To lower costs, have a more business-friendly environment with less regulation, lower taxes and more competitive markets (e.g., reducing the burden of taxation, and improving access to international markets) (DPMC, 2014).

The agenda is designed in such a way that, alongside successful large Australian businesses, small businesses will thrive, be innovation leaders and contribute strongly to national economic growth and competitiveness. It is hoped to strengthen management capabilities, improve the operating environment, reduce red tape and other impediments to entrepreneurship and foster an innovative culture for Australian small businesses.

As mentioned in Chapter 1, the IICA has identified the food and agribusiness sector as one of the industry growth sectors, thereby establishing the FIAL as the Australian food and agribusiness growth centre. Some inspiring stories from the small food businesses that FIAL has worked/connected with in 2018/19 are available in their website (FIAL, 2019b). To date, examples of FIAL funded innovations for the food and agribusiness businesses include:

- Agribots—digitised and automated machines that perform a wide range of agricultural tasks with high efficiency;
- Smart Packaging—redefined transformed packaging for food and beverage industry that: optimises supply chain process; reduces food wastage; improves product security, safety and quality; and provides better insights into customer behaviour;
- Miracle Fruit—both a sweetness enhancer and a potential taste-modifying product with the ability to change sour tastes into sweet ones;
- Cobots—robots that can perform tasks alongside humans;
- Digital Agriculture—digital transformation of agriculture through: precision farming; Internet of things sensors; and data-driven insights for farming;
- Future Protein—the use of insects as alternative sources of food; and
- 5G Networks—the use of fifth generation mobile network for technologies in monitoring, automating, and improving agri-food processes and operations.

2.6.3 The cooperative research centres program

The Cooperative Research Centres (CRC) Program supports industry-led collaborations between industry, researchers and the community to solve industry problems and improve competitiveness, productivity and sustainability of Australian industries (DIIS, 2018e). One of its major focuses is to encourage and facilitate small- and medium-enterprise participation in collaborative research. The CRC and industry growth centres like FIAL work together for increased and more productive food and agribusiness industry-research engagement. During 2015/16, the DIIS also supported the economic agenda of implementing changes to the CRC to include that of creating the new CRC-projects stream for short-term activities with a focus on involving small- and medium-sized enterprises (DIIS, 2018e).

2.7 Challenges facing small food businesses

In Australia, the total household food and non-alcoholic beverages weekly consumption expenditure has increased over time (e.g., 16.1 per cent from 2009/10 to 2015/16). It is one of the three expenditure categories that accounted for half of the weekly household spending on goods and services in 2015/16 (19.0 per cent) (ABS, 2017c). With the Australian population increasing, household food expenditure will definitely increase and, so, increase the demand for domestic food. The Department of Agriculture and Water Resources (DAWR) develops policies and provides services to improve the productivity, competitiveness and sustainability of food-related industries to ensure food security (DAWR, 2016).

Hogan (2017) established that a key driver of increased food demand in Australia, particularly in the millennium decade, was strong growth in income per person. It is also reported that the domestic market is important for Australia's food producers including farmers, food processors and food service providers. Food is a major expenditure category for households, such that the top three food expenditure categories are meals out and fast foods; meat, fish and seafood; and fruit and vegetables. The food industry supplies a broad range of food products and services in the Australian domestic markets. Hogan (2017) noted that there is on-going innovation by the food industry to increase efficiency and effectiveness of food supply as well as to enhance Australia's high level of food security. However, it is important to know whether this is currently happening in the case of small food businesses.

DAWR (2016) stated that examining the food industry sector and the business players therein is important for two major reasons:

- Food security— the adequate and reliable provision of food that is safe, nutritious and affordable. A key role of government is to ensure there is a high level of food security in Australia and, as a net exporter of food and food technology services, Australia also contributes significantly to global food security.
- Economic opportunities for regional farmers and other food providers—household food consumption in the domestic market accounts for around two-thirds of Australia's indicative food production (based on value), although food exports have been increasing recently.

There is a call for Australian businesses, particularly the small food businesses, to be innovative and productive to ensure food security and strong food exports. This is examined in the current study.

Anthill (2016), Australia’s first magazine dedicated to innovation and entrepreneurship,[16] in a recent article, identified the following top 10 challenges Australian small businesses were facing in 2016:

- Cashflow—the “make or break” for many small business owners–to stay on top of their finances to ensure they can operate successfully;
- Profitability—beyond just a stable operating budget–small businesses want to create lasting wealth, driven by profit, and digital innovation is key to increasing profitability;
- Productivity—small businesses are given challenges to stay effective, focussed and productive;
- Connections—small business owners need to network with other business owners to find more new opportunities and markets, and new customers;
- Costumers—costumers are the heart of a business, and small businesses need to attract, retain and maximise them;
- Regulation—how to diminish the burden of regulation;
- Processes—how can small businesses make the processes involved in running their businesses simpler, smoother and even enjoyable;
- Marketing—what marketing tools to use to help the businesses tell their story and grow their businesses;

[16] Anthill is one of Australia’s largest online communities for entrepreneurs, business builders and innovators.

- Time—small businesses should identify the essential, prioritise, focus and balance their work; and
- R&D—given all the above tasks, the solution is to innovate and collaborate.

A more recent article by Lindfield Partners (2018) reveals similar challenges that were facing small businesses in 2018. The article emphasised that small businesses need to implement realistic plans to introduce new services and products with better use of technology to become more profitable and productive. A challenge that is increasing in importance is making time to connect with new partners, business opportunities, market places and new customers (i.e., to engage in collaboration).

Following Anthill (2016) and Lindfield Partners (2018) and noting the Australian small food businesses statistics presented in section 2.5, innovation is really a challenge for the food industry and can be further improved by increasing the proportions of innovative-active small businesses. Though collaboration is increasing for Australian innovative-active small food businesses, the question is, can it be increased also for noninnovators? The small food businesses also perceived that their income, profitability and productivity had improved through innovation; so, to face the above-mentioned challenges, we need to determine what drives the small food businesses to innovate. The present study seeks to examine this.

The DIISR's submission to the House of Representatives Standing Committee on the Economic Inquiry into *Raising the Level of Productivity Growth in the Australian Economy* in September 2009 (DIISR, 2009) reveals that there is also evidence to suggest that small firm size is an impediment to innovation, not just because it inhibits access to technology and networks, but also because small firms may have less-developed management capabilities. It is evident that Australia has a large number of small firms and these firms can contribute significantly to our nation's productivity performance, yet because of their size they face impediments in being able to determine and adopt best practice, both in technology and management. Since the time of that report in September 2009, the question is whether this is still the case, particularly for small food businesses in Australia. The present study also seeks to investigate this question.

Empirical studies on the determinants of innovation in the Australian food sector are very limited; so, a study on small food businesses in Australia using firm-level data is desirable to provide evidence for the challenges as well as to support the above-mentioned agenda in section 2.6.

Storey (1994) provided a good understanding of the behaviour of the small business sector in Australia and how it plays an important role in employment creation, in innovation, and in the economy, in general. He remarked that growth in the number of small businesses is often targeted in government policies. The ABS started examining the characteristics of small business operators in Australia in 1995 through a survey that was supplementary to the ABS monthly Labour Force Survey (see ABS cat. no. 8127.0) but it ceased in 2007. At the same time, the growth and performance of Australian SMEs was investigated from 1996 until 1999 using the ABS Business Longitudinal Survey, but the concept of innovation was not covered.

The latest and a more comprehensive descriptive analysis of Australian small businesses is from the Department of Industry, Innovation, Science, Research and Tertiary Education [DIISRTE] (2012b) report in which a statistical overview of these firms is provided with emphasis on business counts, demographics, innovation and performance. The annual Australian Innovation System (AIS) Report of the DIIS now publishes selected statistics on trends of business innovation and performance. It explores the impact of innovation and related activities on business, industry and national performance. It also highlights innovation policy developments across Australia. The 2017 AIS report provides updates on Australia's innovation performance as well as information on high-growth firms. The report shows that there is a higher rate of labour productivity growth in small high-growth firms than in non-high-growth firms in 2014 over the previous year (DIIS, 2017b).

The ABS has been producing innovation statistics since 1993. Innovation statistics include information on key indicators on business innovation and the use of ICT and related innovation practices by businesses in Australia. These statistics are annually published in ABS (2015a, 2015c, 2017a, 2017b). Whereas substantial cross-sectional modelling work has been published on drivers of innovation using ABS business survey data (e.g., BCS), micro empirical work on the relationships between determinants of innovation, innovation persistence and productivity, particularly on small businesses, is limited due to the confidentiality of firm-level information. Although the ABS has investigated several related topics in the past (e.g., skills shortages, ICT, flexible working arrangements, government assistance, innovation and productivity), none of these specifically looked at the dynamic linkages of innovation persistence and productivity for the different types of innovation (see Wong, Page, Abello, and Pang, 2007; Brunker and Orzechowska-Fischer, 2008; ABS, 2008; Todhunter and Abello, 2011; Soames, Brunker, and Talgaswatta, 2011; Rotaru, Dzhumasheva, and Soriano, 2013; Rotaru and Soriano, 2013;

Rotaru, 2013). Our study is complementary to the existing research on innovation in Australia, including the various relevant publications by the DIIS (e.g., Department of Industry, Tourism and Resources, 2006, 2007; DIISRTE, 2012; Palangkaraya, 2012; Palangkaraya, Spurling, & Webster, 2015, 2016; Hendrickson et al., 2018). None of these papers provided implications for the above-mentioned government agenda and initiatives in relation to the Australian food industry.

2.8 Concluding remarks

This Chapter establishes the definition of small businesses used in our analysis. The concept is similar, but the actual definition may vary from one user (country or institution or researcher) to another. We note that small businesses dominate the Australian business counts and contribute significantly to the Australian economy. Australian small businesses employ nearly one-half of the private sector workforce and contribute approximately one-third of private sector industry domestic product.

We present an overview of the Australian food industry businesses and their growing role in the economy, particularly the small businesses in the food and agribusiness sector, using the ABS data cubes obtained from the 2013/14 BCS. Engagement in any form of innovation activity was found to be present among small food businesses and positive improvement in business performances was evident for innovation-active businesses. The Chapter also explored selected business characteristics like collaboration, export capability, skills used and shortages, ICT use and barriers to their general business activities.

Examining the current government initiatives relating to small business innovation (like the NISA, IICA, CRC and FIAL), as well as the challenges being faced by the Australian small food businesses, we find that there is a great push for the food businesses to be innovative to improve their performance and be competitive to ensure global food security and meet the demand of the increasing number of consumers. To unleash the potential of these small food businesses to innovate and grow, it is imperative to examine more closely what drives them. We need to determine if innovative-active small food businesses that persist to innovate can become globally competitive and productive.

In the next chapter, we review the literature (both national and international) that helps us to: identify the potential key drivers of innovation; understand the dynamics of innovation persistence; and link innovation with business performance growth and productivity dispersion in the small food businesses, particularly in the Australian setting.

Chapter 3: Review of Related Literature

3.1 Introduction

This section provides the theoretical and empirical literature on innovation that describes the key determinants and dynamic relationships examined in this study. The choice of the key determinants discussed in sections 3.2–3.7 is limited to the information that is collected in the ABS BCS and what has been used in the previous ABS cross-sectional studies on business innovation. These include business size, collaboration, ICT, employee skills, labour market flexibility, market competition and export capability. The concept of open innovation under the collaboration factor is also outlined in section 3.3. Section 3.8 explores other drivers of innovation from other Australian studies. Particular attention has also been given to food industry studies on innovation in other countries.

Section 3.9 deals with the underlying theories behind the innovation persistence of businesses and on what generally causes this dynamic behaviour. Some recent empirical studies on innovation persistence, in relation to the current study, are also presented. Literature providing evidence about the dynamic relationship between business innovation and performance is briefly discussed in section 3.10. Before the chapter concludes in section 3.12, an understanding of the concept of productivity dispersion is considered in section 3.11. It is not a new concept but has recently been receiving increasing exposure in the productivity statistics arena of national statistical agencies because of the increasing availability of business-level data.

3.2 Innovation and business size

The earliest work on innovation came from Schumpeter (1942), in which capitalism was described as a form or method of economic change that can never be stationary. The fundamental impulse that sets and keeps the capitalist engine in motion comes from new consumer goods, new methods of production or transportation, new markets, or new forms of industrial organisations that capitalist enterprises create. Schumpeter developed a theory in which an enterprise’s ability to innovate was mainly due to its size, stating that large businesses are the main drivers of innovation, being better resourced and having monopolistic power in the market. Since then, empirical studies on business innovation have proven and disproven this argument, particularly those analyses that work on small- and medium-sized enterprises or even on micro-sized businesses.

Previous international studies on business innovation in the food industry prove that business size really matters when it comes to undertaking any form of innovation. The size of the food businesses is found to be significantly associated with innovation outputs (e.g., Capitanio, Coppola, & Pascucci, 2009, 2010; Smit, Abreu, & de Groot, 2015; Domenech, Martinez-Gomez, & Mas-Verdu, 2014; Ciliberti, Carraresi, & Bröring, 2016b; Zouaghi & Sánchez, 2016; De Martino & Magnotti, 2017). On the contrary, a European food industry study by Traill and Meulenberg (2002) found no significant relationship between company size and innovation. In this study, we provide evidence whether small businesses in the Australian food sector can be strong innovators too.

3.3 Innovation and collaboration

Collaboration can be defined as the arrangement where two or more people or organisations of all sizes and from all sectors, public, private and community businesses, work together for mutual benefit or common goals, including sharing of some technical and commercial risks (DIIS, 2008). Collaboration is highly valued in innovation systems and its role in innovation and productivity needs to be thoroughly investigated. Examining business collaboration among businesses will provide proper insight into the linkages between the businesses, particularly innovation-active businesses and other organisations. Further, these linkages are important in understanding the real business dynamics of innovation and productivity.

According to the Oslo manual (OECD, 2005a), the innovative activities of a business partly depend on the variety of linkages to sources of information, knowledge, technologies, practice, and human and financial resources. One of the external links is innovation cooperation, which requires active collaboration with other businesses or research institutions on innovation activities. The Nelson and Winter (1982) model says that organised R&D efforts of businesses are sources of innovation. This model views innovation as a path-dependent process in which knowledge and technology are established via interaction between various participants (businesses, institutions and society), known as the evolutionary approach. Closely intertwining this process are the systems of innovation approaches (Nelson, 1993; Lundvall, 2010) where external institutions influence the innovation activities of businesses through the transfer of ideas, skills, knowledge and information.

Another model receiving much attention recently that works very well with collaboration is open innovation (OI). Chesbrough (2003) introduced and defined OI as the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation. The OI concept has been applied in several studies. For example, Bigliardi and Galati (2016) indicated that small manufacturing enterprises operating in less innovative industries emphasise lack of collaboration as a barrier to OI. Henttonen and Lehtimäki (2017) show that technology-intensive SMEs engaged in OI for commercialisation rather than for R&D. Marangos and Warren (2017) examined what strategies the senior managers of R&D-intensive SMEs in the life sciences sector conduct concerning OI. Studies by Bigliardi and Galati (2016), Henttonen and Lehtimäki (2017), and Marangos and Warren (2017) also provide good literature reviews on OI in SMEs. An extensive review of literature regarding the adoption of OI in the food industry is presented in Bigliardi and Galati (2013). The recent study by Triguero, Fernadez, and Saez-Martinez (2018) found that OI strategies positively influenced eco-innovation for product innovation and novelty degree (incremental) in the context of the Spanish food and beverage manufacturing industry. The presence of path dependence on eco-innovation is also confirmed. The adoption of OI practices in the food industry is still emerging as a focus of analysis that requires further attention and investigations by researchers using business-level data.

Analysing the relationship between collaboration and innovation in the food industry is not new in the international arena. There is evidence that innovation is influenced when businesses collaborate externally. De Martino and Magnotti (2017) found that partnerships between researchers in academia and research institutes were crucial in boosting the innovative capacity of small food businesses in Italy. Galati, Bigliardi, and Petroni (2016) looked at how networking with innovation partners is needed for food businesses to perform effective OI. Triguero (2019) compared the role of open innovative practices in the adoption of eco-innovation by food and non-food companies in Spain using a survey of business innovation. His paper showed the positive influence of external knowledge sources from market-based, science-based and other sources for the likelihood of introducing eco-innovation in all manufacturing industries. In addition, the joint cooperation and collaboration with market sources increases the probability of eco-innovation in food businesses.

Innovation in Italian food businesses has also been shown to rely on R&D activities and knowledge sourcing with external partners (e.g., universities, customers, suppliers, competitors, public or private institutions) (Maietta, 2015; Ciliberti et al., 2016a, 2016b). Wixe, Nilsson, Naldi, and Westlund (2017) and Caiazza and Stanton (2016) found that innovation in small food businesses had significant association with external collaboration to access knowledge. Grunert et al. (1997) found that interactions among R&D, market orientation and collaboration in Denmark are major determinants of innovation in the food sector. McAdam, McAdam, Dunn, and McCall (2014) observed that horizontal collaboration (i.e., between businesses in the same industry, not competing directly but selling and marketing to similar customers) among SMEs in the UK agri-food sector also plays a significant role.

The concept of supply chain collaboration-partnerships with suppliers at various levels in the chain, as a way to construct more efficient and responsive supply chains, to deliver exceptional value to customers is also one effective form of collaboration. The study by Matopoulos, Vlachopoulou, Manthou, and Manos (2007) has shown that the concept has significant importance for the agri-food industry, not only for innovation but for business growth. However, in Australia, studies on collaboration and innovation in the food industry are minimal and have focused on the descriptive profiling of food and agribusiness industries without quantitative measures with respect to the determinants of innovation (ABS, 2015d).

Collaboration is highly valued in Australian innovation systems. Innovation and collaboration are high priorities for the Australian Government because working with researchers can give Australian businesses a competitive edge. The CRC programme is a good example of the initiative led by the DIIS focusing on collaborative research partnerships between industry entities and research organisations (DIIS, 2018b). In relation to the food industry, FIAL recently released Australia's first food, beverage and agribusiness cluster initiative that would benefit farmers, food suppliers and retailers across Australia. This programme encourages businesses, researchers and educational institutions to work together to build on their comparative advantage and develop innovations (FIAL, 2017). For policymakers like the DIIS and DA, understanding if collaboration enables, or is at least associated with, innovation among small food industry businesses is of great interest.

As stated earlier, collaboration is an important ingredient in the national innovation systems. Businesses working together could generate more creative solutions, and very few successful innovations can be achieved without collaboration (CRC, 2008). Collaboration is also becoming an important determinant of competitive advantage. Innovations are increasingly brought to the market by networks of businesses, selected according to their comparative advantages, and operating in a coordinated manner (MacCormack, Forbath, Brooks, & Kalaher, 2007). Schmidt (2007), using the Canadian Survey of Innovation, revealed that businesses collaborate to share the cost of developing innovative products and processes. He found some evidence that innovators are more likely to collaborate to get access to external R&D and expertise, particularly for businesses receiving public funding. But an important question is whether these associations are also happening in the case of small businesses in Australia. One of the main contributions of this study is demonstrating that collaboration really drives innovation among small food businesses in Australia.

3.4 Innovation and ICT

A conceptual link between the adoption of information and communication technology (ICT) and innovation was established by Köllinger (2005) who argued that ICT has strategic relevance for businesses because it is a valuable source of business innovation providing substantial efficiency gains. ICT technologies that create automated system links lead to more streamlined business processes and enable employees to develop closer links among businesses, their suppliers, customers, competitors and collaborative partners, allowing the businesses to be more responsive to innovation opportunities (Todhunter & Abello, 2011; Domenech et al., 2014; Salim, Mamun, & Hassan, 2016; Galati et al., 2016). The same arguments were discussed and analysed by Gretton, Gali, and Parham (2003) and Tiy, Berry, and Taylor (2013) using Australian data, indicating that ICT plays an important role in business innovation. Gago and Rubalcaba (2007) found that businesses that invest in ICT, particularly those that regard their investment as strategically important, are significantly more likely to engage in services innovation. Also, important studies by Polder, van Leeuwen, Mohnen, and Raymond (2009), and Hall, Lotti, and Mairesse (2012) proved that ICT is truly a significant enabler of innovation. In regard to the food industry, Galati et al. (2016) revealed that ICT was significant for Italian food businesses to perform effective OI.

OECD (2003, pp. 3–4) defined *ICT* as 'goods … that are either intended to fulfil the function of information processing and communication by electronic means, including transmission and display, or which use electronic processing to detect, measure and/or record physical phenomena, or to control a physical process.' In this study, we combine broadband Internet connection, business Web presence and use of e-commerce into an *ICT intensity index* to develop a convenient and meaningful measure of ICT sophistication (i.e., businesses not having broadband connection–low ICT intensity–to those having the three components of innovation–most intense ICT). This index was also applied by Todhunter and Abello (2011) and Tiy et al. (2013). Using the same index, econometric analyses at the ABS have shown that there is a positive and significant association between business innovation and the use of ICT (Todhunter & Abello, 2011; Tiy et al., 2013; Rotaru, 2013; Rotaru et al., 2013; Rotaru & Soriano, 2013; Soriano & Abello, 2015). These studies further reveal that more intense ICT users are more likely to undertake different types of innovation. This relationship is again tested in the current study for the case of small food businesses in Australia.

While the ICT tools are important for any businesses in the modern Australian economy, the use of ICT by the Australian farmers are far more complicated. New ICT equipment and the data it generates are changing how farms are managed. For example, more important application of ICT is in the production process using communication through satellite. Specifically, GPS-enabled technologies are widely used on vegetable and grain farms, and electronic identification and herd management tools are commonly used on dairy farms (see Dufty & Jackson, 2018). As the use of ICT in agriculture mature given the evolving telecommunication infrastructure, the ICT intensity index used in this study should be revisited in any future work.

3.5 Innovation and skills

The general concept of skills refers to productive assets of the workforce that are acquired through learning activities, and/or can be viewed as the abilities of the workforce (Tether, Mina, Consoli, & Gagliardi, 2005). In many studies, skills and skill levels are defined as some combination of education, training and experience (Machin & Van Reenan, 1998; Green, Jones, & Miles, 2007). How do skills relate to innovation? Skills involved in innovation depend on: the nature of the innovation in question (incremental vs. radical; product, process or organisational, etc.); the nature and distribution of skills within and available to an organisation; and the possibility of transforming and growing new skills within enterprises and the wider economy (Green, Jones, & Miles, 2007).

There is evidence that an educated and skilled workforce is essential for successful innovation. The skills of the workforce and management determine the innovation that takes place, which then helps determine the demand for skills in a business, which, in turn, influences the innovation, etc. (Tether et al., 2005). Much innovation knowledge is embodied in people and their skills, and appropriate skills are needed to make use of external sources of innovation (i.e., the role of human capital in a business's engagement in any form of innovation); for example, how well the skills of employees match the needs of innovative businesses and collaborators (OECD, 2005a). According to OI strategy, businesses need smart and technologically-capable managers to properly communicate and exchange ideas with external partners (Marangos & Warren, 2017). Galati et al. (2016) studied how personnel skills were needed for food businesses to perform effective OI.

The link between skills and innovation is supported by human capital theory and resource-based theory. Becker (1994) viewed human capital as directly useful in the production process (and the process connects to innovation). More explicitly, human capital increases the productivity of workers in different tasks. The Australian Workforce and Productivity Agency (2013) compiled international and national literature that establishes skills that play a key role in productivity. The resource-based theory (Grant, 1991) established that both resources and capabilities of a business (hereby, human capital) are central in formulating its strategy that provides direction as well as the primary source of profit. Resources include the skills of employees, which are inputs in the production process, and capabilities that are the capacity of employees to perform tasks.

Toner (2011) reviewed the literature on the role of workforce skills in the innovation process (to incremental innovation, in particular) in developed economies. It draws from the innovation studies discipline, neoclassical human capital theory, institutionalist labour market studies, and the work organisation discipline. It shows that the quantity and quality of workforce skills are a major factor in determining the observed patterns of innovation and are key aspects of economic performance. The quality of human capital, as an important driver of process and product innovation, was also included in the studies of Capitanio et al. (2009, 2010). In the food sector, Huiban and Bouhsina (1998), Avermaete, Viaene, Morgan, Pitts, Crawford, & Mahon, (2004), Smit et al. (2015), Vancauteren (2018), and Brown and Roper (2017) showed that skills of the workforce play a key role in business innovation.

There is growing recognition of the importance of human capital in shaping Australia’s future prosperity. The Australian Council of Learned Academies report argued that building capacity, particularly in the STEM fields , is pivotal to competitiveness in the global economy (Marginson, Tytler, Freeman, & Roberts, 2013). Connolly, Trott, and Li (2012) showed that an increase in the proportion of workers in skilled occupations was followed by an increase in labour productivity, and organisation of human capital was important in determining labour productivity.

In Australia, however, not many studies have investigated the relationship between business innovation and used of resources with STEM. But, in the US, Lieponen (2005) examined the complementarity between employees' skills and businesses' innovation activities and found that high technical skills are complementary with R&D collaboration and product or process innovation and that human capital is seen as an enabling factor in profitable innovation. Lieponen (2005), however, did not specifically separate STEM skills. The ABS has also investigated several innovation-related topics in the past, but none of these specifically looked at the effects of STEM skills and STEM employment on innovation (e.g., Wong et al., 2007; Brunker & Orzechowska-Fischer, 2008; ABS, 2008; Todhunter & Abello, 2011; Rotaru et al., 2013; and Rotaru & Soriano 2013).

The recent Australian study by Soriano and Abello (2015) found that the probability of innovation is higher for businesses with employees having STEM skills than for those without these skills. The impact of the use of STEM skills on the probability of having 'new-to-the-world' type of innovation is also found to be strong and positive. In the work of Soriano and Abello (2015), skills are assessed using the STEM qualifications of employees employed by the businesses. STEM skills are defined to be present in a business, according to the Australian Standard Classification of Education (ABS, 2001), if employees have qualifications of one or more of the following: postgraduate degree, master degree, graduate diploma, graduate certificate, bachelor degree, advanced diploma, and Certificates II and IV, in any of the fields of the natural and physical sciences (including mathematical sciences), IT, engineering and related technologies, and agricultural, environmental and related studies. In the same paper, the STEM and non-STEM skills variables are constructed based on the type of skills used by a business, as reported in the ABS BCS. A business is considered to have used STEM skills if it reported using any of the following skills: engineering, scientific research, IT professionals, and IT support technicians. These are based on subjective responses by businesses to the BCS question about the types of skills used in undertaking core business activities. We note that a particular business may use any of the above STEM skills in combination with other non-STEM skills such as trade, transport, and plant and machinery operations. In this study, we adopt these definitions of STEM and non-STEM skills.

The Van Zon (2001) model demonstrated the link between skills and innovation through R&D. People with STEM capabilities (skills, knowledge and ways of thinking) are employed to drive R&D work. STEM capabilities come primarily from those with formal STEM qualifications, although some people employed in occupations requiring STEM skills may have non-STEM fields as their qualification. The literature review of Stanwick (2011) discussed the kinds of skills that contribute to innovation. Stanwick (2011) concluded that a good educational foundation is the key to promoting successful innovative practice. The paper by Cardamone et al. (2018) established the importance of science in the Italian food industry facilitating the industry-university relationship to encourage knowledge transfers in the agri-food sector, where the high levels of scientific knowledge in fields such as biotechnology or chemistry are required for innovation. Whether the use of resources with STEM skills is driving innovation among the small food businesses remains to be investigated.

3.6 Innovation and labour market flexibility

Is labour market flexibility good for innovation? Can businesses gain and maintain a competitive edge in the ever-changing and uncertain global environment if they allow this flexibility? Labour market flexibility, being a dynamic concept, has received considerable and growing attention in recent years according to Beatson (1995), who defined 'flexibility' as the ability of markets (and the agents that operate in them) to respond to changing economic conditions. There are different forms of labour market flexibility and, following Atkinson (1984), Beatson (1995), Michie and Sheenan-Quinn (2001), Reilly (2001), and Kleinknecht, Oostendorp, Pradhan, and Naastepad (2006), labour market flexibility can be categorised into five types:

- *Numerical flexibility* is the ability of businesses to allow variation in the number of employees or workers employed. Examples are temporary, seasonal, casual, outsourcing and fixed-term workers.
- *Temporal flexibility* is the ability of businesses to allow variability of working hours. Examples are part-time, shift, reduced hours, overtime and leave flexibility.
- *Functional flexibility* is the ability of businesses to allocate their labour force to carry out a wide range of tasks and activities. Examples are multi-skilling, task flexibility and cross-functional working.
- *Locational flexibility* is the ability of businesses to use employees outside the normal workplace. Examples are home-based work, use of mobile phones and tele/outworkers.

- *Financial or wage flexibility* is the ability of businesses to decide wage levels in line with corporate performance. Examples are gain or profit sharing, wage-cutting deals and pay increases based on performance.

Studies examining labour market flexibility (following any of the above types) and innovation have been increasing (Michie & Sheenan-Quinn, 2001; Storey, Quitas, Taylor, & Fowle, 2002; Michie & Sheenan, 2003; Kleinknecht et al., 2006; Zhou, Dekker, & Kleinknecht, 2011; Kleinknecht, Flore, van Schaik, & Zhou, 2014). Kleinknecht et al. (2006) followed Schmooklerian demand-pull theory (see Schmookler, 1966) where higher effective demand increases innovative activity and labour productivity. In relation to labour market flexibility, these researchers found that wage restraint or downward-wage flexibility impedes innovation. In terms of numerical flexibility, the above studies noted that a large inflow of new people (skilled and productive) enriched the pool of innovative ideas within businesses and led to new collaborations. Zhou et al. (2011) found that businesses with high shares of workers on fixed-term contracts tended to have fewer sales of innovative new products whereas high functional flexibility enhanced sales of new products by businesses. Chung (2009) observed that temporal flexibility had an effect on innovation whereas Martinez-Sanchez, Vela-Jimenez, Perez-Perez, and de-Luis-Carnicer (2008) revealed that innovation performance was positively associated with internal functional flexibility and negatively associated with numerical flexibility and outsourcing, but the relationships between them were moderated by interorganisational cooperation. Giannetti and Madia (2013) investigated the relationship between labour market flexibility—proxied by the proportion of workers with different contractual arrangements and other indicators of flexible work relations—and firms' innovative ability. They found that internal flexibility is positively associated with innovation for both high-tech and low-tech businesses; however, greater external flexibility might hinder innovation.

Rotaru (2013) and Rotaru and Soriano (2013) were the first to examine the relationships between four types of flexible working arrangements (flexible working hours, flexible leave, job sharing, and working from home) and innovation using Australian survey data at the business level. Both studies found that all these four factors played important roles in influencing innovation. The degree of relationship varied but was mostly positive and significant. We know of no study on labour market flexibility and innovation in the food industry; hence, this study is a pioneering work that establishes the role of work flexibility on innovation for small food businesses in Australia.

3.7 Innovation and market competition

Studying the relationship between market competition and innovation has long been of interest to economic researchers and policy analysts. Schumpeterian theory states that greater levels of market competition faced by businesses lead to declining innovation, but most empirical studies have found the opposite result. There is a wealth of theoretical literature on the connection between competition and innovation, but a more recent theory by Aghion, Bloom, Blundell, Griffith, and Howitt, (2005) suggests that the relationship between the two has an inverted-U shape. This framework is an attractive one because it reconciles the Schumpeterian and non-Schumpeterian results (i.e., increased competition is associated with more innovation). The industrial organisation theory of Tirole (1988) also emphasised the importance of competitive positioning—that businesses innovate to remain in their competitive position and avoid losing business market share (see Correa (2012) for a similar framework to Aghion et al. (2005)). The empirical work of Alfranca, Rama, and von Tunzelmann (2003) supports the claim that competition is an important factor of technological dynamism in business innovation behaviour.

There is a wealth of international empirical literature that has examined the link between competition and innovation using business-level data, several studies being in Australia (e.g., Rogers 2004; Wong et al., 2007; Griffiths & Webster, 2009; Bhattacharya & Bloch, 2004; ABS, 2008; Soames et al., 2011; Rotaru et al., 2013; Rotaru & Soriano 2013; Soriano & Abello, 2015; Palangkaraya et al., 2016). Soames et al. (2011) obtained empirical results that supported the Aghion et al. (2005) hypothesis. Similar results were also reported by Rotaru et al. (2013), Rotaru and Soriano (2013), and Soriano and Abello (2015) using the ABS BCS data.

In all the empirical investigations in Chapters 6–8, the degree of market competition is divided into four categories: no effective competition (no competitors); minimal competition (1–2 competitors); moderate competition (3–4 competitors); and strong competition (five or more competitors). We are interested to test if the theory of Aghion et al. (2005) holds in the case of small food businesses in Australia. This add to the empirical literature on the link between competition and innovation in the food industry that is currently scant.

3.8 Other drivers of innovation

3.8.1 Export capability

Empirical studies using business-level data in the food industry have also observed some other important determinants of innovation, one being exporting behaviour of businesses. The modern trade and growth theories by Grossman and Helpman (1991), and Aghion and Howitt (2009) suggest that access to export markets affects innovation. The recent work of Aghion, Bergeaud, Lequin, and Melitz (2018) provides evidence where a simple model of trade and innovation predicts that a positive export shock increases market size and, therefore, innovation incentives for more productive businesses. A study on the food industry by Domenech et al. (2014) indicated that the adoption of ICT technologies was a key factor for innovation in agri-food industries in Spain and it was highly influenced by business size and export orientation. Another study of Spanish agri-food businesses showed that export was positively associated with the four types of innovation (Zouaghi & Sanchez, 2016). In a Danish study of Karantininis, Sauer and Furtan (2010), agri-food businesses with export orientation tend to innovate more. Providing evidence on the relationship between export and innovation in small businesses in the food industry has received little attention, although there is evidence showing that Australian businesses engaging in any export activity are more likely to innovate (Soames et al., 2011; Palangkaraya, 2012; Rotaru, 2013; Tuhin, 2016; Tuhin & Swanepoel, 2017).

3.8.2 Financial assistance

Another important driver of innovation found in the literature is having good financial support, either internally or externally, to fund innovations. Getting access to finance is of crucial importance for investing in innovations (Sauer, 2017). In Australia, lack of access to additional funds was the most commonly reported barrier (17 per cent) to undertaking innovation (ABS, 2017b). Rotaru et al. (2013) applied propensity score matching in the context of causal modelling, using the ABS BCS data, and found a statistically significant association between government assistance and innovation. De Martino and Magnotti (2017) also concluded that public funding was crucial in boosting the innovative capacity of small food businesses in Italy. In another food industry study of Traill and Meulenberg (2002), having R&D investment was found to be more highly correlated with product innovation than with process innovation.

3.8.3. Vertical and/or horizontal integration

Another important driver of innovation capacity in the food industry is the vertical and horizontal integration—networking with peer suppliers, food manufacturers, and customers as well as with third parties like government research institutions and consultants. Kuhne, Gellynck, and Weaver (2015) found that vertical networks to traditional food businesses and horizontal network activities for innovation with peers or with third party businesses has a positive effect on the innovation capacity in the traditional food chain. It also highlights that networking among the vertical network members contributes most to the enhancement of the innovation capacity of all member networks.

Vertical integration and networks were also found very important for food business innovation in the Danish study of Karantininis, Sauer and Furtan (2010) on agri-food businesses. They found a strong link between innovation and market structure through integration. Further, the said investigation found that vertical integration, as well as contractual arrangements, are significant determinants of firms' innovation behaviour, and that the direction of integration is important as well. The direction of integration does not matter because both upstream and downstream integration tend to increase product innovation. Moreover, networks also play an important role in innovation activity, whereby network linkages through vertical integration are observed to have positive effects on the introduction of new products by firms. A study of food retailers/wholesalers, food manufacturers and suppliers in three European countries (i.e., Belgium, Hungary, and Italy) established that the locus of innovation is increasingly the network in which the business is embedded (Gellynck & Kühne, 2010). Their findings show that the main barrier for innovation in the traditional food networks was the lack of understanding of the benefits of networking activities for innovation. They pointed out that successful small-to-medium food businesses were using their networks to overcome lack of knowledge, skills and information, and to create possibilities of joint use of resources through vertical integration. Another example of the relationship between innovation and integration is the study of Fortuin and Omta (2009) on Dutch food processing companies. It revealed that food processing indeed relies on the principles of innovation management, and that OI with suppliers and buyers to leverage innovation resources and capabilities are underutilised. But the high pressure of buyers strongly drives innovation, and the effective communication of R&D to enhance marketing and customer orientation is found to be a main driver of innovation success.

In the current study, vertical and/or horizontal integration are not specifically included in the framework or empirical modelling because they are not covered in the ABS BCS; however, the collaboration factor may have included part of it. This is another avenue for future research for the Australian food industry because there is empirical evidence that it influences innovation and, hence, business performance growth.

3.8.4 Other factors

Avermaete, Viaene, Morgan, and Crawford (2003) found that innovation in the food industry depends on business age and regional economic performance. Smith and Hedrickson (2016) also verified the importance of a business's age in their analysis of Australian SMEs. Zouaghi and Sanchez (2016) found a significant impact of the 2007/08 global financial crisis (GFC) on the innovative performance of agri-food businesses. A more recent study by Cefis and Marsili (2019) found that new manufacturing businesses innovating within two years from their entry to the market enjoyed long-term adaptive survival premiums during and after the GFC, and such premiums are contingent on the form of innovation. That is, technological innovations have more effective and enduring premiums than nontechnological innovations, which can be even detrimental to business survival. The year effects were considered in this current study to capture the impact of the GFC. The authors also found a local study that examined the important role of intellectual property in the food innovation process (see Intellectual Property Australia, 2014). IP Australia (2014) used patent analysis to assess the scope, quality and impact of innovative activity in the food sector and showed that Australia exhibits a positive technological specialisation in the food industry and collaboration is prevalent among universities and research institutes.

Another new concept gaining interest among innovation analysts is innovation capability being a driver of innovation, particularly in the food related industries. Innovation capability can be defined as the ability to absorb, to adapt and to transform a given technology into specific management, operations and transaction practices that can lead a business to perform innovation (Zawislak, Alves, Tello-Gamarra, Barbieux, & Reichert, 2012, p. 15). A more recent study by Oliveira, Ruffoni, Maçada, and Padula (2019) was conducted on Brazilian food companies to test the relationship between innovation capability—development capability; operations capability; management capability; transaction capability—and the innovation performance of food companies. The findings revealed that development capability and transaction capability (i.e. the ability to adopt innovation in the business transaction practices) have a substantive impact on the innovative performance of businesses, whereas neither operations capability nor management capability was significantly related to the innovation performance of food businesses. A related study, the effects of diversity in top and middle management teams on business innovation, has also been an important topic in strategic management (Schubert & Tavassoli, 2019).

From the above food industry studies on innovation it can be gleaned that other factors like export, finance, age of businesses, patents, integration, innovation capability, and an external factor like the GFC may be associated with the propensity of businesses to innovate. Unfortunately, patents, vertical and/or horizontal integration, innovation capability and age information are not currently available in our BLD data set.

3.9 Innovation persistence

A vital topic of research in understanding the dynamic behaviour of innovation among businesses is what we term the *persistence of innovation*. This event occurs when the businesses that innovated in the past are significantly more likely to innovate in subsequent periods. Understanding the impact of persistent innovation is important for strategic management and public policy because, if innovation is often persistent in businesses, then government assistance that kick-starts business innovation will have a lasting effect on job creation and economic growth (Hendrickson et al., 2018).

The theoretical justifications of the existence of innovation persistence have been reviewed and deliberated largely from a theoretical viewpoint; however, empirical evidence to support, discriminate or validate these underlying theories has been limited. The studies by Cefis (2003b), Peters (2009), Collombelli and von Tunzelmann (2010), Clausen, Pohjola, Sapprasert, and Verspagen (2012), and Tavassoli and Karlsson (2015) offer comprehensive discussions of these theories. To summarise, there are three complementary theoretical arguments that explain the presence of innovation persistence in businesses:

- *Dynamic increasing-returns hypothesis*—that innovation activity involves significant learning and accumulation of knowledge that increases the probability of subsequent innovation (Nelson & Winter, 1982; Cohen & Levinthal, 1990; Malerba & Orsenigo, 1993). This is based on the evolutionary theory of Nelson and Winter (1982);
- *Success-breeds-success hypothesis*—that successful innovators generate profits on uncertain investments that fund further innovation activities, thereby, locking-in competitive advantages over other resource-constrained businesses (Nelson & Winter, 1982; Stoneman, 1983; Flaig & Stadler 1994); and

- *Sunk-cost-account hypothesis*—that businesses continue to innovate to avoid stranding or wasting investments into human, organisational and physical capital investments (Sutton, 1991; Cohen & Klepper, 1996; Máñez, Rochina, Sanchis, & Sanchis, 2009).

Besides reviewing the above three frameworks, Le Bas and Scellato (2014) provided an extensive overview of the main findings of recent empirical papers (done after 2000) and recommended a new research agenda about the dynamic capabilities of businesses (e.g., management's innovation strategies and abilities to meet customer needs) and innovation persistence. Empirical business-level studies have also shown that the degree of persistence depends on innovation output measures, the timeframe and the industry structure being analysed (Crepon & Duguet, 1997; Cefis & Orsenigo, 2001; Cefis, 2003b; Duguet & Monjon, 2004; Rogers, 2004; Latham & Le Bas, 2006; Raymond, Mohnen, Palm, & van der Loeff, 2006; Peters, 2009; Clausen et al., 2012; Altuzarra, 2017). Investigating German manufacturing and service businesses, Peters (2005) realised that persistent innovation behaviour was highly significant at the business level and that the presence of true state dependence was very visible. In addition, the role of knowledge, provided by skilled employees, has led to the persistence of innovation.

According to Tavassoli and Karlsson (2015), the degree of persistence among the different types of innovation should not be equal because they do not receive the same supporting theoretical arguments. Altuzarra (2017) inspected differences in innovation persistence across different innovation measures in Spanish manufacturing businesses. Results indicated the presence of true persistence[17] on either technological, product or process innovation, alongside the degree of persistence associated with process innovation being higher than for product innovation. In contrast, the findings of Antonelli, Crespi, and Scellato (2012) for Italian manufacturing businesses disclose stronger evidence of persistence for product innovation than for process innovation, with the highest level of persistence appearing for R&D-based innovation activities. Raymond et al. (2006), using three waves of CIS data to study Dutch manufacturing, found no evidence of true persistence in achieving technological, product or process innovation. This may be due to the shortness of the panel data. Cefis and Orsenigo (2001) examined persistence of innovative activities using a transition probability matrix for

[17] True state dependence represents a path-dependent process where the decision to innovate in one period increases the probability to decide, and to succeed, to innovate in the next period (Tavassoli & Karlsson, 2015, p. 1894).

six European countries, and found the existence of strong persistence in innovative activities, although both innovators and noninnovators had high probability to remain in their state. Also, persistence in business innovation tends to increase with business size. The role of regional locations and characteristics on innovation persistence of businesses are also analysed in the work of Tavassoli and Karlsson (2017). The said study found that businesses located in regions with thicker labour market and/or higher extent of knowledge spillovers had higher probability of being persistent innovators, particularly for product innovations.

Analysis of innovation persistence in food businesses is very rare. However, Alfranca et al. (2003), who investigated the persistent technological practices among global food and beverage multinationals, found that own past innovation strongly influenced current innovations within companies. In the same study, the multinational agri-food sector showed a pattern of technological accumulation in which 'success breeds success'. The lack of research in this area, particularly in Australia, justifies the current study as an important addition to the literature on the dynamics of innovation behaviour in the Australian food industry. The current study scrutinises the business dynamism of persistence in the four types of innovation presented in Chapter 1.

3.10 Innovation and business performance

In recent years, policymakers and economic analysts have displayed increasing interest in the measurement of productivity[18] and other aspects of economic performance at the business (or micro) level. A wide variety of studies has been conducted and various tools have been developed to assist analyses of micro-level productivity. Some are applicable to analyses at aggregate level and some to analyses at a more disaggregated level. Some are model-based parametric approaches and others rely on nonparametric methods. These techniques are distinguished by: the research questions they address; the underlying assumptions on which they are based; and the available datasets that are available to be used.

To date, there is much interest in compiling empirical evidence to verify significant relationships between innovation and business performance, and strong demand for analytical work to be conducted on this topic at the micro-level. With the recent availability of business

[18] Productivity is commonly defined as a ratio of a measure of output to a measure of input use. Productivity literature and its various applications reveal that there is neither a unique purpose for, nor a single measure of, productivity. A frequently-stated objective of productivity measurement is to understand technical change. (See OECD (2001) for more details.)

microdata, many country studies have found innovation to be an important driver of productivity growth at the business level (e.g., Rao, Ahmad, Horsman, & Kaptein-Russell, 2001; Cefis (2003a); Hall et al., 2008, 2012; Polder et al., 2009; Raymond, Mairesse, Mohnen, & Palm, 2015; Triguero, Córcoles, & Cuerva, 2014; Cahill, Rich, & Cozzarin, 2015; Bartoloni & Baussola, 2017; Bianchini & Pellegrino, 2017; Sauer, 2017), and also in Australia (e.g., Wong et al., 2007; ABS, 2008; Mullen, Sheng, & Gray, 2010; Nossal, 2011; Nossal & Lim 2011; Soames et al., 2011; Sheng et al., 2011; Palangkaraya et al., 2015; Smith & Hendrickson, 2016; Hendrickson et al., 2018; Khan et al., 2017; Rafi, 2017).

A particular framework that has gained popularity in analysing linkages between innovation inputs, innovation outputs and business performance was developed by Crépon, Duguet and Mairesse [CDM] (1998). It is commonly known as the CDM model. The model includes three relationships: the research equation that links innovation input (e.g., R&D) to its determinants; the innovation equations that relate innovation input to innovation output measures; and the productivity equation that is a production function equating business performance with innovation output. It explicitly emphasises that the innovation outputs influence productivity and not the innovation inputs, though CDM could process the relationship between innovation input and productivity. Since its publication, the CDM model has been applied in many countries (e.g., Leeuwen and Klomp (2001) on the Netherlands; Criscuolo, Haskel and Martin (2003) on the UK; Lööf and Heshmati (2006) on Sweden; Benavente (2006) on Chile; Parisi, Schiantarelli, and Sembenelli (2006) on Italy; Wong et al. (2007) on Australia) finding varying degrees of impact of innovation on productivity. The empirical work of Hall et al. (2008) on Italian manufacturing businesses was the first to apply the CDM model on SMEs and found that there were significant impacts of product and process innovations on productivity. Polder et al. (2009) extended the CDM model by using two innovation input equations (one for R&D and another for ICT investment) that feed into a system of three innovation output equations (i.e., product, process, organisational) which, finally, links to a productivity equation. Applying the extended model to the Statistics Netherlands linked business survey collections resulted in organisational innovation being the only innovation type that led to higher total factor productivity but, when the three innovation types were involved together, there was increased productivity. Using the extended CDM model, Hall et al. (2012) found that R&D investment was more important for innovation and ICT investment was more important for productivity in large Italian manufacturing businesses. Raymond et al. (2015) introduced dynamics into the CDM model that made it more complex to estimate and analyse.

Studies linking innovation persistence with productivity growth are now becoming a popular topic in the innovation analysis literature. With the new trend of business-level panel data (e.g., European CIS) being more publicly available using secured data networks there has been increased research on business innovation and performance. Triguero et al. (2014) observed that persistence (i.e., lagged innovation) in process innovation had a positive effect on employment growth in Spanish manufacturing businesses whereas the effect of product innovation was not significant. When Bianchini and Pellegrino (2017) reexamined the same research question, but, this time, utilising a direct measure of persistence (i.e., a weighted average of innovation occurrences during the period), they found that persistence in product innovation affects both employment growth and the sustainability of job creation. Another Spanish study by Guarascio and Tamagni (2016) found that persistent innovators did not generally outperform the nonpersistent innovators in terms of sales growth. The more recent work of Bartoloni and Baussola (2017) on Italian manufacturing businesses established that several factors (access to external financial sources, market orientations, more qualified workforce, capital deepening, business age, persistent R&D expenditure that were related to technological and nontechnological innovations) are crucial determinants of business performance. Bartoloni and Baussola (2017) demonstrated that innovation activities if undertaken persistently provided significant additional increases in the productivity and profitability of businesses. The link between persistence in innovative activities and business profitability has also been empirically examined by Cefis (2003a). Findings suggest that businesses that are systematic innovators have higher likelihood to keep innovating and earning profits above the average. Hirsch and Gschwandtner (2013) found that R&D intensity had negative influence on profit persistence whereas business size was an important driver of profit persistence in the food industry.

There are few studies that have sought to determine how innovation activities of businesses influence their performance in the food industry. A Canadian study by Cahill et al. (2015) examined the link between innovation and profit in the Canadian food processing industry and other manufacturing industries using business-level data. Their findings showed that profitability was higher for food processing innovators than noninnovators, and that innovators of both product and process had greater profits than businesses that innovated either product or process only. Bhuiyan, Said, Ismail, Jani, and Fie (2016) studied the innovation strategies and performance of food processing SMEs in Malaysia and found significant relationships between sales turnover and product innovations. Sauer (2017) investigated the link between dairy farm innovation and productivity in the Netherlands and found that the introduction of process, organisational and marketing innovations led to significant productivity gains. Sauer (2017) also provided a comprehensive review of empirical literature (from different countries) on the drivers of productivity growth in dairy farms. Traill and Meulenberg (2002) revealed that when businesses are product and market oriented, product innovation drove market growth and profitability.

In Australia, there have been a number of efforts over recent years to use analytical techniques to investigate the association between innovation and productivity using business-level data. Phillips (1997) undertook early work in the Productivity Commission (PC) utilising business-level data,[19] obtained positive and significant association between business innovativeness and sales growth rates. A similar topic was revisited in the Shanks and Zheng (2006) PC project that performed econometric modelling of the relationship between R&D and productivity growth in Australia, but resulted in unreliable estimates of the effects because of the poor quality of the industry-level data. The project suggested that analysis using micro longitudinal data, being developed by the ABS, would prove beneficial for their work as well as address the measurement issues involved in obtaining these data. Wong et al. (2007) used the 2003 ABS Innovation Survey linked with the Economic Activity Survey datasets for several years as well as incorporating unpublished tax data from the ATO. They employed the CDM model to examine factors that affect innovation outputs and productivity. Unfortunately, the results were indicative and exploratory only because of the shortness of the period of data analysed. In the 2008 ABS submission to the Review of the National Innovation System, the ABS again attempted to do simple cross-sectional analysis of the association between innovation activity and business performance. However, very significant challenges in properly measuring business performance at the micro-level were encountered and resulted in unsatisfactory results. Soames et al. (2011) also investigated the relationship between innovation and productivity but the lack of a sufficient time dimension to the ABS data resulted in a cross-sectional analysis being viable only; hence, not obtaining any conclusions regarding causality and its direction. With the availability of the BLD panel data, this study improves the previous studies that the PC and ABS had undertaken and conducts more modern discrete panel data modelling to find significant links between innovation and productivity in small food businesses.

[19] These data were from the first ABS innovation survey in the manufacturing sector.

Besides providing agricultural productivity estimates, drivers of productivity growth in the Australian broadacre agriculture sector have been continuously studied at the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (see, Mullen et al., 2010; Zhao, Sheng, & Gray, 2012; Sheng, Jackson, & Gooday, 2016; Xia, Zhao, & Valle, 2017). Nossal (2011) evaluated the role of innovation adoption within the Australian agricultural innovation process. Making use of the farm-level innovation data collected by ABARES in 2008, this study found that product and process innovations were more frequently adopted than organisational and marketing innovations by the broadacre farmers. Although the study develops a nice conceptual framework to assess innovation process and the drivers that would influence innovation adoption and productivity, the limited set of innovation determinants data at the farm-level did not enable the measurement of the impact of farm innovativeness on productivity growth. However, a follow-up cross-sectional study by Nossal and Lim (2011) on the Australian grains industry established a significant positive relationship between innovativeness and farm productivity among grain growers. Our study is closer to that of Nossal and Lim (2011) because it deals with agricultural food production. Mullen et al. (2010) and Sheng et al. (2011) both looked at the importance of public R&D and investment on productivity growth in Australian broadacre agriculture, and established that it has significantly promoted productivity growth in Australia's broadacre sector. Similarly, the latest work of Khan et al. (2017) in Australia's broadacre agriculture revealed a strong link between R&D and productivity. Links between productivity and R&D are also found to be strong in the agriculture and food sector value chain following the adoption of innovative farming practices, technologies, collaborative research and partnerships with Australian universities (Mallawaarachchi et al., 2009). Also, productivity improvement among smaller farms can be achieved through increasing their ability to access advanced technologies, rather than simply expanding their scale (Sheng, Zhao, Nossal, & Zhang, 2014).

A recent study by Palangkaraya et al. (2015), using the earlier BLD data, showed that Australian SMEs that previously introduced innovations had an annual productivity increase of around 2.7 per cent higher than the noninnovating SMEs and could further raise their productivity by 4.4 per cent if they were to collaborate. The DIIS research work of Rafi (2017) established that businesses participating in the South Australian Innovation and Investment Funds had improved their performance. Smith and Hendrickson (2016) acquired evidence that innovation capability drove higher growth outcomes for young Australian SMEs. Hendrickson et al. (2018), in another DIIS paper, revealed that persistent innovation was behind a high contribution to business growth performance among SMEs in Australia. At the macro-level, the drivers of innovation and productivity growth, and the role of government funding for innovation, were analysed by Elnasri and Fox (2017). The findings suggested that government research agencies and higher education are areas in which investment in R&D led to productivity growth in Australia. In their earlier paper (Elnasri & Fox, 2015), it was concluded that investments in research and innovation, such as information technology, R&D, skills development, design and organisational improvements, and other types of intangible assets are key drivers of productivity growth. Another important finding was that the accumulation of private-sector knowledge capital was a source of positive benefits to market-sector productivity. A positive relationship between high-tech capital use and productivity in the agriculture industry is also evident from the work of Connolly and Fox (2014). Hence, in both macro- and micro-level analyses, a strong linkage between innovation and productivity has been empirically evident in the Australian setting.

Whether the above discussions and findings regarding the dynamics of innovation and productivity growth are also true for small food businesses in Australia is worth investigating. It should provide evidence to support the Government's policies and investments in growing the Australian food industry.

3.11 Innovation and productivity dispersion

Heterogeneity in productivity (or productivity dispersion[20]) has long been observed and analysed, and there is a growing body of empirical studies that consistently have found persistent dispersion in productivity performance among businesses within a particular industry or sector. The increasing availability of longitudinal micro-level data to analyse productivity at the business level allows empirical analysts to further examine the drivers of this phenomenon. The existence of significant and persistent dispersion of productivity is well established (Bartelsman & Doms, 2000; Crisculo, Haskel, & Martin, 2003; Syverson, 2003, 2011; Foster, Grim, Haltiwanger, & Wolf, 2016, 2018; Cunningham et al., 2019). But a deeper understanding of innovation and productivity dynamics, and the heterogeneity of the productivity of businesses, is still in an early stage of development.

There are a number of possible reasons for the existence of large and persistent productivity differences. Syverson (2004) noted that much of the research on reasons for productivity dispersion focuses on supply-side explanations, such as management influences, capital

[20] This refers to the width of the productivity-level distribution among businesses, say, in a particular industry.

vintage effects, and R&D efforts; but demand-side influences such as competitive markets (in particular product substitutability) also play a key role in explaining dispersion. For example, where there are barriers to competition or where products in a market are not easily substitutable, less-productive businesses are able to survive and possibly grow. Removing these barriers makes it more difficult for these businesses to survive or grow and, thus, helps resources to be allocated more efficiently and narrows the productivity dispersion in the market. Another possible reason for the persistence of productivity dispersion is that there can be a number of different products offered, even within narrowly defined industries, such that comparing like with like across businesses is difficult. Some studies (Griffith, Haskel, & Neely, 2006; Kauhanen & Roponen, 2010) attempted to account for this by looking at dispersion within different branches of a single business but found that persistent dispersion remains.

Productivity dispersion has policy relevance in both macroeconomic and microeconomic contexts. From a macroeconomic perspective, the global slowdown in aggregate productivity growth could partly be explained by the widening dispersion in productivity performance across businesses. This could be the case if, for example, low-productivity businesses continue to survive instead of exiting the market, crowding out the growth opportunities for more productive businesses and weighing on aggregate productivity growth. This resource misallocation can have significant effects on aggregate productivity growth. If these low-productivity businesses were to either exit the market or alternatively 'catch-up' to the leading businesses, then aggregate productivity growth would increase. From a microeconomic perspective, reforms that promote competition (Oulton, 1998; Martin, 2008) and increase business dynamism (such as changes to insolvency laws to make it easier for low-productivity businesses to exit) could help with productivity convergence among businesses in a given industry. Policies that promote innovation may increase productivity dispersion by lifting performance at the top end of the productivity distribution. To this end, where productivity dispersion in a particular industry has more to do with outstanding and innovative performance by the top businesses than poor performance by the laggards, then greater dispersion may actually be driving, rather than dragging on, aggregate productivity growth. Diffusion within the industry should then work to close the productivity gap. This means that productivity dispersion, in and of itself, is neither necessarily good nor bad for aggregate productivity growth, although Brown, Dinlersoz, and Earle (2016) found that productivity dispersion is associated with future aggregate productivity growth rather than decline.

Among the existing theoretical discussions on the determinants of the evolution of productivity dispersion, the link between technology and dispersion is found to be the most popular (Ito & Lechevalier, 2009). Ito and Lechevalier's empirical work on Japanese businesses showed that the introduction of ICTs decreased the within-industry labour productivity dispersion as well as when businesses are exposed to international trade. With innovation having a role to play in the reallocation of resources between businesses, Foster et al. (2018) claimed that an underexplored area of empirical research is the evolution of the productivity distribution within the context of innovation dynamics. The pioneering work of Foster et al. (2018) examined the relationship between innovation, entry, productivity dispersion and productivity growth. Motivated by the idea in Gort and Klepper (1982) that a period of intensive transformative innovation within an industry is accompanied by entry, Foster et al. (2018) related innovation and business dynamics associated with innovation to heterogeneity in measured productivity. After a period that is characterised by entrants engaging in substantial innovation and learning, involving success or failure, there is likely to be an increase in dispersion of productivity. Successful innovators are likely to grow resulting in productivity growth, and the maturing of more successful businesses is expected to reduce productivity dispersion. Their empirical work, using the US Census Bureau's longitudinal business database, has shown that young businesses have more dispersion within industries than mature businesses, and nontechnical businesses have greater productivity dispersion than highly technical businesses. To date, new experimental productivity statistics—Dispersion Statistics on Productivity (or DiSP)—are jointly developed and published by the US Bureau of Labor Statistics and the US Census Bureau (see Cunningham et al., 2019).

In Australia, the PC investigated the hypothesis that labour productivity change is driven by resource movements from less-to-more-productive businesses (Bland & Will, 2001), using data on Australian businesses from the ABS's Business Longitudinal Survey—a rich panel dataset collected from Australian businesses for the years 1994/95 to 1997/98. Findings indicated that the movement of resources associated with business entry and exit accounted for only a small share of labour productivity change. However, the study was not able to draw a business conclusion about the relationship between the movement of resources out of less- into more-productive businesses and labour productivity change. Campbell, Nguyen, Sibelle, and Soriano (2019) examined business-level data for Australia using the early iteration of the Business Longitudinal Analysis Data Environment (BLADE) data to assess the level of productivity dispersion within selected Australian industries. This research—a collaboration between the

Treasury and the ABS—is the first step to understand productivity dynamics in Australia at a more granular level and assess the usefulness or limitations of administrative data such as that offered by the BLADE. The empirical results of Campbell et al. (2019) indicate that productivity dispersion has been persistent in six Australian industries (namely, manufacturing, construction, wholesale trade, retail trade, professional scientific and technical services, administrative and support services) and has been increasing over time, which is contrary to international evidence.

A deeper understanding of the heterogeneity of the productivity performance of businesses can inform the potential productivity-enhancing policies needed to help promote income growth and create jobs, particularly for small food businesses in Australia. Where a breakdown in diffusion and, therefore, rising productivity dispersion is identified, policies should aim to improve the transfer of technologies between these businesses. If dispersion is influenced by a persistence of unproductive businesses in the food industry and, therefore, an inefficient allocation of resources, policies aiding the restructuring of unproductive businesses and addressing barriers to entry and exit may be more fruitful to increase small food industry productivity growth.

3.12 Concluding remarks

This section identifies the key factors that are examined and used in the formulation of the hypotheses and the overall conceptual framework for this dissertation, which is presented in the next chapter. Existing theories established that business size, collaboration, ICT, employee skills, labour market flexibility, market competition and export capability are important determinants of business innovation and are examined in the case of the small food businesses in Australia.

The discussion of the three theoretical arguments—dynamic increasing returns, success breeds success, and sunk cost hypotheses—backed up by what studies have been done so far, explains what drives innovation persistence (or state dependence over time) in businesses, large or small. With the strong evidence that innovation drives productivity growth, the dynamics of innovation and productivity growth in small food businesses in Australia is worth investigating. Evidence elicited from this study may support the government's policies and investments in growing the Australian food industry. Providing empirical evidence that connects innovation behaviour and productivity dispersion in the small food business is a novelty to the growing body of literature on productivity dynamics.

The next chapter outlines the various conceptual frameworks for each of the empirical analyses in the study. The key determinants for the empirical analyses are limited to ABS informed data. All hypotheses tested in the empirical chapters are formulated as well as the corresponding methodologies that lead us to answer the research questions enumerated in Chapter 1.

Chapter 4: Frameworks, Hypotheses and Methods

4.1 Introduction

This chapter provides the frameworks and methodologies used in the empirical analyses. The overall conceptual framework of the study is presented in section 4.2. The analytical framework is based on microeconometric approaches dealing with different accounting for the different research questions and dependent variables on innovation. Section 4.3 contains the first analytical framework and associated hypotheses that address the first two research questions outlined in Chapter 1. The methodologies include the random effects probit model, the count model and the multivariate probit model. Section 4.4 deals with research questions 3 and 4 and presents the framework for analysing innovation persistence in the small food businesses. To evaluate persistence of innovation, the main approaches include the use of a TPM, the simple dynamic probit model and the dynamic correlated random effects (CRE) probit model (Wooldridge, 2005, 2013). The last section presents the complete framework, corresponding hypotheses and methods that are employed to address research questions 5 and 6, that is examining the impact of innovation on business performance. The analytical methods include analysis of variance (ANOVA), propensity score matching (PSM), an ordinary least squares (OLS) model, and labour productivity dispersion analysis, which are presented in section 4.5. The chapter concludes with an overall picture of the different methodologies, and links to data requirements and empirical analyses.

4.2 The overall conceptual framework

In view of the literature discussed in Chapter 3 and the research questions outlined in Chapter 1, the overall conceptual framework derived by us and employed in this study is depicted in Figure 4.1.

As Australia continues to compete and grow the share of Australian food in the global market place, to ensure food security and meet the needs of the growing number of consumers, it is imperative that food and non-food businesses be innovative to improve their performance––this is the main thrust of the government's IICA—innovation through development of new products or services, operational processes, marketing strategies and organisational methods, both within the workplace and their external relations. There are significant improvements on this front, but the main challenge remains—why do some firms innovate, and others don't?

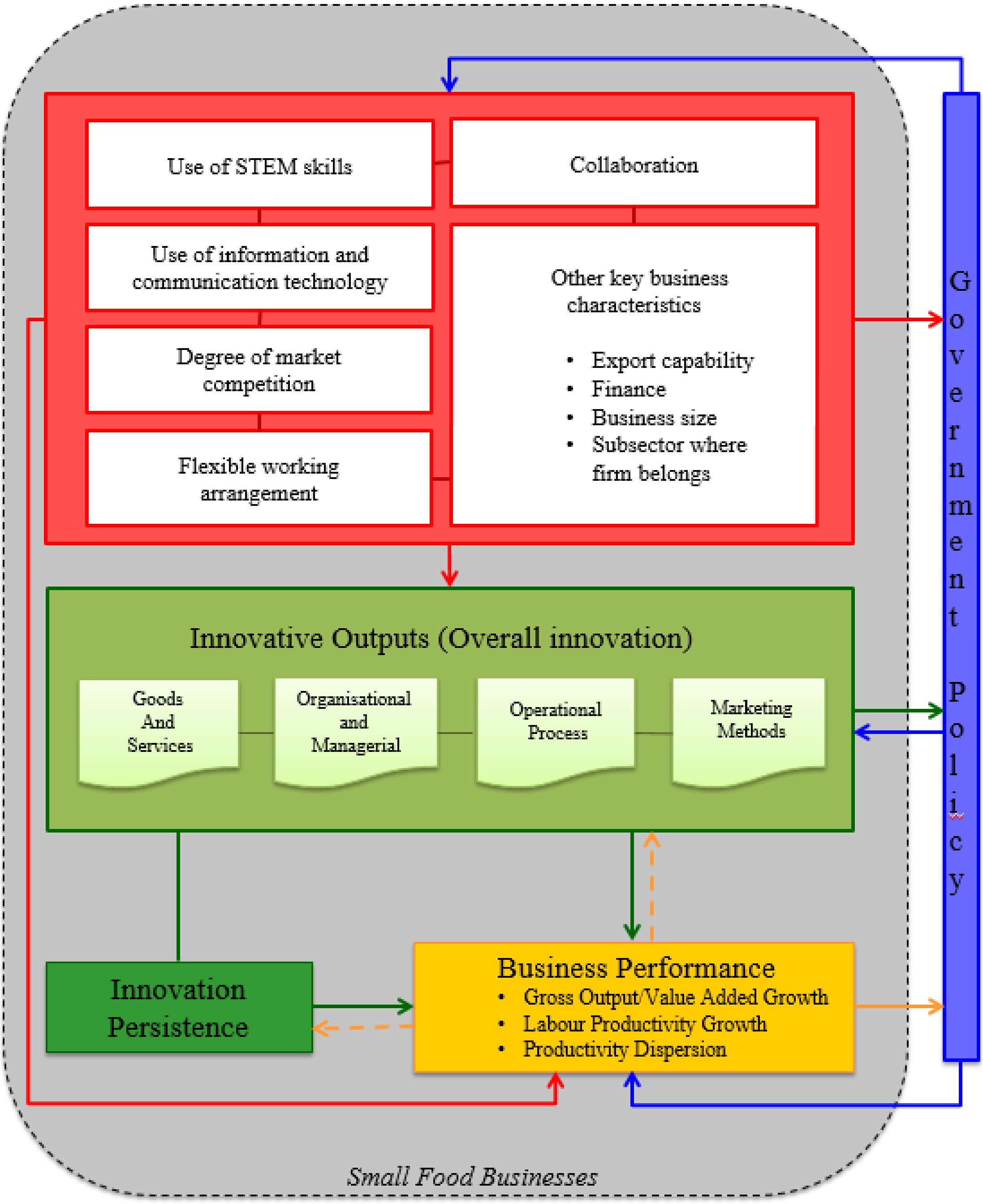


Figure 4.1. Overall conceptual framework for the study[21]

We develop the overall conceptual framework shown in Figure 4.1 to provide empirical evidence on: the main drivers of innovation in small food industry businesses in Australia; how the businesses engage in different types of innovation; if the businesses persist to innovate;

[21] This figure presents the author's own concept for the study.

and, if such dynamic innovation behaviour of businesses will lead to positive improvements in their performance.

The conceptual framework shows the key determinants (red box) for business innovation that are expected to play an important role in small businesses in the Australian food industry. The determinants (i.e., the use of resources with STEM skills, use of ICT, competitiveness, flexible working arrangements, collaboration, export capability, access to finance, business size, and subsector where the firm belongs) are selected based on the theoretical frameworks discussed in Chapter 3. The essence of skills for successful innovation is supported by human capital theory and resource-based theory. The conceptual link between ICT and innovation has been well-established in the works of Köllinger (2005) and Polder et al. (2009). The relationship between market competition and innovation was evident in the work of Aghion et al. (2005) and supported by the industrial organisation theory of Tirole (1988). Labour market flexibility has been well defined in the previous studies of Atkinson (1984), Beatson (1995), Michie and Sheenan-Quinn (2001), Reilly (2001) and Kleinknecht et al. (2006), where the latter study is backed up by the demand-pull theory of Schmookler (1966). Collaboration, being highly valued in the Australian innovation system, has been attested as a good source of innovation in the Nelson and Winter (1982) evolutionary theory. In addition, vertical integration and open innovation warrant the linkage between collaboration and innovation. As earlier mentioned in section 3.8, the modern trade and growth theories by Grossman and Helpman (1991) and Aghion and Howitt (2009) suggest that access to export markets affects innovation. Other factors that have strong connection to innovation—business size and the kind of industry to which the business belongs—have been supported by the early work of Schumpeter (1942).

Although there are other factors believed to have relationships with innovation output (as mentioned in the latter part of section 3.8), the determinants in Figure 4.1 have been limited by the availability of data or information on small food businesses in the ABS BCS for empirical analysis. These selected drivers are believed to encourage businesses in the small food industry in Australia to engage in forms of innovation, thereby providing empirical evidence to support the Australian Government's IICA. Establishing the connections between collaboration, the use of STEM skills, ICT and innovation among small businesses in the Australian food industry are also very important for the NISA (DIIS, 2015b). Such evidence serves as input for the DIIS policy evaluation regarding innovation and productivity growth in the food industry, as stated earlier in section 2.6. The flows from the determinants to innovation and government policy are illustrated by the short red arrows in the framework.

In relation to innovation outputs or outcomes (light green box in Figure 4.1), and following the definition of innovation in Chapter 1, the study focuses on four aspects of innovation—the propensity of businesses to innovate (e.g., for overall innovation), innovation diversity or dimensions (i.e., the four types of innovation), the extent or intensity of innovation, and the dynamics of innovation behaviour (i.e., innovation persistence). Innovation besides having many dimensions is also complex to analyse because it is a continuous process, entails dynamic and nonlinear behaviour, and has a complex diffusion process. The phenomenon of innovation persistence has been theoretically justified in earlier discussions in section 3.9. It is also reinvestigated in Chapter 8 in the context of the observed continuity of innovation activity undertaken by businesses over the period of study and is redefined in section 4.5 below.

The study examines: how large the impacts of key drivers are on the first two aspects of business innovation; evaluates the dynamics of innovation dimensions and investigates how innovation persistence influence business performance (using the growth in gross output and value added, labour productivity growth, and productivity dispersion for each type of innovation used as indicators of business performance); and establishes the implications of the findings for the government's innovation agenda and initiatives (blue box), which, in return (the blue arrows), will benefit the small food businesses in Australia for continued innovation, job creation, global competitiveness, and income growth. There is significant evidence that innovation drives productivity and the current study adds evidence in small food businesses in Australia. The direct relationships between the determinants and business growth performance are also examined under an assumption of exogeneity of business performance, i.e., it is implicitly assumed that output and productivity (measured as level or growth) do not influence business innovation (as depicted by the broken yellow arrow), although the framework shows that such direct relationship have implications to government policies (steered by the solid yellow arrow). The study of Nossal (2011) made a remarked (but not empirically tested) that high productivity growth and improvements in farm business performance can affect future adoption behaviour and innovation expenditure, i.e., productivity growth can significantly affect farm innovation capacity and vice versa. Evidently, Sheng et al. (2014) have suggested, that in the broadacre industry, higher productivity has a statistical impact on farmers' adoption of advanced technologies for larger farm sizes. The influence of business performance on business innovation is beyond the scope of this dissertation and is recognised as future work.

Though not clearly visible in the overall framework, the study also examines these relationships on the food industry subsectors—the small food businesses belonging to the agriculture, forestry and fishing industry (AgriFF), and the manufacturing and wholesale trade industries (non-AgriFF).[22] Specific details about the scope and coverage of these food industry subsectors are explained in Chapter 5.

The directions of all the arrows in Figure 1 show the interdependency relationships between all the components in this empirical investigation. Findings of this study underscore the importance of understanding the key drivers of innovation and performance growth, the enabling environment, and an appropriate platform for policy design, support and development. This understanding is essential for firms to collaborate, innovate and contribute to a productive and progressive economy.

For the overall conceptual framework to work and to support the empirical analyses, the current study formulated some hypotheses and tested them by employing complex dynamic panel data and econometric modelling procedures to firm-level data contained in the ABS BLD CURF. These hypotheses are presented in the following sections.

4.3 Drivers of innovation: hypotheses and methods

Following the overall framework in Figure 4.1, the arrows from the red box to the light green box, as well as the arrows from these boxes to the blue box represent the relationships among the identified key business characteristics (or drivers) and innovation outcomes, and the implications of the findings for the government's innovation agenda and initiatives. In this part of the framework, we specifically address the following research questions:

- *What are the key drivers of innovation in small food businesses in Australia (Research Question 1)?*

[22] These are the only Australian and New Zealand Standard Industrial Classification (ANZSIC) division 1 industries covered in the ABS Business Longitudinal Data (BLD) used in this study. Businesses sampled are predominantly associated with food for human consumption in the above three industry divisions (ABS, 2006).

- *How large are the impacts of these key drivers on overall business innovation for small food businesses belonging to the AgriFF and non-AgriFF subsectors (Research Question 2)?*

To provide empirical evidence to support the proposition that relationships exist between the specified drivers and innovation in small food businesses in Australia, we seek to test the following hypotheses:

- *Small food businesses that collaborate are more likely to innovate (Hypothesis 1)*;
- *Small food businesses that use STEM skills are more likely to innovate* (*Hypothesis 2)*;
- *Small food businesses that have higher ICT intensity are more likely to innovate (Hypothesis 3)*;
- *Small food businesses that have flexible working arrangements are more likely to innovate (Hypothesis 4)*;
- *Small food businesses that face moderate-to-strong competition are more likely to innovate* (*Hypothesis 5); and*
- *Small food businesses that have export capability are more likely to innovate* (*Hypothesis 6).*

To evaluate the above hypotheses, we employ discrete choice models with panel data. In particular, we examine how large the impacts of these key drivers are on business innovation by estimating average partial effects (APEs) utilising the bootstrapping procedure.

We now present the methodological frameworks employed to address the two research questions and the six hypotheses outlined above and follow Wooldridge (2005, 2010) for the theoretical underpinnings of the following four models— the random effects probit, the pooled probit, the count (Poisson) model, and the multivariate probit model. The first two modelling approaches (i.e., the pooled and the random effects probit models) follow Rotaru (2013), and Rotaru and Soriano (2013)—the first ABS methodological papers that explore the implementation, estimation, and the performance of different discrete choice longitudinal data models using the Main Unit Record File of the ABS BLD. These ABS methodological works have only demonstrated the applicability of these two probit models in the context of the Australian small and medium-sized businesses for all the market sectors of the Australian economy without deeper interpretations or considering any policy implications for the modelled results—which is an important component in the current study.

4.3.1 Estimating innovation propensity using random effects probit model

The random effects probit model is one of the most popular and widely-used nonlinear models for binary outcomes with panel data (Greene, 2012; Hensher, Rose & Greene, 2015; Wooldridge, 2005, 2010, 2013). It has been applied to model innovation propensity in the food industry (Triguero et al., 2013; Vancauteren, 2016). A key assumption for this model is that the observed covariates are strictly exogenous, conditional on the unobserved effect. Following Rotaru (2013) and Rotaru and Soriano (2013), we also apply the random effects probit model to estimate the likelihood that small food businesses engage in any type of innovation as well as determine the effects of the potential factors on overall innovation.

For firm *i* at time *t*, let x_{it} be a column vector of (observed) explanatory variables including a constant term. We consider the dependent variable, y_{it}, as a binary response variable taking the value 1 if the *i*-th business innovated (any type of innovation) in the *t*-th year, and 0 otherwise. Assume that the values taken by y_{it} are determined by a latent variable y_{it}^{*}, given by:

$$y_{it}^{*} = x_{it}^{'}\beta + \alpha_i + \varepsilon_{it} \quad , \text{ where } i = 1,2,\ldots,n \; ; \; t = 1,2 \;,\ldots,T \tag{4.1}$$

where y_{it}^{*} is the unobserved binary variable that corresponds to y_{it}, the observed dichotomous variable for business *i* at time *t*, where the relationship between y_{it} and y_{it}^{*} is defined by:

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^{*} > 0 \\ 0 & \text{if } y_{it}^{*} \leq 0 \end{cases} \quad ; \tag{4.2}$$

x_{it} is a vector of observed covariates including a constant term, as stated earlier;

β is a column vector of fixed, yet unknown, population parameters;

α_i denotes the random component (unobserved heterogeneity); and

ε_{it} is the error term, such that $\varepsilon_{it} | \, x_{it} \sim N(0,1)$.

For a balanced panel, the random effects probit model has the form:

$$\begin{aligned} P\left(y_{it}=1\middle|x_i,\alpha_i\right) &= P\left(y_{it}^*>0\middle|x_{it},\alpha_i\right) \\ &= P\left(x_{it}'\beta+\alpha_i+\varepsilon_{it}>0\middle|x_{it},\alpha_i\right) \\ &= \Phi\left(x_{it}'\beta+\alpha_i\right). \end{aligned} \tag{4.3}$$

Note that x_{it} appears in the model, although $x_i=(x_{i1},x_{i2},...,x_{iT})$ is in the conditioning set and where $\Phi(\cdot)$ is the normal cumulative distribution function for ε_{it} conditional on x_i and α_i.

It follows that the joint probability function is:

$$P\left(y_{i1},...,y_{iT}=1\middle|x_i,\alpha_i\right)=\prod_{t=1}^{T}P\left(y_{it}\middle|x_{it},\alpha_i\right). \tag{4.4}$$

The relationship between y_{it} and α_i above is linear and additive in functional form, and we assume independence between regressors and the unobserved heterogeneity.

The conditional distribution of α_i (assuming the normal distribution) is given by:

$$\alpha_i\mid x_i\sim N\left(0,\sigma_\alpha^2\right) \tag{4.5}$$

and α_i is independent of the error term, ε_{it}. The random effects probit model is estimated using the method of maximum likelihood. To measure the relative importance of the unobserved effect, the correlation between the composite latent error, say, $v_{it}=\alpha_i+\varepsilon_{it}$, across any two time periods (*t* and *s*), is defined as:

$$Cov\left(v_{it},v_{is}\right)=\frac{\sigma_\alpha^2}{\sigma_\alpha^2+\sigma_\varepsilon^2}=\rho \tag{4.6}$$

In this case, σ_α^2 is the variance of the unobserved effects; σ_ε^2 is the variance of the idiosyncratic component; and $\sigma_\alpha^2+\sigma_\varepsilon^2$ is the composite error. The significance of the estimate for ρ is tested using a likelihood ratio test.

The modelling conducted here is static in relation to the response variable, and, as such, it is not possible to establish the existence or direction of causality between the various conditioning (explanatory) variables and the propensity to innovate. The average partial effects (APEs) can then be computed to obtain the marginal effects across the distribution of all observable covariates in the balanced sample. The APEs have the advantage of being comparable across the models investigated in this study, an advantage that is not often preserved with the estimated regression coefficients. In our study, the APE of any discrete variable (as are most of our covariates) can be thought of as measuring the discrete increment in the probability of a small food business to innovate, averaged over the distribution of the unobserved variable(s), usually done by conditioning on a set of values.

Following Rotaru and Soriano (2013), the APE for a binary variable, x_h, is estimated by:

$$A\hat{P}E_{x_h} = \frac{1}{n}\left[\sum_{i=1}^{n}\left[\Phi\left(x_{it}'\hat{\beta}_c \mid x_h = 1\right) - \Phi\left(x_{it}'\hat{\beta}_c \mid x_h = 0\right)\right]\right] \tag{4.7}$$

where $\hat{\beta}_c = \hat{\beta}\Big/\sqrt{1 + \hat{\sigma}_\alpha^2}$.

The statistic in equation (4.7) is simply the average of the discrete differences in the predicted probabilities. Robust standard errors for the APEs are calculated by the bootstrapping method. The same technique has been thoroughly explored in Rotaru (2013). To complement each of the estimated APEs, we also examine its distribution focusing on the quantiles (particularly the 25th and 75th percentiles, largest and smallest values), variance, skewness and kurtosis. The empirical results and APEs for equation (4.3), as well as summary statistics and analyses for the distributions of the APEs, are presented in section 6.2.

4.3.2 Sensitivity of the innovation propensities using the pooled probit model

If the estimate for ρ in equation (4.6) is not significantly different from zero, then the random effects probit estimator is not necessarily preferable to be used over the pooled effects probit estimator. One can employ the pooled probit model, which does not directly deal with the unobserved firm-specific effects α_i, and just compute for panel-robust standard errors for all the parameters for the overall innovation propensity model. Hence, for a balanced panel, the pooled probit model can be represented as:

$$\begin{aligned} P\left(y_{it} = 1 \middle| x_i\right) &= P\left(y_{it}^* > 0 \middle| x_{it}\right) \\ &= P\left(x_{it}'\beta + \varepsilon_{it} > 0 \middle| x_{it}\right) \\ &= \Phi\left(x_{it}'\beta\right). \end{aligned} \tag{4.8}$$

In equation (4.8), the latent variable, y_{it}^{*}, follows that of equation (4.1) but excluding the term α_i; and $\Phi(\cdot)$ is the standard normal cumulative distribution function, as noted above. The joint probability follows directly from the marginal probabilities by multiplying the individual marginal probabilities. Because equation (4.8) ignores the unobserved heterogeneity, one can make adjustment in the estimation by computing panel-robust standard errors. The pooled probit model is attractive in that it is simple to implement and to interpret, and because robust standard errors can be obtained without imposing specific distributional forms. APEs can also be estimated, as in equation (4.7), but with $\hat{\beta}_c = \hat{\beta} \big/ \sqrt{\hat{\sigma}_{\varepsilon}^{2}}$. The model has also been widely used and provides a good reference for the random effects probit model (Greene, 2012; Hensher et al., 2015; Wooldridge, 2005, 2010, 2013). In the current study, we utilise the pooled probit model to confirm the resulting relationships between overall innovation and covariates obtained using equation (4.3).

The empirical models for both equations (4.3) and (4.8) are presented in section 6.2.

4.3.3 Understanding the extent of innovation: count model using Poisson regression

By applying the Poisson regression model, we broaden our analysis and determine the relationship between the key drivers and the intensity of innovation (i.e., the total number of types of innovation participated in by the small food businesses—an additional aspect of business innovation).

When the variable to be explained takes on nonnegative integer values, as in this study where a particular business undertakes a number of different types of innovation, we have a *count* variable.[23] Instead of having a dependent variable, y_{it}, as a binary response variable, taking the value 1 if the *i*-th business innovated in the *t*-th year and 0 otherwise, we let y_{it} be a nonnegative count variable (i.e., y_{it} can take on integer values, 0, 1, 2, ..., for any time *t*). For the Poisson model, the conditional probability density function for firm *i* in year *t* is specified as:

$$P\left(Y_{it} = y_{it} \middle| x_i\right) = \frac{\mathrm{e}^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!}, \qquad (4.9)$$

[23] This assumes that the different types of innovation are independent and separable.

with the conditional mean $\lambda_{it} = E\left(Y_{it} \mid x_i\right)$ (see Hausman, Hall, & Griliches, 1984; Wooldridge, 2010, p. 724). The most common conditional mean is $E\left(Y_{it} \mid x_i\right) = \exp(x'_{it}\beta)$. Computing the APEs for an explanatory variable on the mean is straightforward with Poisson regression and an exponential mean function. It is obtained by simply multiplying $\hat{\beta}$ by the average outcome $\bar{y}$ for any arbitrary continuous explanatory variable, whereas, for discrete changes, the differences in predicted values (for two chosen values of x_h) are averaged across all *i*.

To account for unobserved heterogeneity α_i, as well as address possible over- or under-dispersion, we employ a Gamma Poisson model with $\lambda_{it} = E\left(Y_{it} \mid x_i\right) = \exp\left(x'_{it}\beta + \alpha_i\right)$. Here, $y_{it}, y_{is}\,(t \neq s)$ are independent, conditional on x_i, α_i, and the α_i s are independent of x_i and have a Gamma distribution[24] (Wooldridge, 2010, p. 760). The Poisson model has previously been applied in innovation analyses (e.g., Blundell, Griffith, & van Reenen, 1995; Allison & Waterman, 2002; Dhamvithee, Shankar, Jangchud, & Wuttijumnong, 2005; Jasper & Stanley, 2017).

Details of the empirical model, analysis and results are presented in section 6.3.

4.3.4 Understanding correlations between innovation dimensions: multivariate probit

To complement the analyses for the random effects probit model results for overall innovation and the count model results, a multivariate panel probit model is also estimated using simulated maximum likelihood estimation (see Cappellari & Jenkins, 2003; Greene, 2012; Wooldridge, 2010, 2013). The same technique was employed by Soames et al. (2011) and Srholec (2016) in their research work on innovation. In this study, we employ a multivariate probit model to further investigate the correlation structure between the four types of innovation, and to estimate simultaneously the effect of the drivers for all innovation outcomes.

We consider the four-equation multivariate latent process given by:

[24] This is also known as the negative binomial model.

$$
\begin{aligned}
y^*_{it(1)} &= x'_{it(1)}\beta_{(1)} + \varepsilon_{it(1)}\text{, where } i = 1,2,\ldots,n\text{ ; } t = 1,2,3,4 \\
y^*_{it(2)} &= x'_{it(2)}\beta_{(2)} + \varepsilon_{it(2)} \\
y^*_{it(3)} &= x'_{it(3)}\beta_{(3)} + \varepsilon_{it(3)} \\
y^*_{it(4)} &= x'_{it(4)}\beta_{(4)} + \varepsilon_{it(4)}
\end{aligned}
\tag{4.10}
$$

where

$$
y_{it(m)} = \begin{cases} 1 & \text{if } y^*_{it(m)} > 0 \\ 0 & \text{if } y^*_{it(m)} \le 0 \end{cases} \quad , m = 1,2,3,4 \tag{4.11}
$$

and $\varepsilon_{it(m)}$, *m=1,2,3,4,* are error terms distributed as multivariate normals, each with mean zero, and variance-covariance matrix V, where V has values 1 on the diagonal and correlations $\rho_{kl} = \rho_{lk}$, $l \ne k$, $l,k = 1,2,3,4$, as off-diagonal elements. Note that the above model is a simultaneous system of four binary probit equations, where the dependent variable, $y_{it(m)}$, is a binary response variable taking the value 1 if the *i*-th business innovated a particular type of innovation (i.e., product innovation (*m*=1); organisational or managerial innovation (*m*=2); process innovation (*m*=3); or marketing innovation (*m*=4)) in the *t*-th year, and 0 otherwise.

Details of the empirical model, analysis and results are presented in section 6.4.

4.4 Dynamics of innovation dimensions: Hypotheses and methods

Understanding if the businesses that innovated in the past are more likely to innovate in subsequent periods is important in the dynamic process of innovation as: learning and new knowledge accumulates; successful innovations generate profits to fund other innovations; and investments are not wasted when businesses continue or persist to innovate. Analysis of innovation persistence in food businesses is scarce and the current study is a significant addition to the empirical literature.

In this section, we outline the hypotheses and describe the technical details of the methods that address the following research questions:

- *Does innovation persist among small food businesses in Australia (Research Question 3)? and*

- *Does the degree of innovation persistence vary between the different types of innovation (Research Question 4)?*

In view of the three theoretical arguments and previous empirical studies presented in section 3.9 and to provide empirical evidence to support the proposition that true state dependence is evident in the small food businesses in Australia, the following hypotheses are tested for each type of innovation—new products, new operational process, new organisational or managerial process, and new marketing methods innovations—and for overall innovation:

- *Small food businesses that innovate in period t-1 are more likely to innovate in period t (Hypothesis 7); and*
- *The degrees of innovation persistence are the same for the different types of innovation (Hypothesis 8).*

Because small food businesses may behave differently when engaging in the different types of innovation, it is necessary to distinguish each of them (i.e., conduct the analysis for each innovation dimension) when analysing innovation persistence. In addition to analysing the lag effects of innovation behaviour (including the initial conditions), we revisit *Research Questions 1* and *2* and examine if the significant determinants of innovation are similar for all types of innovation (i.e., testing again *Hypotheses 1 to 6* in section 4.3 but, this time, for each type of innovation, utilising both the simple dynamic probit model and the dynamic CRE probit model. The associated components in the overall conceptual framework illustrating the dynamics of innovation dimensions with implications for the government's innovation policy are illustrated by the addition of the small green box connected to innovation outputs (light green box) in Figure 4.1.

To empirically observe the nature of innovation persistence happening among the small food businesses in Australia and its implication for the three theoretical hypotheses (i.e., dynamic increasing-returns, success-breeds-success, sunk-cost-account), we use the following approaches: the transitional probability matrix, the simple dynamic probit model, and the dynamic CRE probit model.

4.4.1 Evidence of innovation persistence using a transition probability matrix

To address *Research Questions 3* and *4,* and *Hypothesis 8,* we utilise the approach of Cefis and Orsenigo (2001) and Cefis (2003) of using a TPM. We first define a *state* being the innovation behaviour of businesses in each time period *t,* i.e., being innovation-active in a particular type of innovation (active innovator) or not being innovation-active at all (active noninnovator). Then, a sequence of *states* is modelled as a stochastic process approximated by a two-state Markov chain with transition probabilities formulated as:

$$P\left[Y_t = b |\ Y_{t-1} = c\right] = \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix} = \text{TPM} \tag{4.12}$$

where each term in the TPM measures the probability of moving from *state c* in period *t–1* to *state b* in period *t* for the random variable *Y*. In our study, *Y* refers to engaging in a particular type of innovation (i.e., new product, new operational process, new organisational/managerial process, or new marketing method inovation) or for any of the four types of innovation. The TPM provides useful information for analysing innovation persistence because it measures the probability that a small food business moves, for example, from being a product-active innovator to a product-active noninnovator or just remains a product-active innovator, while moving from one period to another for all the time periods examined in the data. This is particularly important in the context of the small food industry being a traditional sector where analysis of innovation persistence is uncommon. Using TPM for our short panel information initially shows the inter-temporal stability in undertaking a particular type of innovation as well as adds to justifying if the three theoretical arguments discussed in section 3.9 are occurring in small food businesses.

Following Cefis (2003), the probabilities in the TPM, being unknown parameters, are estimated using the first-order autoregressive (*AR(1))* process for the stochastic variable Y_t given by:

$$Y_t = (1-q) + \theta Y_{t-1} + \upsilon_t, \tag{4.13}$$

where $\theta_1 = p_1 + q_1 - 1$ and υ_t is the error term assumed to be uncorrelated and normally distributed $(0, \sigma^2)$ random variables. The bootstrapping procedure was applied using STATA MP 15 to estimate the standard errors associated with the transition probabilities. The application of TPM methodology in innovation persistence or state-dependence studies has been employed by Bartoloni and Baussola (2009), Antonelli et al., (2012, 2013) and Tavasolli and Karlsson (2015) but, to the best of the author’s knowledge, our study is a pioneering effort using the ABS micro-level data in the Australian innovation literature.

Following Cefis and Orsenigo (2001) and Roper and Hewitt-Dundas (2008), in the context of innovation persistence, we provide some meaningful interpretations to the obtained transition probabilities (in our case, from the 2×2 TPM) by examining the sum of its diagonal elements. The case of *weak innovation persistence* is observed if the sum of the diagonal elements of the TPM is equal to or greater than 100% but not all terms in the diagonal are equal to or greater than 50%. However, if all the elements in the diagonal of the TPM are equal to or greater than 50% then *strong innovation persistence* is evident. Further, if all the elements in the diagonal of the TPM are less than 50% then innovation persistence is not really evident.[25]

Using the TPM, Peters (2005) and Tavasolli and Karlsson (2015) added straightforward calculation of a state-dependence measure (called *observed or unconditional state dependence* (USD)) given by:

$$\text{USD} = P\left[Y_t = e |\ Y_{t-1} = e\right] - P\left[Y_t = e |\ Y_{t-1} = d\right] \tag{4.14}$$

where *state e* is the state of being an active innovator and *state d* is an active noninnovator state. The USD, measured in percentage points, reveals how much of the probability of being in the active-innovator state in year *t* can be explained by the difference between being innovative and non-innovative in year *t-1*. It can be shown that the estimated value for USD in a 2×2 TPM is equivalent to the estimate of the parameter θ in equation (4.13). It is important to note that this state-dependence measure does not condition on any observed or unobserved characteristics of the small food businesses.

Details of the empirical analysis and results are presented in section 7.2. Obtaining a state-dependence measure is discussed in the next two methods.

4.4.2 Establishing state dependence using a simple dynamic probit model

State dependence characterises a causal behavioural relationship (or what is known as a path-dependent process) where the decision to innovate in one period increases the likelihood of deciding, successfully implementing, and introducing innovation in the following period (Tavassolli & Karlsson 2015, p. 1894). A good way to test the occurrence of state dependence among small food businesses (i.e., *Hypothesis 7*) uses a simple dynamic probit model for panel data. In this model, the dynamics have a relatively simple structure, representing a first-order

[25] Ropers and Hewitt-Dundas (2008) called this transient innovation.

Markov process where only the first lag of the dependent variable is included. For a balanced panel, the simple dynamic probit model has the form:

$$\begin{aligned} P\left(y_{it}=1\middle|x_i, y_{i,t-1}\right) &= P\left(y_{it}^{*}>0\middle|x_{it}, y_{i,t-1}\right) \\ &= P\left(\phi y_{i,t-1}+x_{it}'\beta+\varepsilon_{it}>0\middle|x_{it}, y_{i,t-1}\right) \\ &= \Phi\left(\phi y_{i,t-1}+x_{it}'\beta\right), \end{aligned} \tag{4.15}$$

where ϕ is a scalar state-dependence parameter; $\Phi(\cdot)$ is the normal cumulative distribution function for ε_{it} conditional on $x_i, y_{i,t-1}$; and ε_{it} is the idiosyncratic error which summarises the effect of other time-varying unobservable variables, where $\varepsilon_{it} \mid x_{it}, y_{i,t-1} \sim N(0,1)$. The indicator function is similar to that in equation (4.2). Again, following Rotaru and Soriano (2013) and Rotaru (2013), the bootstrapping technique is implemented for robust statistical inferences of equation (4.15).

Following equation (4.7), the APE for a binary variable, z_k (to include that of lagged y_i), is given by:

$$APE_{z_k}=\frac{1}{n}\left[\sum_{i=1}^{n}\left[\Phi\left(\hat{\phi}_a y_{i,t-1}+x_{it}'\hat{\beta}_a \mid z_k=1\right)-\Phi\left(\hat{\phi}_a y_{i,t-1}+x_{it}'\hat{\beta}_a \mid z_k=0\right)\right]\right]. \tag{4.16}$$

The subscript a in equation (4.16) denotes the parameter estimates divided by $\sqrt{\sigma_{\varepsilon}^{2}}$. Again, robust standard errors for the APEs are calculated via the bootstrapping method, as used by Rotaru and Soriano (2013) and Rotaru (2013).

This simple dynamic model has also been applied in the econometric analysis of innovation persistence (Peters, 2005, 2009; Matrinez-Ros & Labeaga, 2009; Tavasolli & Karlsson, 2015) but without the bootstrapping procedures. The empirical application, model and results are presented in section 7.3.

4.4.3 Modelling state dependence with unobserved heterogeneity allowing for correlations: dynamic correlated random effects probit model

The previous random effects probit models (equation (4.3)) do not allow for any correlation between the unobserved heterogeneity α_i and the covariates, x_{it}, so to relax this assumption, Mundlak (1978) and Chamberlain (1984) extend the random effects probit models to allow for a specific type of dependence between firm-specific effects and the explanatory variables. This relationship is linear and assumed to be normally distributed with functional form expressed as:

$$\alpha_i = \psi + \bar{\mathrm{x}}_i{}'\gamma + u_i, \quad \alpha_i \mid \bar{\mathrm{x}}_i \sim N(\psi + \bar{\mathrm{x}}_i{}'\gamma, \sigma_u^2) \tag{4.17}$$

where $\bar{\mathrm{x}}_i$ refers to the group/cluster means of the time-varying variables[26] in x_{it} across all time periods; and σ_u^2 is the conditional variance of $\alpha_i \mid x_i$. It then follows that the Mundlak/Chamberlain random effects model takes the form:

$$P\left(y_{it} = 1 \middle| \bar{\mathrm{x}}_i, \alpha_i\right) = \Phi\left(x_{it}'\beta + \psi + \bar{\mathrm{x}}_i{}'\gamma + u_i\right). \tag{4.18}$$

Because we are interested in the testing the existence of true state dependence (as in equation (4.15)) another challenge in any dynamic random effects modelling is that the unobserved firm effects, captured by α_i , are likely to be correlated with $y_{i,t-1}$. With relatively short panel data, the initial conditions, y_{i0}, are also likely to play an important role in the current study; and ignoring this correlation is not recommended and would lead to inconsistent estimates.[27] Note that there is a strong reason to believe that most businesses sampled, for example in the ABS BCS (around 71.0 per cent of the innovation-active businesses in 2006/07), had already started their innovation activities before the starting period of our study (i.e., 2006/07); hence, the need to include the initial conditions in the dynamic model.

To model both types of dependence, i.e., that coming from the unobserved firm-specific effects as well as the persistence of the outcomes, including the initial conditions, we applied the Wooldridge (2005) conditional maximum likelihood estimation which also incorporates the Mundlak/Chamberlain approach in equation (4.15). This model is specified as:

[26] This model excludes the time period dummy variables and other time-invariant regressors.
[27] See Wooldridge (2005, 2010, p. 626) for more discussion of the initial conditions problem.

$$
\begin{aligned}
P\left(y_{it}=1\middle|x_i, y_{i,t-1},\ldots,y_{i0},\bar{\mathrm{x}}_i,\alpha_i\right) &= P\left(y_{it}^{*}>0\middle|x_{it}, y_{i,t-1}, y_{i0},\bar{\mathrm{x}}_i,\alpha_i\right) \\
&= P\Big(\phi y_{i,t-1}+x_{it}'\beta+\psi+\delta y_{i0}+\bar{\mathrm{x}}_i{}'\gamma+u_i+\varepsilon_{it} \\
&\qquad >0\Big|x_{it}, y_{i,t-1}, y_{i0},\bar{\mathrm{x}}_i,\alpha_i\Big) \\
&= \Phi\left(\phi y_{i,t-1}+x_{it}'\beta+\psi+\delta y_{i0}+\bar{\mathrm{x}}_i{}'\gamma+u_i\right),
\end{aligned} \tag{4.19}
$$

where $\alpha_i=\psi+\delta y_{i0}+\bar{\mathrm{x}}_i{}'\gamma+u_i,\quad u_i\sim N(0,\sigma_u^2)$, and u_i is independent of $\bar{\mathrm{x}}_i$ and y_{i0}.

It can also be shown that $\alpha_i\mid y_{i0},\bar{\mathrm{x}}_i\sim N(\psi+\delta y_{i0}+\bar{\mathrm{x}}_i{}'\gamma,\sigma_\alpha^2)$. Because y_{it} given $(y_{i,t-1},\ldots,y_{i0},\bar{\mathrm{x}}_i,u_i)$ follows a probit model and the u_i s are normally distributed, equation (4.19) is similar to the previous Chamberlain/Mundlak random effects model. The difference here is that the conditioning set also includes the initial conditions and lag effects.

Following equation (4.16), we estimate the APE for a binary variable, w_k, using:

$$
APE_{w_k}=\frac{1}{n}\left[\sum_{i=1}^{n}\left[\begin{array}{l}\Phi\left(\hat{\phi}_a y_{i,t-1}+x_{it}'\hat{\beta}_a+\hat{\psi}_a+\hat{\delta}_a y_{i0}+\bar{\mathrm{x}}_i{}'\hat{\gamma}_a\mid w_k=1\right)\\ -\Phi\left(\hat{\phi}_a y_{i,t-1}+x_{it}'\hat{\beta}_a+\hat{\psi}_a+\hat{\delta}_a y_{i0}+\bar{\mathrm{x}}_i{}'\hat{\gamma}_a\mid w_k=0\right)\end{array}\right]\right] \tag{4.20}
$$

where the subscript *a* denotes the original parameter estimates divided by $\sqrt{1+\hat{\sigma}_u^2}$. Again, robust standard errors for the APEs are calculated via the bootstrapping method, following Rotaru and Soriano (2013) and Rotaru (2013).

The empirical application, model and results are presented in section 7.4.

4.5 Impact of innovation on business performance: Hypotheses and methods

No Australian study to date has simultaneously observed whether different types of growth (i.e., using the growth in gross output, gross value added, labour productivity growth) and magnitudes of productivity dispersion are supported by persistence in different types of innovation (product, operational process, organisational and marketing methods). Preliminary analysis by the DIIS suggests that product and marketing innovation drives mostly sales and output growth, whereas employment growth is driven more by organisational and process innovation (Hendrickson et al., 2018). Following the micro-empirical studies, both international and national, reviewed and discussed in section 3.10, and to provide empirical evidence about the existing relationships between the key drivers of business innovation, innovation persistence, performance growth and productivity dispersion among small food businesses in Australia, we hypothesise that:

- *The Australian small food businesses that engage in any/a particular form of innovation are more likely to be productive than those of non-innovation active businesses (Hypothesis 9)*;
- *Persistent innovation-active small food businesses have higher performance growth (in terms of gross output, value added and labour productivity) than nonpersistent innovation-active businesses (Hypothesis 10); and*
- *There is an association between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia (Hypothesis 11).*

Investigating the dynamics of innovation and productivity growth and dispersion now completes the picture of the overall framework in Figure 4.1.

The innovation-persistence measures to address *Hypothesis 10* are compiled following the definition in Hendrickson et al. (2018). Innovation persistence describes the extent of continuity of innovation activity over the four periods for this study (i.e., 2007/08 to 2010/11). Hence, we operationally created innovation-persistence measures according to the number of times a business in the four-year panel reported that it introduced or implemented any new or significantly improved innovation. That is, a small food business that introduced an innovation in one, two, three or four out of the four years is classified as an intermittent, regular, persistent, and highly persistent innovator, respectively. If a business is noninnovation active for four consecutive years, it is classified as a persistent noninnovator. Innovation-persistence measures are also compiled for each type of innovation—new goods and services, new operational process, new organisational or managerial process, and new marketing methods innovations—and for overall innovation.

There are various approaches, both parametric and nonparametric techniques, to analyse business performance. For examining the dynamic linkages between innovation inputs, innovation outputs and business performance, the CDM framework and models, discussed in section 3.10, are the most well-used, particularly if the coverage and quality of the firm-level innovation information and financial data are adequate for the empirical application (see Hall et al., 2008, 2012; Polder et al., 2009; Raymond et al., 2013). But in a short panel and where no business-level R&D and capital expenditures data are available, following the empirical works of ABS (2008), Soames et al. (2011), Palangkaraya et al. (2015), Hendrickson et al. (2018) and Campbell et al. (2018), analytical methods such as productivity regression modelling, propensity score matching, and labour productivity dispersion analysis are adequate to assess the impact of innovation on business performance among small food businesses in Australia. Before discussing each of these analytical methods, we need to review first the business performance measures or indicators that are applied in the analysis.

4.5.1 Business performance measures

Productivity is commonly defined as a ratio of an aggregate (or overall) measure of outputs to an aggregate measure of inputs (OECD, 2001). Looking at the productivity literature, and its various empirical applications, there is no single measure of, nor a unique purpose for, productivity. According to the OECD productivity manual, the goals of productivity measurement are the following: tracing technical or technological change; identifying efficiency change; identifying real cost savings in production; benchmarking production processes; and assessing living standards. There are many different productivity measures and choosing what to apply depends on what a researcher wants to achieve as well as what data (and their quality) are available. Single factor productivity measures relate to a single measure of input only (e.g., labour productivity, capital productivity) whereas multifactor productivity measures involve a number of inputs. In relation to the current study, we are interested in firm-level productivity measures that relate gross output to one input and those which use the value added concept.[28]

Labour productivity

In this study, we utilise labour productivity as an indicator of performance. It is calculated by simply dividing a measure of output—either based on gross output (GO) or value added (VA)—by a measure of labour input, formulated as:

[28]The current study is unable to conduct total factor (or multi-factor) productivity analysis because of the unavailability of data collected through the ABS BLD CURF.

$$LP_{it} = \frac{Output_{it}}{Labour\ input_{it}} \quad , \tag{4.21}$$

where i and t denote business and time subscripts, respectively. Labour productivity only partially reflects the productivity of labour in terms of the personal capacities of workers or the intensity of their effort; and the ratio in equation (4.21) depends to a large degree on the presence of other inputs (like capital and intermediate inputs).

GO-based labour productivity is widely employed in business-level research. It has a different interpretation from VA measures because GO represents a business' output sold in the market. Dispersion in GO labour productivity, therefore, reflects the dispersion in the sales per worker of firms. However, the GO-based labour productivity measure masks varying intermediate usage across firms, and is sensitive to substitution between factor inputs and intermediate inputs, notably through outsourcing. It is often argued that GO is not a good indicator of a business' efficiency (Schreyer & Pilat, 2001) though some efficiency gain is expected as a consequence of input substitution. The VA measure is more meaningful and generally favoured for estimating labour productivity (Cobbold, 2003).

In this study, VA is also used as an output measure. Business-level VA (calculated as GO less intermediate inputs) represents an individual business' contribution to the economy and, in theory, this should aggregate to gross domestic product because aggregated final demand is equal to aggregate value added for the overall economy (hence, it is mostly used when analysing micro-macro linkages). If we have all the businesses in the Australian food industry, then the sum of their value added is the total gross domestic product in the industry involved. VA-based labour productivity is less sensitive to input substitution than GO-based measures and is the widely-used measure of living standards as well as for wage policy analysis.

We note that both measures are revenue-based labour productivity measures, given the absence of business-level prices needed to calculate quantity-based labour productivity. This means that changes in productivity levels in this dissertation are in terms of nominal labour productivity (dollars per labour unit).

4.5.2 Analysing variations in business performance growth using ANOVA

Besides providing descriptive statistics of the business performance measures defined above, we firstly investigate if there is a significant mean difference in growth performance between small food businesses according to the key drivers of innovations described in our conceptual framework using one-way ANOVA. Then we examine the mean growth differences for innovation-active and noninnovation-active businesses according to the key drivers using two-way ANOVA. All the testing of mean difference is done for each type of innovation and for overall innovation (i.e., engaging in any of the four types of innovation). The ANOVAs demonstrate which among the grouping have performed relatively well in terms of the business growth measures and if the performance status remains similar between the different types of innovation.

The one-way ANOVA is used to determine whether the mean of a dependent variable Y_i (sometimes called the "outcome" variable) is the same in two or more unrelated, independent groups (grouped according to the independent variable). The outcome variable should be a continuous variable whereas the independent variable is normally a categorical variable. It is typically used when there are three or more independent groups because an *independent t-test* is more commonly used for two groups. With two independent variables for grouping, the two-way ANOVA is applied. This compares the mean differences between groups split on two factors (or covariates) and it aims to understand if there is interaction between the two factors on the dependent or outcome variable. Readers interested on the mathematics behind ANOVA may consult any statistics books because it is a commonly-used statistical tool.

Descriptive statistical analysis of the performance growth measures and ANOVA results are presented in section 8.2.

4.5.3 Impact analysis using propensity score matching

PSM is a popular technique that simulates a randomised, controlled experiment in a setting of observational studies. In the current study, PSM controls and limits selection bias by matching each innovation-active small food business with one (or more) non-innovative business(s) that have the same or similar observed characteristics. By simulating a randomised control trial with the broadest range of business characteristics possible at the time, we are able to investigate the causal influence of innovation persistence on business performance outcomes like growth in gross output, value added and labour productivity.

The PSM procedures

Caliendo and Kopeinig (2008) provide practical guidance for the implementation of PSM. Heinrich, Maffioli, and Vázquez (2010) also develop a primer tailored for practitioners. As described in the above studies, PSM can, generally, be implemented in four steps.

Step 1. Estimate the propensity scores

There are two important choices that need to be carefully made in estimating the propensity scores: the correct specification of the model and the proper identification of the covariates in the model. With regard to the specification of the model, most empirical applications tend to use a binary model that is either a logit or a probit. With regard to choosing the variables for the model, Heinrich et al. (2010) noted that the existing explicit criteria used in determining the treatment participation (in our case, business innovation) should be considered to identify the explanatory variables.

Step 2. Choose a matching algorithm

There are many matching algorithms described in the PSM literature and there is no clear rule as to which the preferred algorithm is. The choice depends on the context and the aim of the analysis (Caliendo & Kopeinig, 2008). Coca-Perraillon (2006) and Heinrich et al. (2010) pointed out that all techniques share common elements, which include:

- an operational (or standard) definition of similarity (or distance) between propensity scores and covariates;
- a decision regarding the number of controls to be matched to each treated unit;
- a decision on whether the matching should be done with or without replacement; and
- whether one should use weights or not.

As a guideline, matching with replacement is recommended when the size of the control group is small or when there is little overlap in the distributions of the propensity scores for the two groups. More information about matching algorithms can be found in Parsons (2001, 2004) and Coca-Perraillon (2006, 2007).

Step 3. Perform diagnostics to evaluate the assumptions and the quality of matching

The validity of the PSM depends on whether the key assumptions have been met, namely, the conditional independence and the common support conditions. The *conditional independence assumption* states that, after controlling for the observable covariates, the potential outcomes for receiving or not receiving treatment are independent of the treatment assignment. The *common support assumption* states that if there is a set of covariates, then, for each value of the covariate, there is a positive probability of both receiving and not receiving treatment. A thorough discussion of these assumptions is available in Heinrich et al. (2010). With regard to assessing the quality of matching, it can be undertaken by using some standard test procedures like the standardised bias test, the t-test, the joint significance test, and the pseudo R-squared test. Caliendo and Kopeinig (2008) provide an elaborate description of these procedures.

Step 4. Estimate the treatment effect

Once the diagnostic tests are successfully conducted, we finally proceed to the estimation of the treatment effects and their associated standard errors. One common way to estimate the treatment effect is by averaging the differences in outcomes between each paired observation. The standard errors are conventionally calculated using the bootstrapping method.

Matching algorithms

In doing the PSM, an analyst needs to select an algorithm to match the estimated propensity scores of the treated units to the nontreated units. If the propensity scores match perfectly, the task is relatively straightforward because the pairs can be constructed by simply matching the treated units with the corresponding control units that have the same propensity scores. However, this does not seem to be the case, in practice, because the propensity scores do not match exactly and, therefore, the need for a more complex algorithm is warranted. Note that when deciding on the choice of a matching algorithm, there are some important considerations. The first is in regard to the desired measure of proximity between matched units, where, for example, the analyst might be interested in imposing a restriction on the maximum distance allowed between the propensity scores of a matched pair. The second concerns the weighting function to be assigned to the units or to the neighbourhood of units. (See Essama-Nssah (2006) for more details about the first two considerations.) The third is whether the matching should be done with or without replacement. That is, one should also consider whether the units that have already been matched can be reconsidered for other matches as well and, thus, perform a one-to-one or one-to-many matching.

For the current study, we consider three of the most commonly employed matching algorithms, namely:

- *the nearest neighbour matching*—the simplest method that matches the treated unit (i.e., a firm that innovated) to the control units based on the closest propensity score;

- *the radius matching—*it is similar to the nearest neighbour but it specifies a caliper (i.e., maximum propensity score distance by which a match can be made). It uses not only the nearest neighbour within each caliper, but all of the comparison group members within the caliper; as such, the algorithm corrects for bad matches that might result from the implementation of the nearest neighbour algorithm; and

- *the kernel matching*—a nonparametric approach that uses weighted averages of all (or nearly all) the units in the control group to construct the counterfactual outcome, with the highest weight being assigned on those with scores closest to the treated unit. A major advantage of this algorithm is a lower variance because more information is being used.

Further explanations of these matching techniques can be found in Caliendo and Kopeinig (2008) and Heinrich et al. (2010).

Since its inception, PSM has been applied to a wide variety of studies. Stuart (2010) provides a good overview of the evolution of the method and summarises the literature on its methodological development and uses in various fields. Although PSM has been widely applied across various disciplines, its application to evaluating the relationships between innovation and business performance has been limited. One example is Almus and Czarnitzki (2003), where the authors looked at the effects of public R&D subsidies in Eastern Germany, on the innovation activities of firms. Other examples include Heijs and Herrera (2004) and Herrera and Nieto (2006), involving similar analyses for Spain. A UK study by Foreman-Peck (2010) made use of PSM to assess the effectiveness and efficiency of the current SME innovation policy in the UK. To date, there are several Australian studies that applied PSM in social analyses, but we know only one ABS-DIIS innovation study that examined the impact of innovation on business performance (Hendrickson et al., 2018).

Details of the empirical analysis and results are presented in section 8.3.

4.5.4 Panel data regression modelling of business performance and innovation persistence

To complement the results in the PSM analysis, we also assess the magnitude of the cumulative effect of the persistence of innovation on business performance outcomes by undertaking ordinary least squares regression on the 'matched sample'—the businesses in the treatment group plus the corresponding matched businesses in the control group.

The model can be written as:

$$Log\ (\Delta Y_{i,[t,t+1]}) \ = \ p'_{it}\theta + x'_{it}\beta + \varepsilon_{it} \quad \text{, where } i = 1, 2, \ldots, n \text{ ; } t = 1, 2, 3 \tag{4.22}$$

where

$Y_{i,[t,t+1]}$ is a business performance growth from period *t* to *t+1* for the *i*-th business;

p_{it} is a categorical innovation persistence variable with the following subcategories:

- Innovation-active in all four years;
- Innovation-active in three years only;
- Innovation-active in two years only;
- Innovation-active in one year only;
- Non-innovation active in all years;

x_{it} is a vector of observed covariates including a constant term;
θ, β are vectors of fixed, yet unknown, population parameters; and
ε_{it} is the error term, such that $\varepsilon_{it} \sim N(0, \sigma^2)$.

Two different model specifications are used. The first one uses a dummy variable (0/1) for each of the innovation persistence subcategory whereas the second model treats the innovation persistence variable as purely categorical. The estimated coefficients for the persistence variables show the added effect of innovation persistence on business performance growth (in percentages) between the beginning and the end of the study period, compared with those businesses not undertaking innovations during the period.

We also test if there is evidence to support significant mean differences in the business performance growth between small food businesses of varying innovation persistence in each type of innovation using the ANOVA.

The empirical application, model and results are presented in section 8.4.

4.5.5 Productivity dispersion analysis

In recent years, policymakers and economic analysts have exhibited growing interest in the measurement of productivity dispersion. Some analysts are interested mainly in measuring the dispersion at the industry division levels whereas others are concerned with the variation of business productivity and productivity growth at the subindustry level. A concern among economists and statisticians over recent years is the increasing dispersion in industry productivity. Although Australia's labour productivity performance has been better than many other developed countries (OECD, 2017), a deeper understanding of productivity dynamics and the heterogeneity of small food business' labour productivity is useful in informing the government's potential productivity-enhancing policies needed to further improve the Australian food industry.

Measuring productivity dispersion

Productivity dispersion is a measure of how productivity differs between businesses within a given industry, which is related to the width of the productivity distribution. Three main statistics are typically employed to measure dispersion: the standard deviation, interquartile range and the 90-10 differential. Other measures, such as the difference between a fixed number of frontier businesses and the rest (Andrews, Criscuolo, & Gal, 2016) or 90-50 differential (Berlingieri, Blanchenay, Calligaris, & Criscuolo, 2017) have also been used. Of the main measures, the standard deviation is sensitive to outliers that are often present in business-level datasets.

The approach presented in this chapter uses the interquartile range (IQR) to measure dispersion, given that this measure is robust to outliers. In essence, the IQR measure shows how much more productive a business at the 75th percentile of the labour productivity distribution is than a business at the 25th percentile. Following Bartelsman and Wolf (2017), we take the natural logarithm of labour productivity prior to calculating the IQR; therefore, our IQR is calculated as follows:

$$IQR = p_{75}(\ln LP_{it}) - p_{25}(\ln LP_{it}) \tag{4.23}$$

Taking the natural logarithm of labour productivity gives the exponent of the IQR intuitive interpretation. It shows how many times more productive the upper quartile is than the lower quartile, as shown in the following expressions:

$$e^{IQR} = e^{p_{75}(\ln LP_{it}) - p_{25}(\ln LP_{it})} = \frac{e^{p_{75}(\ln LP_{it})}}{e^{p_{25}(\ln LP_{it})}} = \frac{p_{75}(LP_{it})}{p_{25}(LP_{it})} \tag{4.24}$$

The VA-based labour productivity is selected for the IQR estimation. Dispersion in VA-based labour productivity represents varying business contributions to the economy per worker. This gives the dispersion measure an intuitive appeal because it reflects the variation under aggregate productivity statistics. The existing relationship between the key drivers of business innovation, innovation persistence and labour productivity dispersion among small food businesses in Australia (*Hypothesis 11*) is assessed using some cross-tabulations and graphs.

The empirical application, model and results on productivity dispersion analysis are presented in section 8.5.

4.6 Concluding summary

In this chapter, the overall conceptual framework for the current study is conveyed and all the hypotheses corresponding to the first six research questions are framed. To achieve the objectives and help answer all the research questions, we employ various econometric modelling procedures, including the bootstrapping technique, leading to policy implications in relation to Australian small food businesses. The statistical computing involved the use of both SAS and STATA MP software packages. A summary of the analytical methods used in the current study is presented in Figure 4.2.

The nature and source of data used in the empirical analyses, utilising all the methods discussed here, are described in the next chapter. The next chapter also introduces the main data source, ABS BLD, and the construction of the small food businesses panel data used in Chapters 6 to 8.

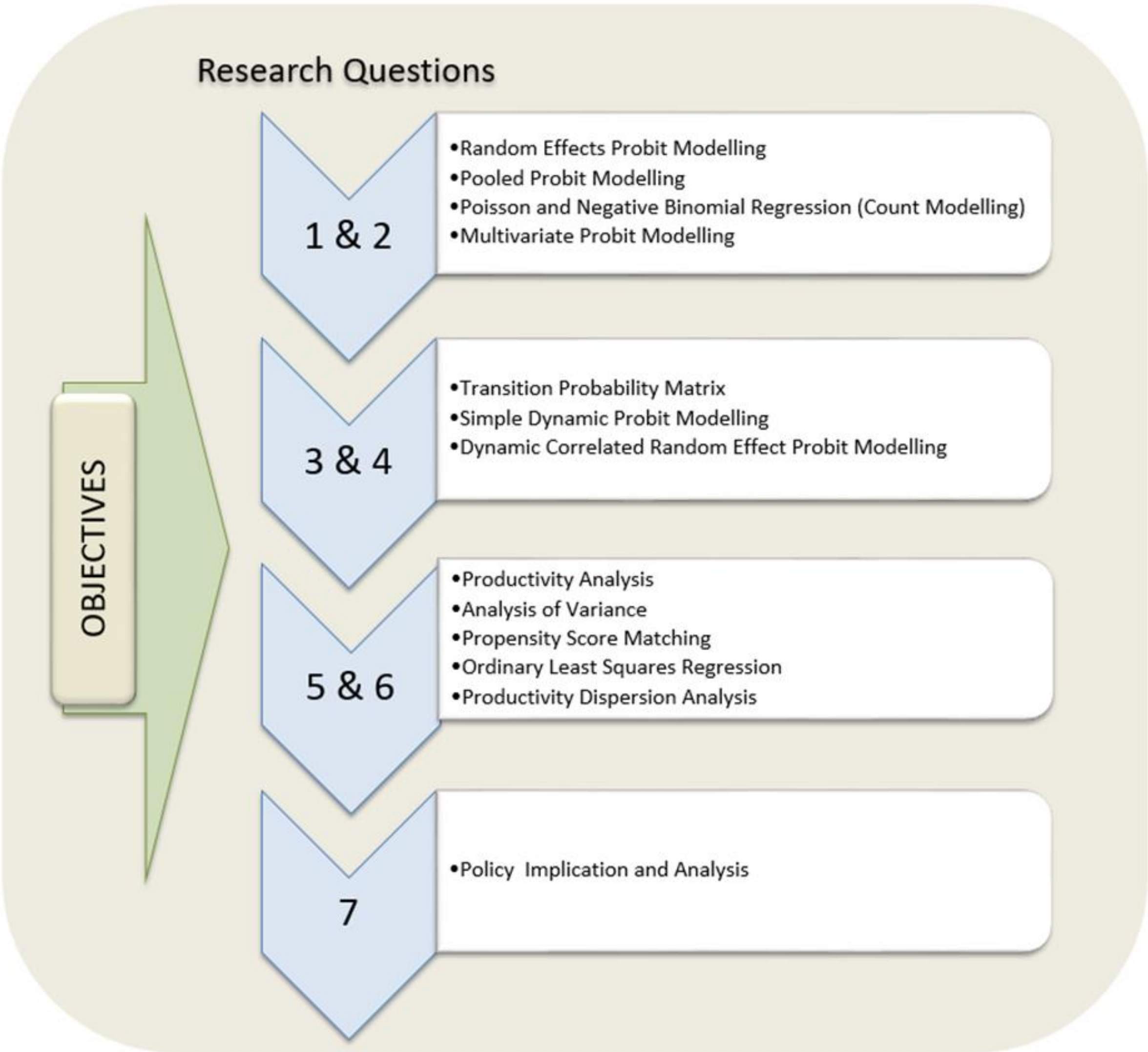


Figure 4.2. Methodological framework for the study.

Chapter 5: Data and Variables

5.1 Introduction

In Chapter 4, we establish the overall conceptual framework and methodologies used in the empirical analyses. All the hypotheses corresponding to the research questions that we aim to address are outlined. Both the conceptual and analytical frameworks lead to identifying what data are required in the econometric analyses for evaluating the status and main drivers of innovation and its impact on business performance among small businesses in the food sector in Australia. In this chapter, we describe in detail our sources of data as well as provide descriptive analytics of the actual panel of businesses sampled for empirical investigation.

Section 5.2 starts with the introduction of the ABS business panel data environment from which all the integrated confidentialised business microdata are kept and managed–the ABS BLD. BLD contains panel microdata on information of small and medium businesses from which the expanded confidentialised unit record file is created. These microdata are the most detailed information available and are generally the responses to individual questions on the BCS survey questionnaire that is briefly described in section 5.2. Then, section 5.3 discusses the mechanics, procedures and protocols in accessing the confidentialised microdata.

The construction of the panel data for the small food businesses in Australia is shown in section 5.4, followed by the creation of the variables used in the empirical modellings in section 5.5. Descriptive data analysis is presented in section 5.6, followed by an assessment of the balanced panel data extracted, and variables compiled for business performance modelling. Some concluding remarks are made in section 5.7.

5.2 The ABS business longitudinal database

The ABS BLD is the primary database and source of business micro data used in this dissertation. It is a longitudinal survey of businesses that was first implemented in 2005, following the earlier ABS development of the Business Longitudinal Survey (BLS) between 1994 and 1999. It was designed with the aim of measuring micro drivers of business performance over time. A panel sample of a cohort of small and medium businesses is selected each year and observed for five years with no changes to the sample. The BLD is specifically designed for longitudinal purposes and not to produce aggregated/population information or estimates. To date, there exist seven panels of BLD (see ABS (2019b)).

Information included in the BLD is sourced from business characteristics data obtained in the ABS Business Characteristics Survey and financial data drawn from two main administrative sources: Business Activity Statements (BAS) from the ATO; and the value of merchandise imports and exports of goods from the Department of Human Affairs. The ATO data included in the BLD are supplied to the ABS under the *Income Tax Assessment Act 1936* which requires that such data are used only for statistical and research purposes.

To provide BLD data access to external researchers, the ABS released the BLD CURF under the provisions of the *Census and Statistics Act 1905*, which allows for the release of data in the form of unit records where the information is not likely to enable the identification of a particular person or organisation (i.e., no names or addresses of survey respondents are on the BLD CURF). Additional steps such as perturbation of BAS data, perturbation and top coding of employment data, and reduction of detailed BCS data items have been done to protect the confidentiality of respondents. We note that the methodology applied to perturb financial and employment data does not impair the comparability between sampled selected businesses within a time period or over time. Confidentiality processes were designed to ensure the integrity of the dataset and optimise its content, while maintaining the confidentiality of respondents (see ABS (2019b) for more details).

The scope of businesses in the BLD is restricted to the ATO maintained population, i.e., businesses with simple structure. The statistical unit for the BLD is the Australian business number (ABN); hence, the term business or firm is interchangeable with the ABN unit. ABS assigns each business record or observation a unique randomly-generated business identifier (i.e., *ABSBID*) that is held constant over the five-year period covered in each panel. The BLD includes both nonemploying and employing businesses in the Australian economy except for large businesses (i.e., business with at least 200 employees) and/or complex businesses (i.e., business with multiple ABNs).

The sample design for each BLD panel is stratified on the basis of industry division (following ANZSIC 2006 classification) and business size (i.e., nonemploying businesses, businesses with 0–4 employees, businesses with 5–19 employees, and businesses with 20–199 employees). The geographical location of a business (i.e., state/territory) is not included in the stratification and in the BLD itself. The BLD sample design ensures that enough live/active business sample remains in each stratum at the end of five years.

The volume of data included in the BLD is substantial and it is not possible for the ABS to assure the quality of each individual data items; hence, users of BLD data have the responsibility to fully examine, validate and check the quality of the data they use. Data may be missing in the BLD due to changes in the survey questions, sampled businesses ceasing operation (either temporary or permanent death), and sampled businesses undergoing structural change, survey nonresponse and other reasons. Data cleaning was needed to compile the required dataset and variables for this study.

5.2.1 The Business Characteristics Survey

The Business Characteristics Survey is the ABS instrument that collects key indicators of business performance and activity, use of information technologies, and innovation in Australian businesses annually (for more detailed information for each of these topics, see ABS (2017a, 2017b)). Most of the data items included in the BCS are categorical in nature (i.e., require a yes/no response) and cover topics such as cooperative arrangements; innovation practices and barriers; use of information technology; market share and competition; barriers to business performance; employment arrangements; and skills utilised within the business. The reference period for the data included in the BCS is 30 June of the relevant year.

The detailed key indicators of business use of IT and innovation in Australian businesses obtained from the BCS are published in the ABS catalogue no. 8166.0 (see ABS (2017b)) whereas selected characteristics (including geographic markets in which businesses sold goods or services; business finance; business innovation; changes to business performance or activity; barriers to innovation and skills shortages) of Australian business are presented in the ABS catalogue no. 8167.0 (see ABS (2017a)).

Figure 5.1 below is a schematic diagram of how the business-level data sourced from the BCS are linked to the ATO financial information via the ABN as the linking identifier to form the BLD data used in this study.

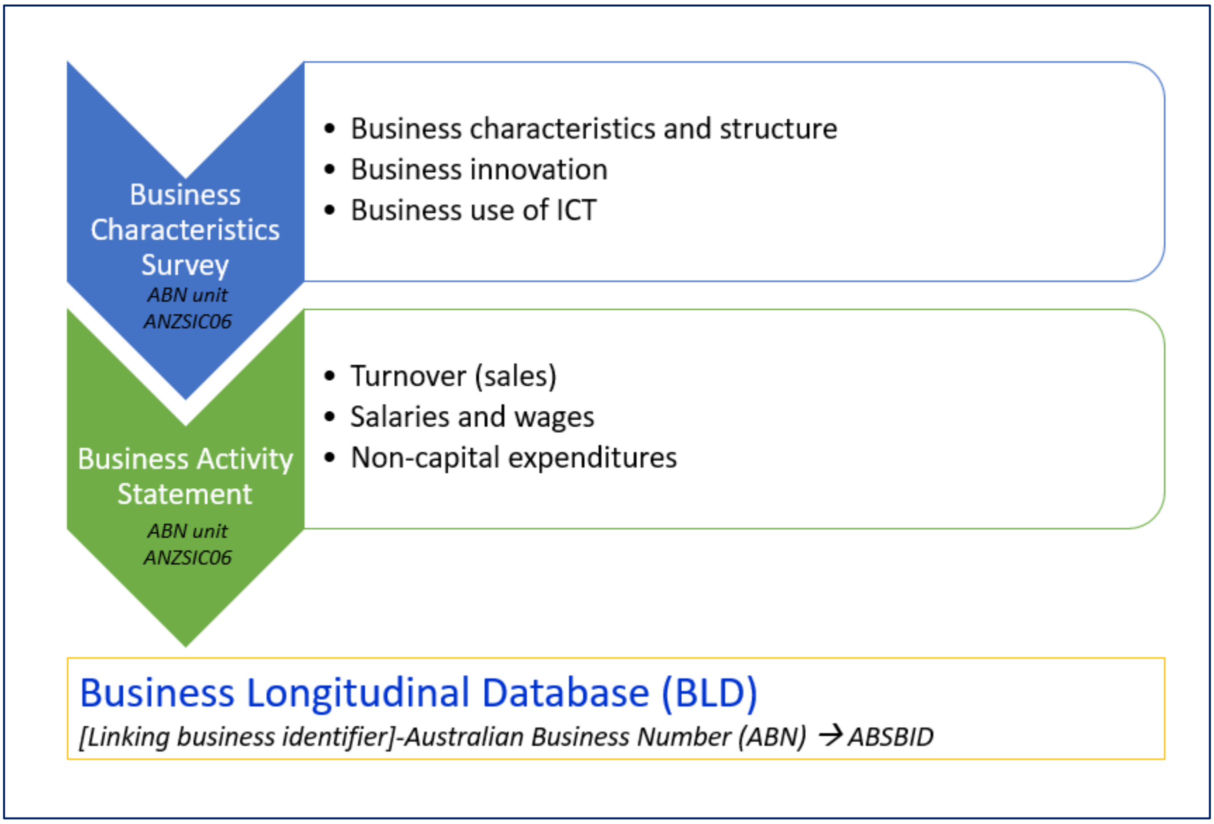


Figure 5.1. Linkages between the BCS and BAS to form the BLD

5.3 Accessing the BLD CURF via ABS Data Laboratory (DataLab)

Access to confidentialised data (BLD CURF) is completed following the ABS Protocol in accessing data through the ABS DataLab. The DataLab is the data analysis solution that allows researchers from federal and state government agencies, as well as from other Australian organisations, including universities, to conduct interactive (real time) complex analysis of microdata such as the BLD CURF in a virtual but secured ABS environment.[29]

Access to the ABS DataLab is restricted to authorised users subject to their completion of appropriate training, submission of a research project proposal designed for statistical purposes, and compliance with some legal documents. To become authorised or accredited researchers, users need to be approved by the ABS after meeting the following requirements:

[29] For more information on the ABS Data Laboratory, see Parker (2017).

- Demonstrate the appropriate knowledge and experience necessary to handle personal information as well as the commitment to protecting and maintaining the confidentiality of the microdata;
- Demonstrate experience in the use of at least one of the statistical/analytical languages (e.g., SAS, SPSS, Stata, R, RStudio, Anaconda) available within the DataLab;[30]
- Successfully complete the mandatory DataLab training and pass the written examination;
- Sign the ABS Individual Undertaking and Declaration of Compliance; and
- Work for an institution which has signed a Responsible Officer Undertaking.

Under the ABS/Universities Australia Agreement, staff and students from participating universities may freely access the DataLab.[31] Not all users of the DataLab can access the BLD microdata (i.e., most external users only submit codes for ABS staff to execute and run), so a specific agreement and approval on the use of the ABS BLD CURF was sought on 29th March 2017 and granted by the ABS BLD Data Custodian in 4th May 2017 for us to see and clean the microdata. It is for this reason that the current study was able to access (including seeing/visualising/cleaning) and analyse individual data items in the expanded BLD CURFs and utilise them in the research investigations reported.

All the DataLab analytical and modelling results for the current study passed through the ABS Customised and Microdata Delivery Unit for checking and the clearance process before they were released to the author for empirical analyses. Failure to comply with the strict conditions in the use of ABS microdata in the DataLab would have resulted in the revocation of UNE's access as well as a fine of 120 penalty points ($21,600) or imprisonment for two years, or both.

5.4 Constructing the Balanced Food Industry Panel Data

For the purpose of this study, all of the empirical analyses mainly utilised the third panel of the ABS BLD CURF (ABS, 2013). This particular BLD CURF comprised one panel that was drawn from the in-scope Australian business population at 30th June 2007. This panel contains data from this one sample over five years (2006/07–2010/11). The total sample size is 3,075.

[30] Note: ABS does not provide training assistance for coding or methodological queries.
[31] Approval to use these data for PhD research at the University of New England (UNE) was provided by the UNE Contact Officer and after the DataLab training was completed at ABS on 5th April 2017.

The BLD sample design was based on the panel that represents the Australian business population when the panel was first introduced in the BLD.

The requirement to include the food industry component in the first three panels of the ABS BLD arose in 2003 following the commissioned project of the Department of Agriculture, Fisheries and Forestry (DAFF) to analyse the business performance of small and medium businesses in the Australian food industry. This component was developed by including an additional sample in the three relevant industry divisions: agriculture, forestry and fishing (AgriFF); manufacturing (MFG); and wholesale trade (WT) (i.e., non-AgriFF = MFG and WT). It is defined by the 2006 Australian and New Zealand Standard Industrial Classification (ANZSIC06) classes predominantly associated with food for human consumption in the above three industry divisions (ABS, 2006). The third BLD CURF panel is the last panel to include the food industry component (ABS, 2013) in the currently existing seven BLD panels.

Of the 3,075 businesses sampled for the third BLD Panel, 984 businesses are flagged belonging to the food industry. Table 5.1 presents the distribution of the sampled units by business size. As already mentioned, the volume of data included in the BLD is substantial and users should clean and check their quality before using them in any analysis. After cleaning and quality checking the food industry sample, particularly the data items required for the panel modelling, the current study used a balanced panel of 417 small businesses, 237 belonging to AgriFF industries and 180 coming from the non-AgriFF industries. Although part of the original BLD, the medium-sized food businesses are not included in our study.

The panel analysis, discussed in Chapters 6, 7 and 8, is shortened to four years (i.e., 2007/08–2010/11) because the questions on business use of STEM skills and flexible working arrangements were not available in the 2006/07 BCS questionnaires.

5.5 Panel Data Variables Creation and Visualisation

This subsection describes the compilation of the variables following the conceptual framework presented in Chapter 4. These variables were used in the construction of hypotheses and in all the empirical analyses. Graphical results, which illustrate the distribution of each variable using the food industry sample and subsector samples, are also provided.

Table 5.1

Food Industry Panel Sample Size in the ABS BLD CURF Panel Three, 2006/07–2010/11

	Nonemploying businesses *No.*	Micro (1–4 persons) *No.*	Small (5–19 persons) *No.*	Medium (20–199 persons) *No.*	All business size groups *No.*
BLD Sample					
AgriFF	144	144	132	129	549
non-AgriFF	135	111	96	93	435
Total	***279***	***255***	***228***	***222***	***984***
Sample used in the empirical analysis					
AgriFF	64	88	85		237
non-AgriFF	59	56	65		180
Total	***123***	***144***	***150***		***417***

5.5.1 Innovation variables

As previously defined in the Chapter 1, innovation covers the four broad types (or dimensions):

- *Goods or services*: Any good or service or combination of these that is new to a business (or significantly improved). Its characteristics or intended uses differ significantly from those previously produced/offered.
- *Operational processes*: New or significantly improved methods of producing or delivering goods or services of a business (including significant change in techniques, equipment and/or software).
- *Organisational/managerial processes*: New or significantly improved strategies, structures or routines of a business that aim to improve performance.
- *Marketing methods*: New or significantly improved design, packaging or sales methods aimed to increase the appeal of goods or services of a business or to enter new markets.

There are three statuses of innovation, namely:

- *Introduced or implemented*: the business successfully introduced or implemented an innovation during the reference period (although the innovation does not need to have been commercially successful);

- *Still in development*: the business was in the process of developing, introducing or implementing an innovation during the reference period but work on the innovation was still in progress at the end of the period; and
- *Abandoned:* the business abandoned the development and/or introduction of an innovation during the reference period (i.e., work on the innovation ceased without full introduction occurring).

As mentioned in Chapter 1, in defining the 'innovation' variables, the current study focused on innovation-active businesses. A business is called 'innovation-active' if it engaged in any innovation activities that were implemented, still in development or abandoned during the period. Note that, in the BCS, businesses could report more than one type of innovation. Table 5.2 below describes the different innovation (dependent) variables used in our modelling.

Table 5.2

Variables for Business Innovation

Innovation Indicator	***Nature and types of data***	***Range of values***
Innovation (binary)	Business engaged/not engaged in any types of innovation (i.e., overall measure of innovation)	0/1 dummy
Innovation (binary) – for a particular type of innovation	Business engaged/not engaged in this type of innovation, say: • Goods and services • Operational processes • Organisational/managerial processes • Marketing methods	0/1 dummy
Innovation Intensity	Count data: • No innovation activity at all • Exactly one type of innovation • Exactly two types of innovation • Exactly three types of innovation • Exactly four types of innovation	0 to 4

For the food industry sample, 40.6 per cent of the small businesses were engaged in any type of innovation whereas 59.4 per cent were noninnovation active (see Figure 5.2). The percentage of innovation-active small businesses in the sample was higher than the reported innovation rate in Figure 2.8.

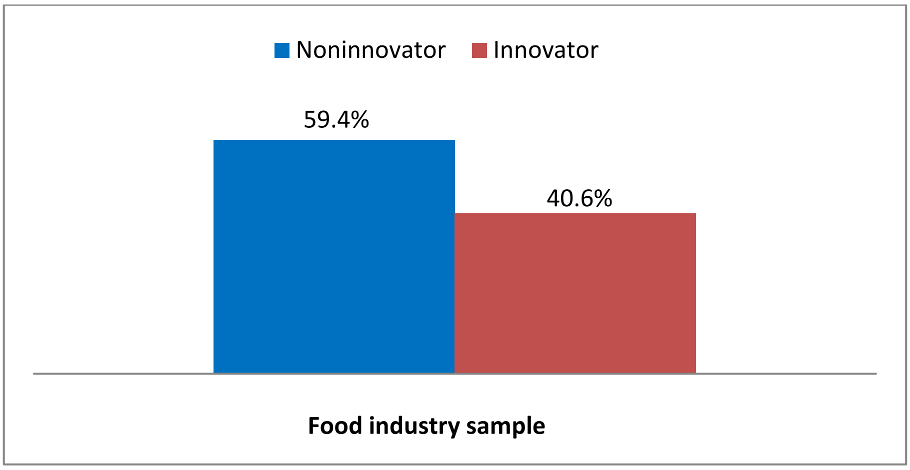


Figure 5.2. Innovation-active and noninnovation-active businesses in the Food Industry sample, 2007/08–2010/11.

Of the 40.6 per cent innovating small food businesses, 21.6 per cent of sampled businesses belonged to the non-AgriFF subsector whereas 19.1 per cent were from the AgriFF subsector, as presented in Figure 5.3 below. The percentages of sampled business innovators and noninnovators in the non-AgriFF industries were equivalent, whereas in the AgriFF sample, the percentage of noninnovating businesses was nearly double (i.e. 37.8 per cent) that for innovators.

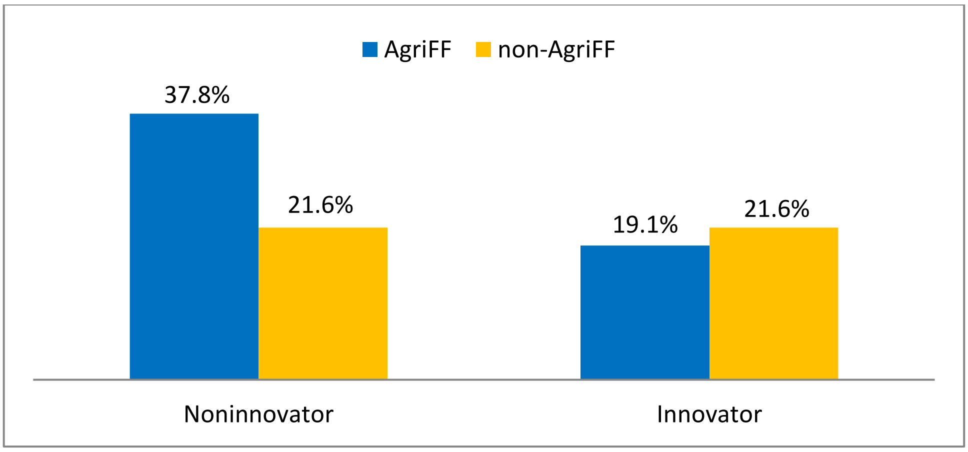


Figure 5.3. Innovation-active and non-innovation-active businesses in the subsector samples, 2007/08–2010/11.

Overall, a relatively large number of the sampled small food businesses in Figure 5.4 introduced new or significantly improved operational processes that were innovations. This behaviour from our sample was similar to the case of the innovation-active businesses in the food and agribusiness growth sector profiled in Figure 2.9. For the food industry sample and the AgriFF subsample, marketing methods, and goods and services revealed almost similar numbers of innovative-active businesses, which is again the same as what was exhibited in Figure 2.9 by the small food agribusinesses. Whereas, for the case of innovating businesses in the non-AgriFF subsample, the percentages of businesses were similar for the marketing methods, operational processes, and goods and services types of innovation.

The patterns of innovation over the four-year period for the overall sample and subsamples are graphically presented in Appendix B.

The profile of different types of innovation introduced or implemented by small food business included in the sample is presented in Figure 5.5. The number of businesses decreased as the innovation intensity increased. There was a slight increase in the intensity of innovation (i.e., between exactly three and four types of innovation) in the non-AgriFF sample.

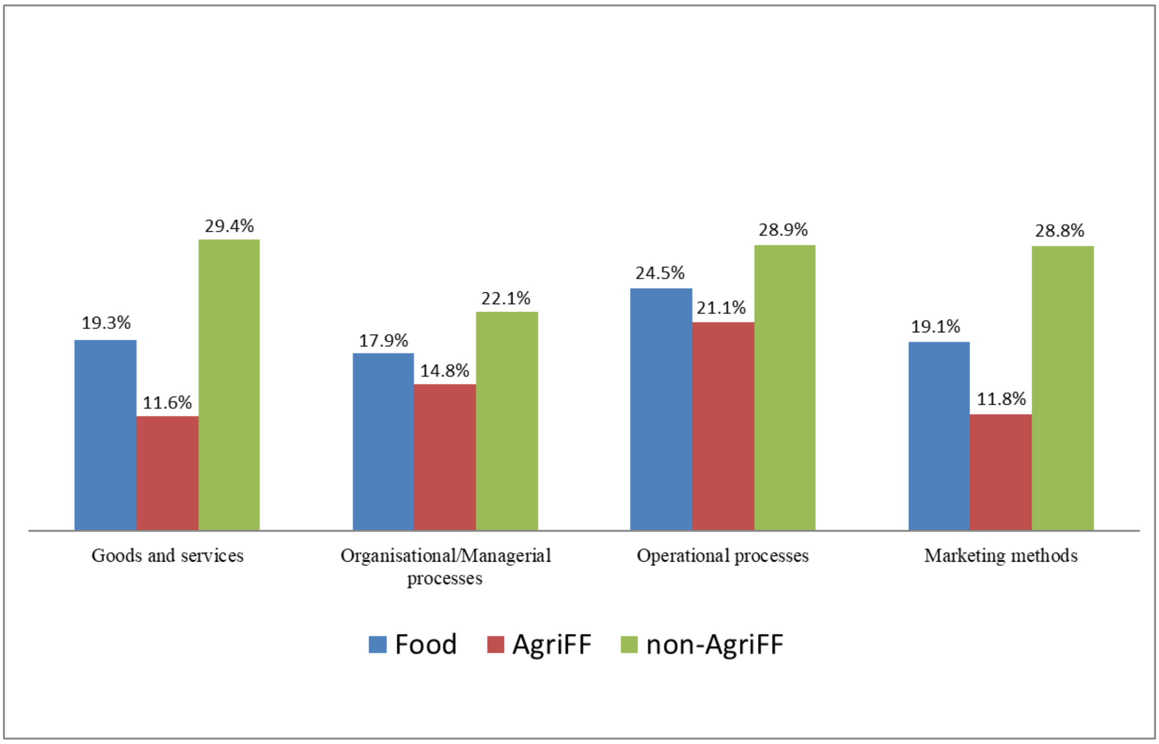


Figure 5.4. Innovation-active businesses in the sample, by type of innovation, by industry sector, 2007/08–2010/11.

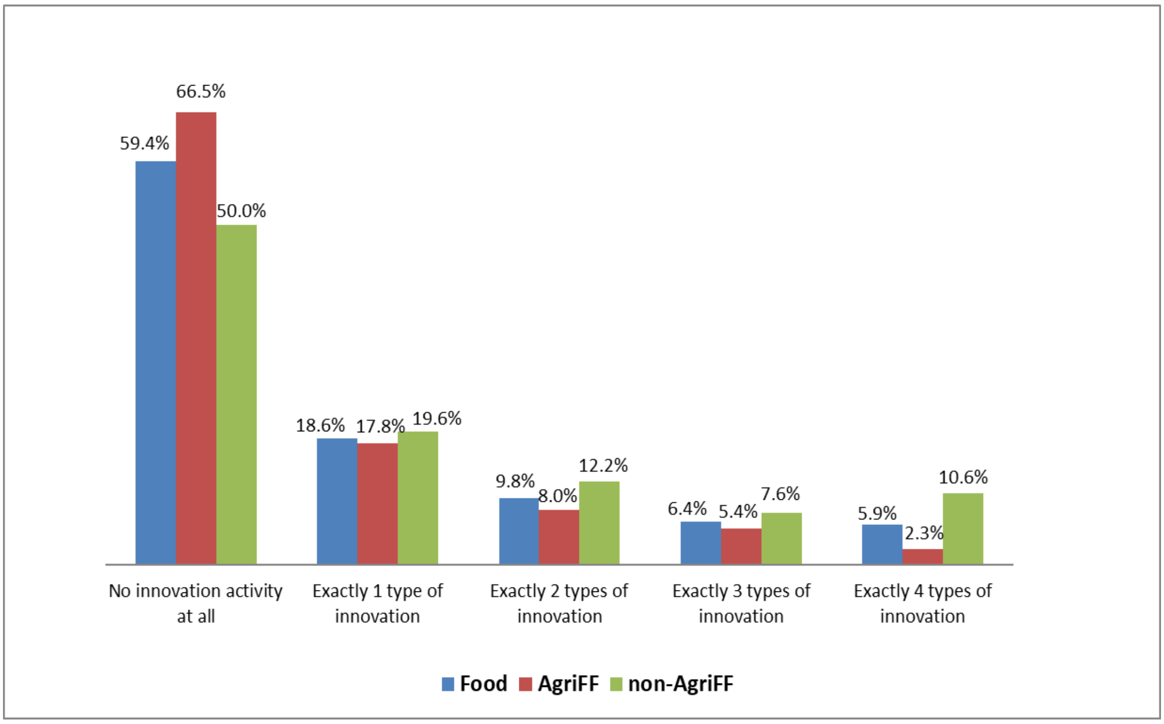


Figure 5.5. Innovation intensity of businesses in the sample, by industry sector, 2007/08–2010/11.

5.5.2 Collaboration variable

For the purpose of this study, collaboration is measured as a binary response when a business is involved in any of the following collaborative arrangements: joint R&D, joint buying, joint production of goods and services, integrated supply chain, joint marketing or distribution, and other collaborative arrangements specified by the business. It can be simple partnerships between suppliers and customers, linked networks on common interests, or associations of like industries, industry or business groups, research institutes, joint ventures and entities. The following collaboration indicator is compiled in Table 5.3.

Table 5.3

Variable for Business Collaboration

Description	***Range of values***
Collaboration (binary) Business was involved/not involved in any collaborative arrangements	0/1 dummy

Among small innovating businesses in the food industry sample, 11.1 per cent of the businesses were involved in at least one type of collaborative arrangements during the period of study (see Figure 5.6). The proportion was lower than what was reported in Figure 2.14 for the food and agribusiness growth sector's businesses which was 16.1 per cent. The presence of non-collaborative innovators were nearly three times higher (29.1 per cent) than for collaborative innovators. On the other hand, the percentage of collaborators among the sampled noninnovators was similar (approximately 5.0 per cent) to that of the noninnovators in the food and agribusiness growth sector in Figure 2.14. Most of the sampled noninnovating small food businesses did not engage in any form of collaborative arrangements. In terms of the samples in the two subsectors, there was a higher number of small food businesses engaging in any form of collaborative arrangements in the non-Agriff industries than the AgriFF industries, as exhibited in Figure 5.7.

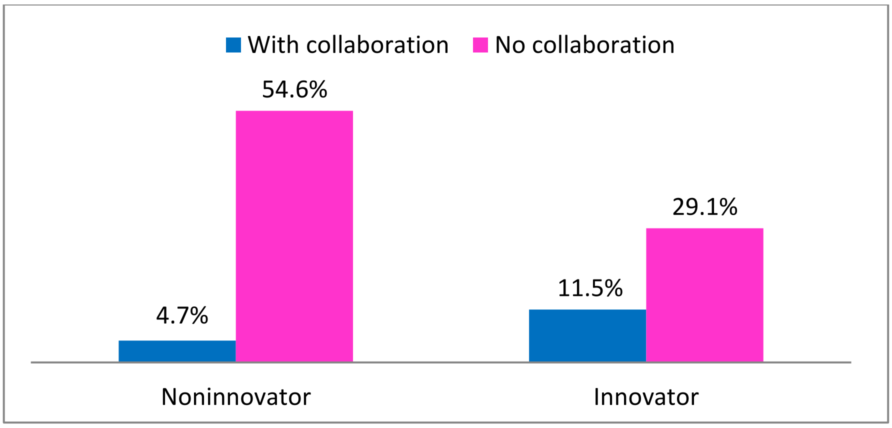


Figure 5.6. Collaborative arrangements of businesses in the Food Industry sample, by innovation status, 2007/08–2010/11.

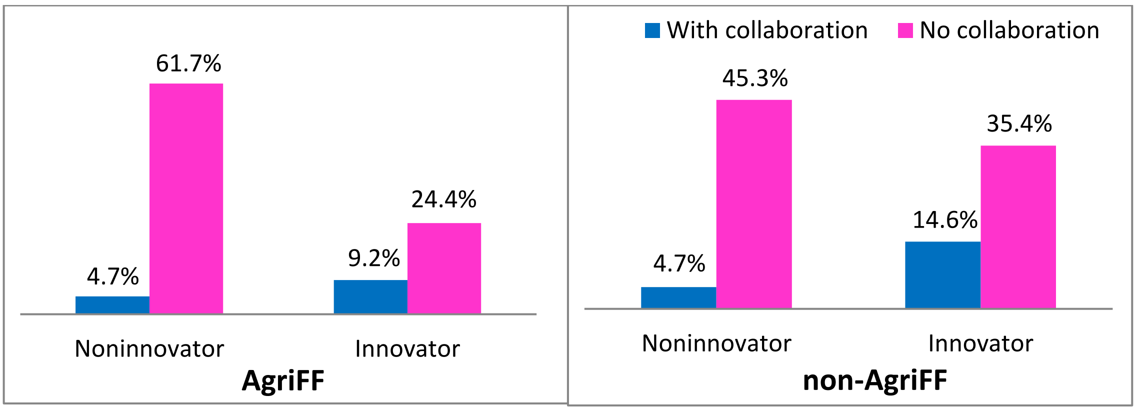


Figure 5.7. Collaborative arrangements of businesses in the Subsectors, by innovation status, 2007/08–2010/11.

5.5.3 ICT variables

For the ICT variables, we combined them into an *ICT intensity index* when businesses had broadband Internet connection, had Web presence and/or used e-commerce. This index provided a convenient and meaningful measure of ICT sophistication, from businesses not having broadband connection (low ICT intensity) to having the three components of innovation (most intense ICT). It was also applied by Todhunter and Abello (2011), Tiy et al. (2013), Rotaru (2013), Rotaru et al. (2013), and Rotaru and Soriano (2013). The ICT categorical variables are defined in Table 5.4 below.

Table 5.4

Variables for Business Use of ICT

Description	***Range of values***
ICT intensity • Most intense *Business had broadband connection, Web presence, and places or receives orders via the Internet or Web* • High *Business had broadband connection, Web presence, but does not receive orders via the Internet or Web* • Moderate *Business had broadband connection, but has no Web presence* • Low *Business does not use broadband connection*	0/1 dummy (each category)

Using the context of the food industry sample, we found higher intensity for small food businesses having broadband connection only (19.2 per cent for innovation-active and 34.2 per cent for noninnovators) (Figure 5.8). Noticeably, innovating small food businesses in our sample have websites and also do transactions via the Internet (13.1 per cent), again similar behaviour was reflected in Figure 2.20 for the food and agribusiness growth sector. When it comes to the subsectors, the categories in the ICT intensity variable [i.e., low ICT, moderate ICT, high ICT, and most intense ICT] were combined to form two binary dummy variables (i.e., business uses low-to-moderate and high-to-most-intense ICT) because of the presence of high correlations between the original four categories in the subsector samples. This was brought about by the reduced number of observations in the subsector samples. It is evident in Figure 5.9 that the intensity of ICT usage is higher in the non-AgriFF sample than in the AgriFF sample, particularly among innovating small food businesses.

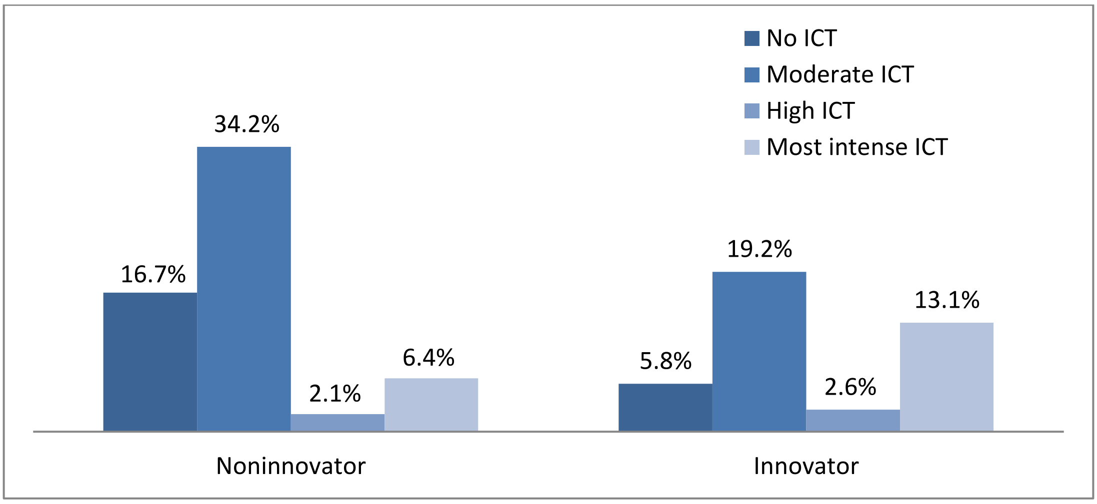


Figure 5.8. Business use of ICT in the food industry sample, by innovation status, 2007/08–2010/11.

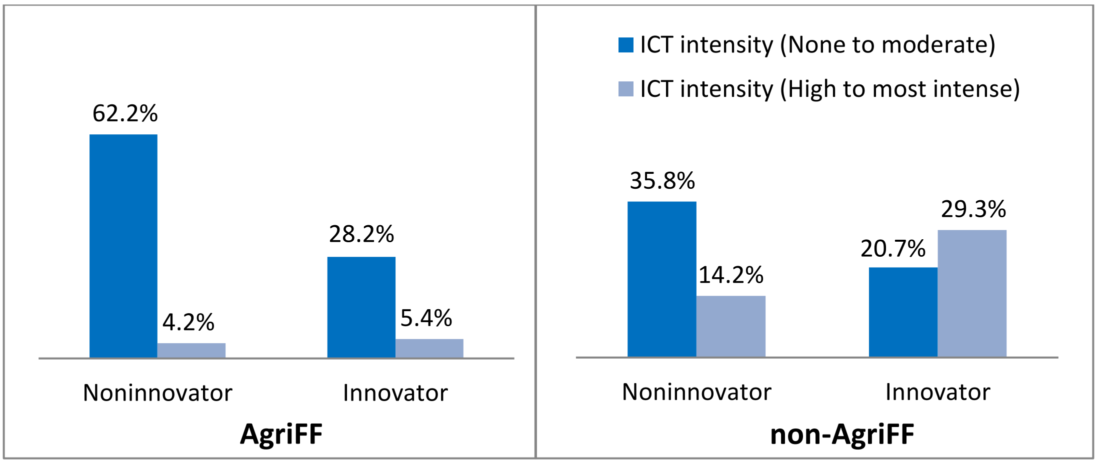


Figure 5.9. Business use of ICT in the subsectors, by innovation status, 2007/08–2010/11.

5.5.6 STEM skills variable

Following the work of Soriano and Abello (2015), the STEM-skills variables are compiled based on the type of skills used by a business, as reported in the ABS BCS. A business is considered to have used STEM skills if it reported using any of the following skills: engineering, scientific research, IT professionals, and IT support technicians. These are based on subjective responses by businesses to the BCS question about the types of skills used in undertaking core business activities. We note that a particular business may use any of the above STEM skills in combination with other non-STEM skills such as trade, transport, and plant and machinery operations. The binary STEM/non-STEM skills variable is defined in Table 5.5.

Table 5.5

Variable for Business Use of STEM Skills

Description	***Range of values***
STEM Skills (binary) Business reported using/not using any of the following types of STEM skills: • Engineering • Scientific and research • IT professionals • IT support technicians Note that the following types of skills were considered as non-STEM skills: trade; transport, plant and machinery operation; marketing; project management; business management; and financial.	0/1 dummy

Figure 5.10 below presents the sample percentages of small food businesses using and not using any of the STEM skills. More businesses used non-STEM skills than STEM skills in undertaking their core business activities; however, the use of STEM skills was higher for innovating than for noninnovating businesses in the food industry sample (i.e. 14.5 per cent against 8.9 per cent). The same scenario is also reflected in Figure 2.17 for the Australian food and agribusiness sector as well as in the subsectors in Figure 5.11 below.

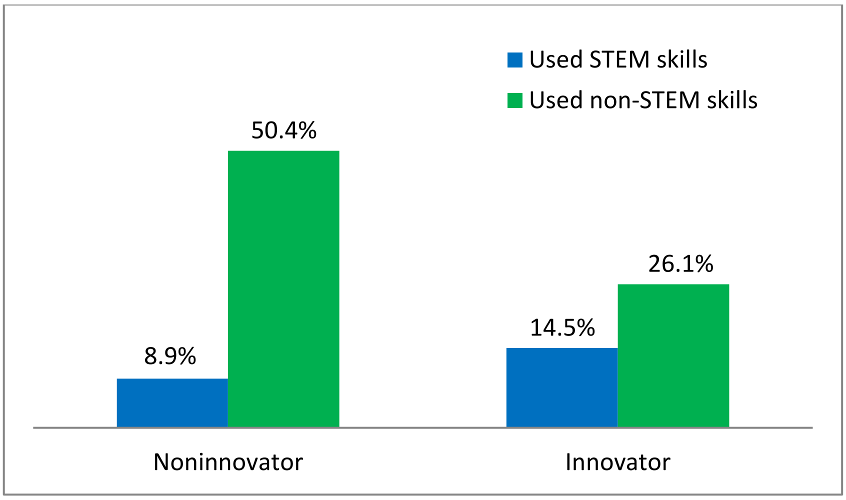


Figure 5.10. Business use of STEM skills in the food industry sample, by innovation status, 2007/08–2010/11.

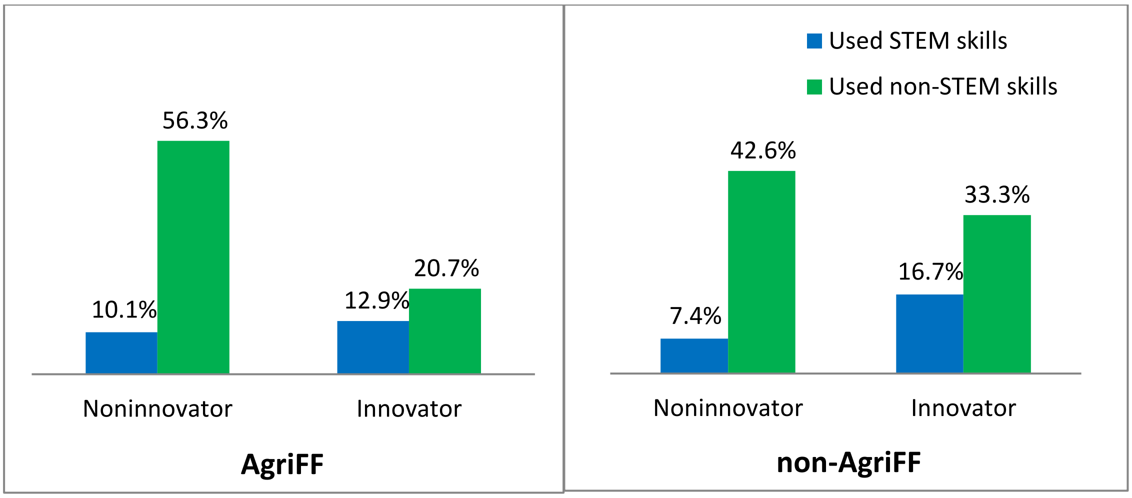


Figure 5.11. Business use of STEM skills in the subsectors, by innovation status, 2007/08–2010/11.

5.5.7 Degree of market competition variables

In this study, the degree of market competition is divided into four binary variables: business reported zero competitors; business reported 1–2 competitors; business reported 3–4 competitors; and business reported at least five competitors. These categories are defined in Table 5.6.

Table 5.6

Variables for the Degree of Market Competition

Description	***Range of values***
Degree of competition in the market: • No effective competition (0 competitors) • Minimal (1–2 competitors) • Moderate to strong (3–4 competitors) • Strong (5 or more competitors)	0/1 dummy (each category)

Strong market competition was faced by both innovating and noninnovating small food businesses in the overall sample (i.e., approximately 22 per cent for both). About seventeen per cent of noninnovators faced no competition at all, which is much higher than the 3.7 per cent for innovation-active businesses (see Figure 5.12). Interestingly, the same overall behaviour was observed among businesses in the AgriFF sample. A different story is exhibited in Figure 5.13 when looking at the non-AgriFF sample. Both innovating and noninnovating small food businesses in the non-AgriFF sample have the same increasing pattern of sample percentages from no competition to having strong competition. We were unable to compare the above behaviours of our sample with the case of the Australian businesses in the food and agribusiness growth sector because there were no published percentages for the latter.

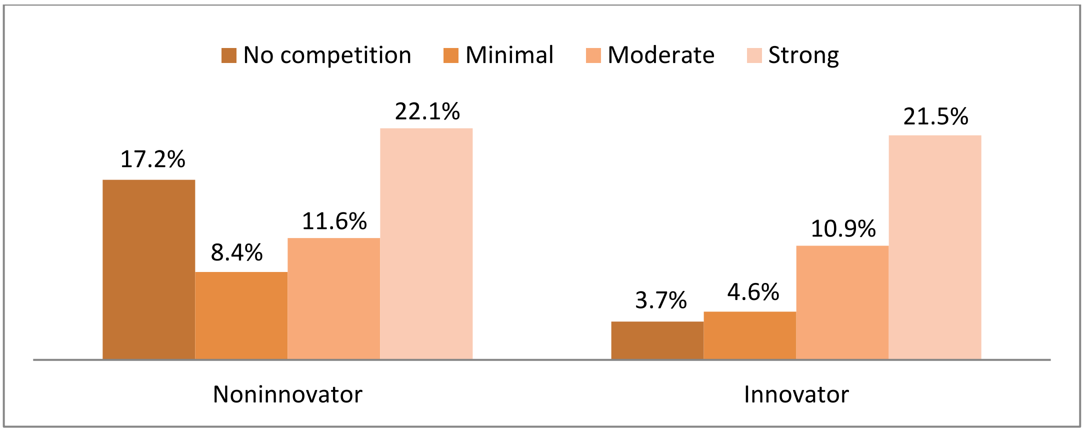


Figure 5.12. Degree of market competition in the food industry sample, by innovation status, 2007/08–2010/11.

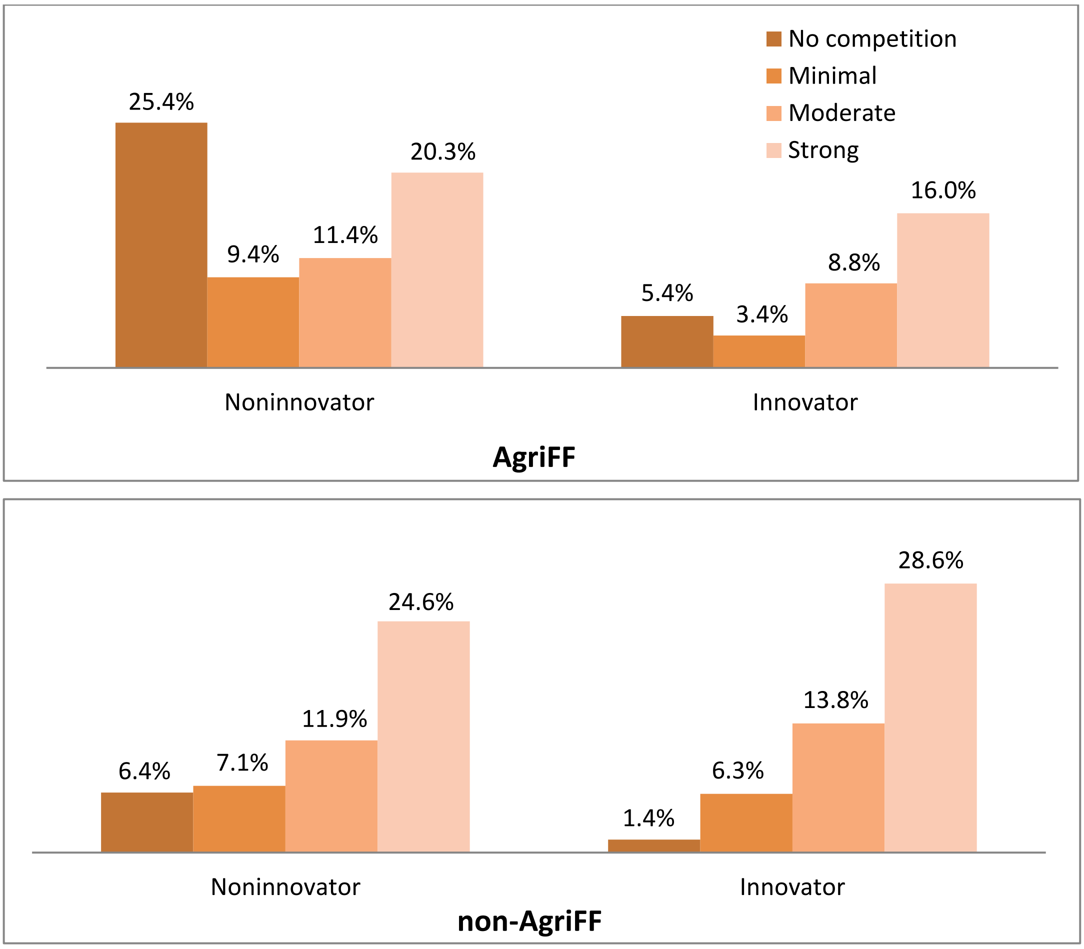


Figure 5.13. Degree of market competition in the subsectors, by innovation status, 2007/08–2010/11.

5.5.8 Flexible working arrangements variable

The variable for flexible working arrangements in this study follows the work of Rotaru (2013) and Rotaru and Soriano (2013), as described in Table 5.7.

The presence of labour market flexibility (26.7 per cent) is evident among innovating small food businesses in the overall sample, as depicted in Figure 5.14, and was highly manifested in the non-AgriFF sample (34.9 per cent). Noninnovating businesses had a higher percenbtage of businesses reporting not offering any flexible working arrangements to their employees (38.2 per cent) and the percentage was even higher in the AgriFF sample (45.4 per cent) (Figure 5.15).

Table 5.7

Variables for the Business Labour Market Flexibility

Description	***Range of values***
Flexible Working Arrangements (binary) Business offered the following working arrangements to their employees: • Flexible working hours: This includes employees being able to deal with non-work issues and the selection of their own shifts and rosters; • Flexible leave: This includes paid parental leave and flexible use of personal sick, unpaid or compassionate leave, ability to buy extra annual leave, cash out annual leave or take leave without pay; • Job sharing: This refers to the availability of job sharing; and • Working from home: This refers to the ability for staff to work from home.	0/1 dummy

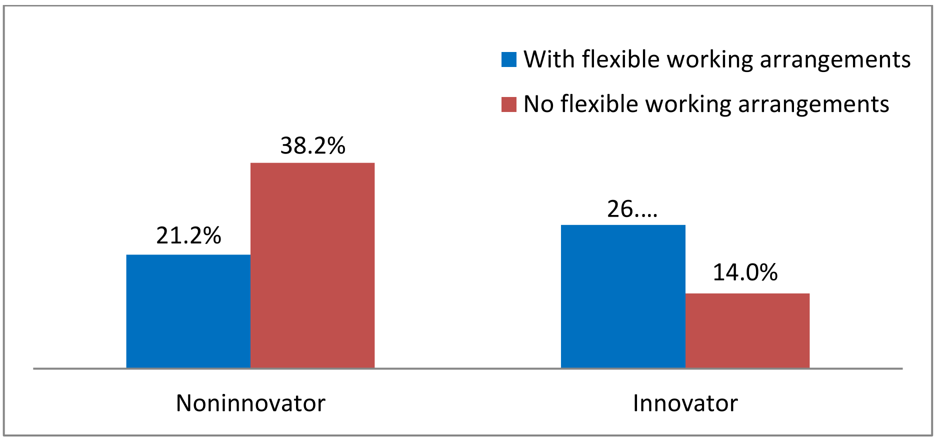


Figure 5.14. Flexible working arrangements in the food industry sample, by innovation status, 2007/08–2010/11.

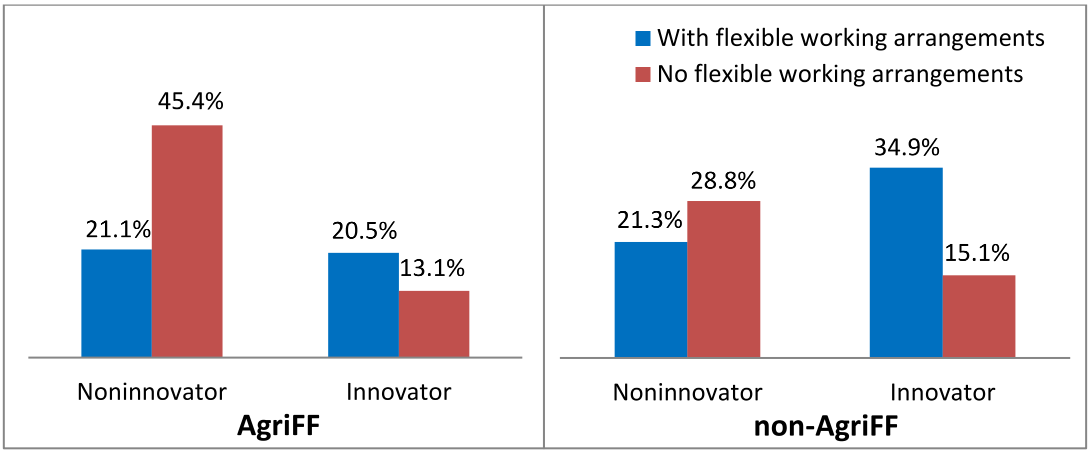


Figure 5.15. Flexible working arrangements in the Subsectors, by innovation status, 2007/08–2010/11.

5.5.9 Other key business characteristics variables

The other key business characteristics employed in the modelling are constructed in Table 5.8 below. The selection of these business characteristics has been mainly based on three recent research publications of ABS on innovation (see Rotaru (2013), Rotaru et al. (2013) and Soriano and Abello (2015) for more information about the justification for their selection).

Overall, in the food industry and subsector samples, there were fewer nonemploying small food businesses than employing businesses. This was also true for both innovation-active and non-innovation-active small businesses in all three samples (see Figures 5.16 and 5.17).

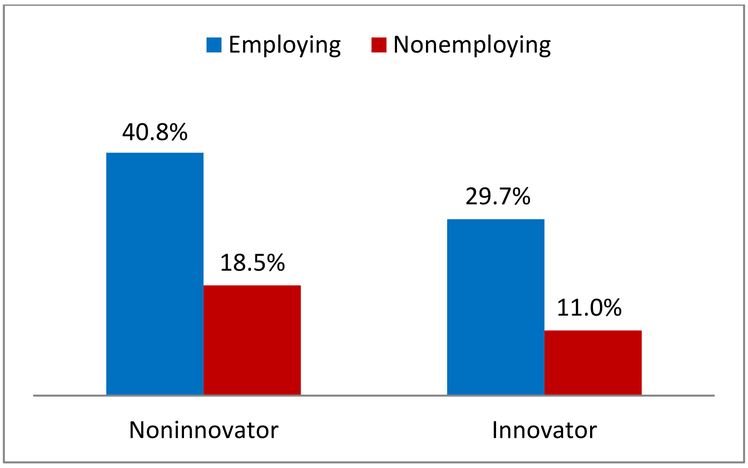


Figure 5.16. Food Industry sample, by innovation status, by business size, 2007/08–2010/11.

Table 5.8

Variables for Other Key Business Characteristics and Time Period

Description	***Range of values***
Business size (number of employees): • Nonemploying • Employing (1–19 employees)	0/1 dummy (each category)
Sub-industry where business belong (based on ANZSIC06): • Agriculture, forestry and fishing (AgriFF) • Manufacturing and Wholesale trade (non-AgriFF)	0/1 dummy (each category)
Export capability: Business sold goods and services to overseas geographic markets/within Australian geographic markets (i.e., local area where business is located; outside local area but within State; outside state/territory but within Australia only)	0/1 dummy
Financial assistance (Debt or Equity): Business sought/not sought debt or equity finance. Debt finance includes any finance that the business must repay whereas equity finance includes any finance that is provided in exchange for a share in the ownership of the business.	0/1 dummy
Financial Year: • 2007/08 • 2008/09 • 2009/10 • 2010/11	0/1 dummy (each category)

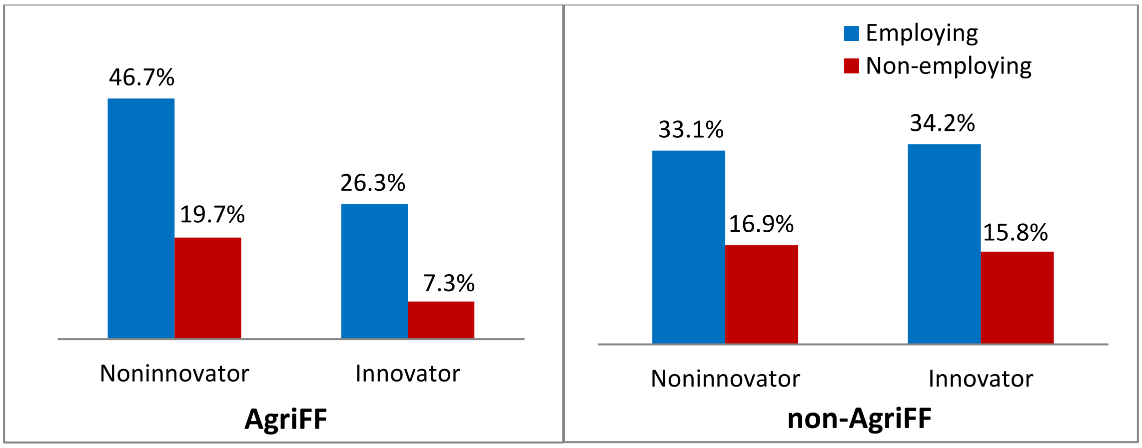


Figure 5.17. Subsector samples, by innovation status, by business size, 2007/08–2010/11.

In terms of the business export capability variable (in Figures 5.18 and 5.19), innovating small food businesses in the overall sample had higher export capability (nearly double that of noninnovators) whereas almost half of noninnovating businesses showed non-export capability (54.7 per cent). Similar behaviour was found with the food and agribusiness growth sector, as depicted in Figure 2.16. The export capability percentages were very small, as they were in the AgriFF subsector sample for both innovators and noninnovators (approximately 4 per cent). In of the non-AgriFF subsector sample, a higher percentage of innovation-active businesses engage in export (14.2 per cent) than in the overall sample.

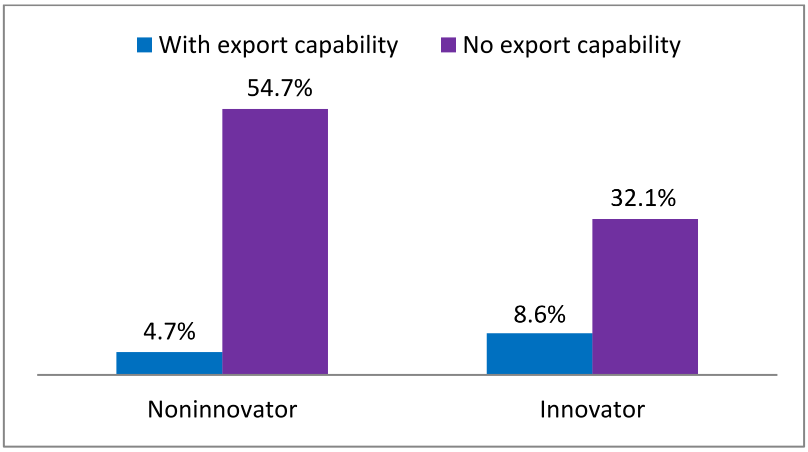


Figure 5.18. Business export capability in the food industry sample, by innovation status, 2007/08–2010/11.

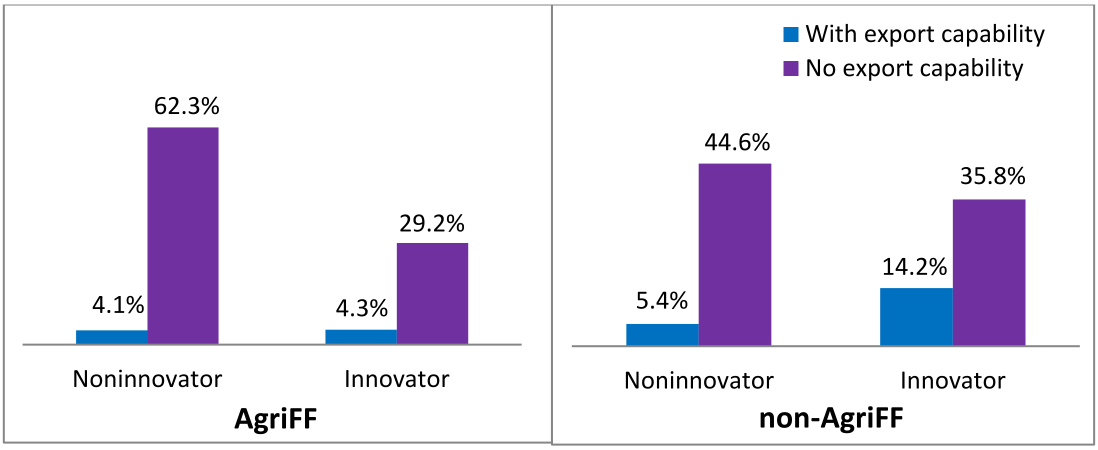


Figure 5.19. Business export capability in the subsectors, by innovation status, 2007/08–2010/11**.**

For the case of the financial assistance variable, Figures 5.20 and 5.21 show that a greater percentage of both innovating and noninnovating small food businesses did not seek any form of debt or equity financial assistance. The same behaviour was observed in the subsector samples.

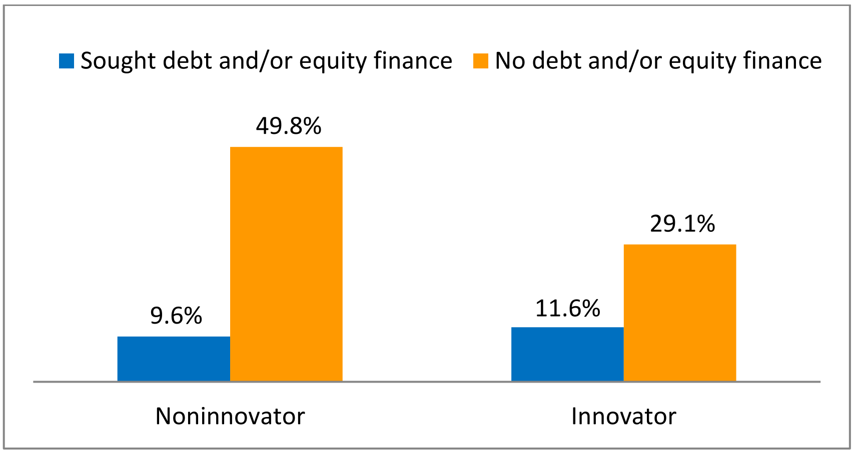


Figure 5.20. Business that sought debt or equity finance in the food industry sample, by innovation status, 2007/08–2010/11.

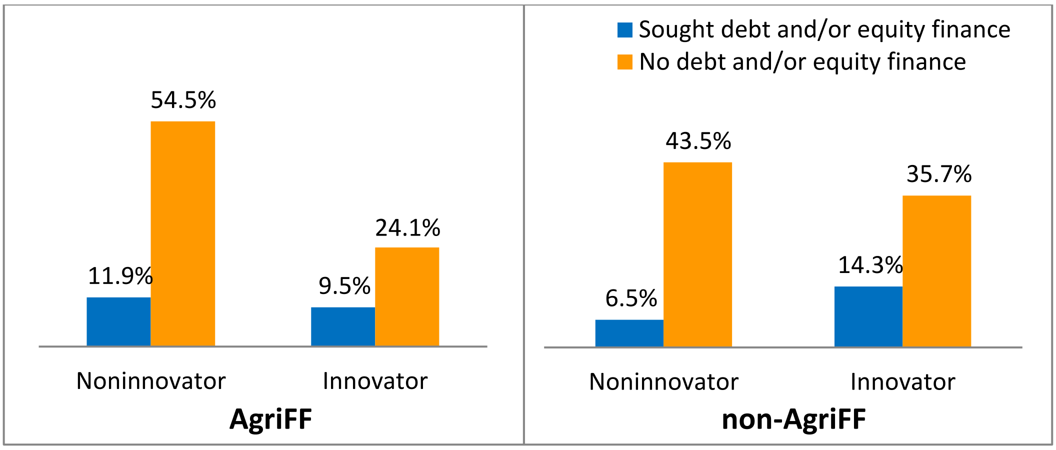


Figure 5.21. Business that sought debt or equity finance in the subsectors, by innovation status, 2007/08–2010/11.

Table 5.9 below shows the summary statistics calculated for all the variables in the Food Industry sample whereas Tables 5.10 and 5.11 reveal the summary statistics for the subsector panels. These tables are another way of summarising the graphical illustrations discussed above, but this time there is no distinction between innovators and noninnovators.

It is gleaned from Table 5.9 that there are large proportions of businesses: employing; facing strong market competition; having moderate ICT intensity; and selling products and services to domestic markets only, with variabilities nearly similar in terms of standard deviations. In Tables 5.10 and 5.11, having low to moderate ICT intensity and local market dominated the proportions of sample businesses in the AgriFF and non-AgriFF.

Table 5.9

Summary Statistics for the Food Industry Panel Data Variables, 2007/08–2010/11

Variable	Mean	*SD*	Min	Max	Observations (N)
Innovation	0.406	*0.491*	0	1	1668
Sub-industry (AgriFF)	0.568	*0.495*	0	1	1668
Sub-industry (non-AgriFF)	0.432	*0.495*	0	1	1668
Business size (Nonemploying)	0.295	*0.456*	0	1	1668
Business size (Very small)	0.345	*0.476*	0	1	1668
Business size (Small)	0.360	*0.480*	0	1	1668
Business size (Employing)	0.705	*0.456*	0	1	1668
With collaboration	0.162	*0.369*	0	1	1668
Market competition (None)	0.209	*0.406*	0	1	1668
Market competition (Minimal)	0.130	*0.337*	0	1	1668
Market competition (Moderate)	0.225	*0.418*	0	1	1668
Market competition (Strong)	0.436	*0.496*	0	1	1668
ICT intensity (None)	0.224	*0.417*	0	1	1668
ICT intensity (Moderate)	0.534	*0.499*	0	1	1668
ICT intensity (High)	0.047	*0.212*	0	1	1668
ICT intensity (Most intense)	0.195	*0.396*	0	1	1668
Used STEM skills	0.234	*0.424*	0	1	1668
Export capability (Local only)	0.868	*0.339*	0	1	1668
With flexible working arrangements	0.478	*0.500*	0	1	1668
Sought debt and/or equity finance	0.212	*0.409*	0	1	1668
Financial year 2007/08	0.250	*0.433*	0	1	1668
Financial year 2008/09	0.250	*0.433*	0	1	1668
Financial year 2009/10	0.250	*0.433*	0	1	1668
Financial year 2010/11	0.250	*0.433*	0	1	1668

Table 5.10

Summary Statistics for the AgriFF Subindustry Panel Data Variables, 2007/08–2010/11

Variable	Mean	*SD*	Min	Max	Observations (N)
Innovation	0.335	*0.472*	0	1	948
Business size (Nonemploying)	0.270	*0.444*	0	1	948
Business size (Very small)	0.371	*0.483*	0	1	948
Business size (Small)	0.359	*0.480*	0	1	948
Business size (Employing)	0.730	*0.444*	0	1	948
With collaboration	0.139	*0.346*	0	1	948
Market competition (None)	0.308	*0.462*	0	1	948
Market competition (Minimal)	0.128	*0.334*	0	1	948
Market competition (Moderate)	0.201	*0.401*	0	1	948
Market competition (Strong)	0.363	*0.481*	0	1	948
ICT intensity (None to moderate)	0.904	*0.295*	0	1	948
ICT intensity (High to most intense)	0.096	*0.295*	0	1	948
Used STEM skills	0.230	*0.421*	0	1	948
Export capability (Local only)	0.916	*0.278*	0	1	948
With flexible working arrangements	0.416	*0.493*	0	1	948
Sought debt and/or equity finance	0.214	*0.410*	0	1	948
Financial year 2007/08	0.250	*0.433*	0	1	948
Financial year 2008/09	0.250	*0.433*	0	1	948
Financial year 2009/10	0.250	*0.433*	0	1	948
Financial year 2010/11	0.250	*0.433*	0	1	948

Table 5.11

Summary Statistics for the Non-AgriFF Subindustry Panel Data Variables, 2007/08–2010/11

Variable	Mean	*SD*	Min	Max	Observations (N)
Innovator	0.500	*0.500*	0	1	720
Business size (Nonemploying)	0.328	*0.470*	0	1	720
Business size (Very small)	0.311	*0.463*	0	1	720
Business size (Small)	0.361	*0.481*	0	1	720
Business size (Employing)	0.672	*0.470*	0	1	720
With collaboration	0.193	*0.395*	0	1	720
Market competition (None)	0.078	*0.268*	0	1	720
Market competition (Minimal)	0.133	*0.340*	0	1	720
Market competition (Moderate)	0.257	*0.437*	0	1	720
Market competition (Strong)	0.532	*0.499*	0	1	720
ICT intensity (None to moderate)	0.565	*0.496*	0	1	720
ICT intensity (High to most intense)	0.435	*0.496*	0	1	720
Used STEM skills	0.240	*0.428*	0	1	720
Export capability (Local only)	0.804	*0.397*	0	1	720
With flexible working arrangements	0.561	*0.497*	0	1	720
Sought debt and/or equity finance	0.208	*0.406*	0	1	720
Financial year 2007/08	0.250	*0.433*	0	1	720
Financial year 2008/09	0.250	*0.433*	0	1	720
Financial year 2009/10	0.250	*0.433*	0	1	720
Financial year 2010/11	0.250	*0.433*	0	1	720

5.6 Innovation persistence, business performance and productivity data and variables

For the innovation persistence, business performance and labour productivity empirical analyses, discussed in Chapter 8, a study of a subset of the balanced panel of the ABS BLD CURF is presented earlier in Table 5.1. Of the 417 businesses sampled for the food industry, the current study only utilised a balanced panel of 240 small businesses, 133 belonging to the AgriFF sector and 107 coming from the non-AgriFF sector. The reasons for the reduction of the sample were the presence of missing financial information (e.g., sales, wages) from the BAS data for 177 of the 417 sampled small food industry businesses. Most of these businesses with missing information belonged to the nonemploying businesses or sole traders (66 per cent).

Table 5.12 presents the distribution of the newly assembled balanced sampled units with complete financial information by business size.

Table 5.12

Food Industry Panel Sample Size for PSM and Productivity Analysis (2006/07–2010/11)

	Nonemploying businesses	Micro (1-4 persons)	Small (5-19 persons)	Medium (20-199 persons)	All business size groups
Sample used in the PSM and Productivity					
AgriFF	1	62	70		133
Non-AgriFF	6	42	59		107
Total	***7***	***104***	***129***		***240***

5.6.1 Innovation persistence variables

The innovation persistence variables were compiled following the definition in Hendrickson et al. (2018). Innovation persistence describes the degree of continuity of innovation activity over the period, in this case, over the four years. Hence, we defined innovation persistence according to the number of times a business in the four-year panel reported that it introduced or implemented any new or significantly improved innovation. For example, in Table 5.13, a small food business that introduced an innovation in one out of the four years is classified as *Intermittent innovator*. The rest of the terms for innovation persistence are listed in Table 5.13.

Table 5.13

Defining Innovation Persistence

Innovation status	*Incidence of innovation in a four-year panel*
Noninnovator	0 years
Intermittent innovator	1 of four years
Regular innovator	2 of four years
Persistent innovator	3 of four years
Highly persistent innovator	all four years

5.6.2 Business performance measures

Three business growth performance measures, comprising two business outcomes measures and a labour productivity for each outcome measure, are presented in Table 5.14 below. The derivation of these measures followed the methodologies described in section 4.5. The labour productivity measure is expressed as defined in equation (4.21).

Table 5.14

Defining Business Performance Measures

Measure	*Derivation (Source)*	*Growth measure*
Gross output (GO)	Total Sales (BAS)	GO growth (2007/08–2010/11) $
Value added (VA)	Total Sales – Non-Capital Expenditures (BAS)	VA growth (2007/08–2010/11) $
Labour productivity (LP)	GO/Wages and salaries (BAS) VA/Wages and salaries (BAS)	LP growth (2007/08–2010/11) Ratio

The descriptive analyses and associated summary statistics for the innovation persistence and business growth performance measures are presented in the empirical analyses in Chapter 8.

5.7 Concluding remarks

This chapter comprehensively discusses how the different panels of data on small food businesses were constructed and where they are sourced. Most importantly, the variables used in all the empirical analyses are clearly defined based on how they were asked in the ABS BCS. The chapter also discloses how we were able to access the detailed and confidentialised business information using the ABS DataLab.

Visualising the counts of innovating and noninnovating small food businesses in the three balanced sample panels (for Food, AgriFF and non-AgriFF sectors), we found that the relative frequency of innovators and noninnovators vary according to business size, collaboration, ICT, employee skills, labour market flexibility, market competition and export capability in the small food businesses in Australia. Moreover, the profile of the balanced food sample used in this study matched the profile of the small Australian businesses in the food and agribusiness growth sector presented in Chapter 2.

The next chapter presents the empirical models and findings for evaluating the status and main drivers of innovation in small businesses in the food sector in Australia.

Chapter 6: Key Drivers of Innovation in Small Food Businesses in Australia: Empirical Models and Results[32]

6.1 Introduction

In Chapter 2, we provided comprehensive assessments of the status of innovation in the Australian food industry, particularly of the food and agribusiness growth sector. We found evidence of engagement in forms of innovation among small food businesses and improvement in business performance was evident for innovation-active businesses. Engagement in collaboration, having exporting capability and practising internet commerce are more likely among innovation-active businesses compared with noninnovation-active small food businesses. Transport, plant and machinery operations skills are found to be the most-used staff skills for innovation-active small businesses in the food and agribusiness growth sector. We also examined the current government initiatives relating to small business innovation such as the NISA, IICA, CRC and FIAL and outlined the current challenges facing Australian small food businesses. In Chapter 3, a review of both the theoretical and empirical studies provided a backdrop to the current study in identifying the potential key drivers of innovation and helped in the formulation of the conceptual framework and guiding hypotheses in Chapter 4. Using the methodological frameworks in section 4.3 and applying them using the ABS BLD CURF panel data, compiled in Chapter 5, this chapter now presents the empirical models and findings for evaluating the status and main drivers of innovation in small businesses in the food sector in Australia.

Each major section in this chapter is mainly divided into two parts—the empirical model specification and the empirical findings (i.e., discussion of the results for the models). Section 6.2 contains the estimation of innovation propensity for overall innovation (including a sensitivity analysis). Analysis of the extent of innovation (i.e., innovation intensity) is presented in section 6.3, followed by an assessment of correlations between the types of innovation in section 6.4. Findings are outlined in section 6.5 and recommendations are made in section 6.6 to conclude the chapter.

[32] Some materials in this chapter focusing on the results in sections 6.2 and 6.4 are published with the following citation: Soriano, F.A., Villano, R.A., Fleming, E.M., and Battese, G.E. (2018). What's driving innovation in small businesses in Australia? The case of the food industry, *Australian Journal of Agricultural and Resource Economics*, 63(1), 39–71. A copy of this publication is attached in the Appendix H.

6.2 Estimating the propensity of businesses to innovate (overall innovation)

6.2.1 Empirical model specifications

We now empirically test the following hypotheses, using the random effects probit model outlined in section 4.3, to provide evidence that would support the proposition that relationships exist between the specified drivers and innovation in small food businesses:

- *Small food businesses that collaborate are more likely to innovate (Hypothesis 1)*;
- *Small food businesses that use STEM skills are more likely to innovate* (*Hypothesis 2)*;
- *Small food businesses that have higher ICT intensity are more likely to innovate (Hypothesis 3)*;
- *Small food businesses that have flexible working arrangements are more likely to innovate (Hypothesis 4)*;
- *Small food businesses that face moderate-to-strong competition are more likely to innovate* (*Hypothesis 5)*; and,
- *Small food businesses that have export capability are more likely to innovate* (*Hypothesis 6).*

A balanced panel of 417 small food businesses with 237 and 180 businesses belonging to the AgriFF and the non-AgriFF sectors, respectively, is employed in this modelling. Although we have five waves of BCS in our BLD CURF, the panel analysis here has been shortened to four years (i.e., 2007/08–2010/11) because the questions regarding two determinants (business use of STEM skills and flexible working arrangements) were not in the 2006/07 BCS questionnaire.

The empirical model following equations 4.1 and 4.3 is specified as:

$$P(y_{it} = 1|x_i, \alpha_i) \quad = \quad P(y_{it}^* > 0|x_{it}, \alpha_i) \tag{6.1}$$

where the dependent variable, y_{it} , is a binary response variable taking the value 1, if the *i*-th business engaged in any of the four types of innovation (i.e., overall innovation) in period *t,* and 0 otherwise. The dependent variable is limited to overall innovation only and the aspect of innovation dimensions (i.e., engagement in a particular type of innovation) is dealt with later in section 6.4 and Chapters 7 and 8. Note that a business can engage in more than one type of innovation. The latent variable is formulated as:

$$y_{it}^{*} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2 + \ldots + x_{kit}\beta_k + \alpha_i + \varepsilon_{it},\ k = 16,\ i = 1,2,\ldots,417,\ t = 1,2,3,4. \quad (6.2)$$

The observed explanatory variables, x_k, k=1,2,..,16, included the following business characteristics: the business belongs to subsector non-AgriFF (x_1); the business is nonemploying (x_2); the business has collaboration arrangement (x_3); the business faces minimal competition (x_4), moderate competition (x_5), and strong competition (x_6); the business uses moderate ICT (x_7), high ICT (x_8), and most intense ICT (x_9); the business uses STEM skills (x_{10}); the business has export capability[33] (x_{11}); the business has flexible working arrangements (x_{12}); the business seeks debt and/or equity financing (x_{13}); and there are three time-period dummies (x_{14}, x_{15}, x_{16}) (for year effects). The construction of these variables followed that of Tables 5.3 to 5.8 in Chapter 5. We note that a key assumption for this model specification is that the observed covariates are strictly exogenous, conditional on the unobserved effect, α_i. We also assume that there is independence between the covariates and the unobserved heterogeneity and that the error term, ε_{it}, conditional on the observed covariates, follows a standard normal distribution.

We estimate the parameters, $\beta_0, \beta_1, \beta_2, ..., \beta_{16}$, for the above random effects probit model using the maximum likelihood method executed in STATA 15 MP. To complement the empirical results and to get a better indication of the effects of the main drivers on overall innovation, the average partial effects (APEs), defined by equation (4.7), are calculated for all the covariates. Robust standard errors for the estimators of parameters and the APEs are obtained using the bootstrapping method. Further examination of the distribution of the estimated APEs is done by calculating summary statistics (e.g., percentiles, mean, median, variance, kurtosis, skewness). The goodness-of-fit of the model is evaluated using the *F-test* statistics, AIC and BIC criteria. The empirical findings are presented in the next subsection.

[33] In this analysis, the export capability variable is defined as the business selling products to local and/or overseas markets. Following the ABS BCS, local (geographic) market includes the immediate area, town or city in which the business is located as well as outside this area but within Australia.

6.2.2 Results for the models

This section presents the empirical results of the model specified in the previous section. The random effects probit model is applied to the food industry panel of businesses and the same modelling procedure is also applied to the balanced panel samples created for businesses belonging to the AgriFF and non-AgriFF subsectors. The estimated APEs in all models are to be interpreted with reference to a business belonging to the AgriFF subsector (for the food industry sample only), which is small, does not collaborate, has low ICT intensity, has no effective competition, does not use STEM skills, has no debt or equity finance, has export capability, and does not have any flexible working arrangements, during the period 2007/08 (i.e., the base year).

The empirical results are compared with those of other ABS and DIIS studies that used cross-sectional modelling and employed data collected in the same survey (i.e., BCS) as well as with the findings coming from previous international food industry studies.

6.2.2.1 Findings for the food industry

Table 6.1 presents the estimated coefficients and their bootstrapped standard errors (SEs) for the random effects probit model of overall innovation propensity. The overall innovation propensity measures the likelihood of businesses to engage in any form of innovation. The estimated coefficients for the dummy variables for industry and size of business are not significant, contrary to the results of Zouaghi and Sanchez (2016), although the latter covered all Spanish businesses in the food sectors. Despite these results, it is important that these two covariates remain in the model because this information is used in the BCS survey design to generate the randomly sampled businesses in the food industry, and the current modelling did not apply any weights. The estimated proportion of the total variance contributed by the panel-level variance component ($\hat{\rho}$) is significantly different from zero (with the likelihood ratio chi-square test statistic having the value 118.57 with *p*-value 0.0001). It indicates that this component accounts for more than 44 per cent of the variability of the composite error. The significance of the panel-level variance component is consistent with the findings of Triguero et al. (2013) and Vancauteren (2016). Therefore, controlling for unobserved effects is important and justified in the context of this analysis. The log-likelihood, AIC and BIC results (including a likelihood ratio test statistic with value 118.0) confirm the goodness-of-fit of the model compared with the pooled probit model, as exhibited in Table 6.6 in section 6.2.3.

Table 6.1

Random Effects Probit Regression Results for (Overall) Innovation and Average Partial Effects for Selected Key Drivers of Innovation

Variable	Coefficient		*SE*	APE†		*SE*
Innovation (Response variable)						
Sub-industry (non-AgriFF)	0.14		*0.13*	0.034		*0.037*
Business size (Nonemploying)	0.22		*0.14*	0.052		*0.033*
With collaboration	0.68	***	*0.12*	0.172	***	*0.029*
Market competition						
Minimal	0.50	***	*0.18*	0.114	***	*0.041*
Moderate	0.87	***	*0.16*	0.207	***	*0.035*
Strong	0.67	***	*0.15*	0.156	***	*0.033*
ICT Intensity						
Moderate	0.25	**	*0.12*	0.061	**	*0.029*
High	0.73	***	*0.24*	0.183	***	*0.057*
Most intense	0.71	***	*0.20*	0.177	***	*0.048*
Used STEM skills	0.58	***	*0.13*	0.144	***	*0.033*
Export capability (Local only)	–0.33	**	*0.16*	-0.080	**	*0.040*
With flexible working arrangements	0.68	***	*0.11*	0.171	***	*0.028*
Sought debt and/or equity finance	0.23	**	*0.11*	0.055	**	*0.025*
Financial year						
2008/09	–0.45	***	*0.13*	-0.109	***	*0.030*
2009/10	–0.50	***	*0.12*	-0.121	***	*0.029*
2010/11	–0.52	***	*0.13*	-0.126	***	*0.033*
Intercept	–1.33	***	*0.23*			
Log-likelihood	–844.89					
AIC	1725.77					
BIC	1823.32					
Sigma	0.894		*0.085*			
rho (ρ)	0.444	***	*0.047*			
Number of observations (n)	1668					

Note: The asterisks, ***, ** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.
†Average partial effects for selected key drivers of innovation.

Overall, the three key business characteristics (i.e., collaboration, use of STEM skills and ICT intensity) are found to be statistically significant at the 5% level in explaining the innovation behaviour of small businesses in the food industry. All of the APEs are found highly significant except for the APE of moderate ICT intensity which is small compared with the rest, but still significant at the 5% level. The distributions of the estimated APEs are presented in Table 6.2 below. We note that all of the distributions are skewed to the left, which implies that there were a significant number of small food businesses where the effects of the drivers were positive, but relatively small in magnitude. Therefore, the results suggest that there are potential avenues to intensify the effects of the key drivers on the propensity to innovate among small food businesses.

Collaboration is positive and highly significant, implying that small food businesses reporting involvement in any collaborative arrangement are more likely to innovate (i.e., acceptance of *Hypothesis 1,* that small food businesses that collaborate are more likely to innovate). This conforms to the findings in ABS (2008), Rotaru (2013), Rotaru *et al*. (2013), Rotaru and Soriano (2013) and DITR (2006) where collaboration was found to strongly drive overall innovation among Australian businesses. The corresponding APE result shows that after averaging across all small food businesses and time periods, assuming all other variables constant, having some form of collaboration is associated with an increase of more than 17 per cent in the propensity to innovate. The APEs for collaboration at the 25th and 75th percentiles are 15.9 per cent and 19.6 per cent, respectively. This indicates that, even after accounting for unobserved heterogeneity, engaging in collaborative arrangements plays an important role in the likelihood of a business to innovate. This result further confirms that joint R&D collaboration between small food businesses and universities, private and public organisations and other businesses plays a key role in business innovation (Grunett et al., 1997; Maietta, 2015; Caiazza & Stanton, 2016; Celiberti et al., 2016a, 2016b; De Martino & Magnotti, 2017; Sauer, 2017; Wixe et al., 2017). This result also implies that small businesses in the Australian food industry can gain external knowledge, acquire technology and improve their technical capability to boost their innovation performance through collaboration. Considering that only 16.2 per cent of businesses in our sample are currently engaged in some form of collaboration, there are still some potential positive impacts for innovation in the food industry if we can push the remaining 83.8 per cent small food businesses to collaborate. Access to external knowledge through collaborations is an important factor that drives the survival and growth of local food producers (Wixe et al., 2017).

Table 6.2

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Random Effects Probit Model)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	75	Largest	Variance	Skewness	Kurtosis
Sub-industry (non-AgriFF)	0.012	0.029	0.037	0.040	0.042	0.000058	-1.041	3.157
Business size (Nonemploying)	0.018	0.045	0.057	0.062	0.065	0.00015	-0.993	3.001
With collaboration	0.080	0.159	0.183	0.196	0.200	0.00087	-1.205	3.603
Market competition								
Minimal	0.053	0.091	0.120	0.141	0.147	0.00076	-0.494	1.956
Moderate	0.105	0.172	0.218	0.244	0.253	0.0016	-0.623	2.149
Strong	0.077	0.129	0.164	0.188	0.196	0.0012	-0.555	2.038
ICT Intensity								
Moderate	0.023	0.052	0.066	0.073	0.075	0.00020	-1.053	3.222
High	0.088	0.166	0.197	0.210	0.215	0.0012	-1.247	3.709
Most intense	0.084	0.160	0.189	0.203	0.208	0.0011	-1.240	3.694
Used STEM skills	0.042	0.131	0.153	0.166	0.170	0.00074	-1.227	3.758
Export capability (Local only)	-0.097	-0.094	-0.086	-0.071	-0.031	0.00027	1.117	3.372
With flexible working arrangements	0.080	0.157	0.181	0.196	0.200	0.00091	-1.186	3.535
Sought debt and/or equity finance	0.018	0.048	0.059	0.065	0.067	0.00014	-1.076	3.289
Financial year								
2008/09	-0.133	-0.129	-0.115	-0.099	-0.030	0.00052	1.053	3.258
2009/10	-0.148	-0.143	-0.128	-0.109	-0.034	0.00065	1.035	3.205
2010/11	-0.155	-0.150	-0.134	-0.114	-0.036	0.00072	1.027	3.180

Businesses require resources with a broad range of technical and non-technical skills and capabilities working together to foster innovation (Cunningham, Theilacker, Gahan, Callan, & Rainnie, 2016). Small food businesses usually lack skills and resources; hence, they need external partners/networks to realise innovations (Caiazza & Stanton, 2016; Galati, Bigliardi, & Petroni, 2016). Even horizontal collaboration between businesses in the Australian food industry should be encouraged (McAdam et al., 2014). The above results also support the Nelson and Winter (1982) model and the systems of innovation approaches by Nelson (1993) and Lundvall (2010). It is interesting that the results are supportive of the OI models and with the results in Bigliardi and Galati (2013).

The use of STEM skills is positively associated with the likelihood of innovation (i.e. acceptance of *Hypothesis 2*, that small food businesses that use STEM skills are more likely to innovate based on the empirical result). It implies that small food businesses that use STEM skills in their production are significantly more likely to engage in any one of the four broad types of innovation than other businesses. Its impact is about 14 per cent with the 25th and 75th percentiles at 13.1 per cent and 16.6 per cent, respectively. These results are consistent with Soriano and Abello (2015) for all business sizes in all industries. The results are also consistent with Palangkaraya et al. (2016) on science and research core skills having significant positive association with any types of innovation in Australian businesses. The significant relationship between employee skills and innovation has also been observed in Huiban and Bouhsina (1998), Avermaete et al. (2004), Capitanio et al. (2009, 2010), Smit et al. (2015), Vancauteren (2016) and Brown and Roper (2017). This implies that the quality of the human capital in small food businesses has a strong influence on innovation propensity. A recent Australian farm study exemplified a very strong link between skills and training, innovation and productivity (Xayavong, Kingwell, & Islam, 2015).

There is a strong relationship between ICT intensity and the likelihood that a small food business will undertake innovative activity (i.e., acceptance of *Hypothesis 3*, that small food businesses that have higher ICT intensity are more likely to innovate, based on the sample evidence). The empirical results indicate that, all other things being held constant, moving from moderate to high and more intense ICT increases the likelihood of innovation. They imply that small businesses in the food industry that engage in more sophisticated forms of ICT are significantly more likely to innovate. Averaging across all small food businesses and time periods, assuming all other variables constant, small food businesses using high ICT intensity are 18.3 per cent more likely to innovate than businesses using low ICT intensity. The APEs for high ICT intensity at the 25th and 75th percentiles are 16.6 per cent and 21.0 per cent, respectively. Todhunter and Abello (2011), Rotaru et al. (2013), Tiy et al. (2013) and Soriano and Abello (2015) found similar results in their cross-sectional analyses. The results support the findings of Galati et al. (2016) that ICT plays a crucial role for effective OI performance for food businesses as well as the work of Domenech et al. (2014) on the adoption of ICT innovations in the agri-food sector. ICTs have been transforming economic activities in all sectors, particularly farming (including the food industry) for technological innovation and improvement in agricultural output (World Bank, 2011; Lamb, 2013; Salim et al., 2016).

Having flexible working arrangements was found to be significant and had a strongly positive effect on a business's propensity to innovate. This finding led to non-rejection of *Hypothesis 4*, that small food businesses that have flexible working arrangements are more likely to innovate. This means that a small food business is more likely to innovate if it offers flexible working arrangements for employees. Rotaru (2013) and Palangkaraya et al. (2016) obtained similar results for Australian businesses. The findings also conform with Storey et al. (2002), Michie and Sheenan (2003), Kleinknecht et al. (2006), Martinez-Sanchez et al. (2008), Chung (2009), Zhou et al. (2011) and Kleinknecht et al. (2014).

Market competition had a positive and highly significant association with the propensity to innovate, indicating that the more competitors that small food businesses face, the more likely they are to innovate. Having either a moderate or strong degree of market competition led to highly significant effects; hence, we cannot reject *Hypothesis 5*, which states that small food businesses that face moderate-to-strong competition are more likely to innovate. In addition, we found that even small food businesses that face minimal competition in the Australian market are also highly and significantly more likely to innovate. The results support the anti-Schumpeterian frameworks which suggest that the strongest effect is felt when small food businesses have three to four competitors (moderate competition) in the market, which is a similar finding to that of Soames et al. (2011). This highest impact is reflected in the estimated APE in Table 6.1, which is an increase of more than 20.7 per cent in the probability for small food businesses to innovate. The APEs at the 25th and 75th percentiles were also higher at 17.2 per cent and 24.4 per cent, respectively. This complements the result of Smit et al. (2015) where weak association was found between competition and innovation but aligns with the theoretical works of Aghion et al. (2005) and Correa (2012). Therefore, this result suggests that there is a strong potential for the whole food sector to increase the level of innovation as more players enter the market.

The geographic market for the food industry from which the small businesses sell their goods or services played an important role in the propensity to innovate. Compared with a small food business that operates only locally, expanding the business operations of small food businesses to overseas markets positively and significantly affects the likelihood to perform any form of innovation. In fact, the recent work of Tuhin (2016) indicated that innovation and export behaviour of Australian small and medium businesses were interrelated, and that exporters were 7 per cent to 10 per cent more likely to be innovators, which shows some consistency with the findings of Domenech et al. (2014) and Zouaghi and Sanchez (2016). Our findings reveal that, if our reference small food business switched to only selling any of its products locally, it would result in a decrease of 8.0 per cent in the likelihood of innovation. Because the impact is found significant at the 5% significance level, based on our sample evidence, we accept Hypothesis 6, that small food businesses that have export capability are more likely to innovate.

Access to finance is of crucial importance for investing in innovations (Sauer, 2017). The estimated coefficient in our model further reveals that small food businesses which sought debt and/or equity finance were significantly more likely to innovate. Moreover, the APE of 5.5 per cent in the likelihood of innovation was also found significant at the 5% significance level. The lack of financial resources suffered by small agri-food businesses influenced innovation, but public funding can boost their innovation capacity (Caiazza & Stanton, 2016; De Martino & Magnotti, 2017). This result shows that small food businesses in Australia can benefit from government financial assistance to help sustain their innovation activities.

Inclusion of year effects in our balanced panel is important because it controls for the unexpected variation or special events that may affect the response variable. In terms of the year effects, the results indicate that, all other things being held constant, the association is negative and significant moving onwards from 2007/08. This perhaps reflects the effect on a small food business's likelihood to engage in any form of innovation during the global financial crisis that occurred in 2008. A similar negative impact was also evident from the work of Zouaghi and Sanchez (2016).

6.2.2.2 Findings for food industry subsectors

In this subsection, we modify the food industry model by dividing the food industry balanced sample into two subsamples, the AgriFF panel (n_s=948 observations or 237 businesses), and the non-AgriFF panel (n_s=720 observations or 180 businesses). Although we found non-significance in the estimated coefficient for the variable (the business belongs to the non-AgriFF subsector, in the food industry model results), we are interested to further investigate the likelihood of businesses to innovate in each of the subsectors and examine which factors drive them to innovate. As mentioned earlier in Chapter 5, in the subsector models, the categories in the ICT intensity variable (i.e., business uses moderate ICT (x_7), high ICT (x_8), and most intense ICT (x_9)) were combined to form two binary dummy variables (i.e., business uses low-to-moderate and high-to-most-intense ICT) because of the presence of high correlations between the original four categories in the subsector samples. This was brought about by the reduced number of observations in the subsector samples.

The empirical model for each of the subsectors has been reduced in terms of the number of covariates with the latent variable formulated as:

$$y_{it}^{*} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2 + \ldots + x_{13it}\beta_{13} + \alpha_i + \varepsilon_{it} \ , \quad i = 1, 2, \ldots, n_s \ ; t = 1, 2, 3, 4 \qquad (6.4)$$

and the results using the random effects probit modelling are presented in Table 6.3.

The random effects results for the models for the subsectors are consistent with our expectations. The sign of the estimated coefficients for all covariates in the AgriFF and non-AgriFF subsectors are consistent with the food industry results. However, the coefficients of a few explanatory variables are found not statistically significant, as for the food industry results. Coefficients of the export capability and finance variables are found not significant in both samples, which are contrary to the results of Domenech et al. (2014), Tuhin (2016), Zouaghi and Sanchez (2016) and Sauer (2017). This may be due to the fact, that in our food industry sample, about 78.9 per cent of innovating businesses only sold their products locally and about 71.5 per cent of innovating businesses did not seek any financial support such as debt and equity. In addition, the estimated coefficients in the AgriFF subsector for the minimal market competition variable and the year 2008/09 effect are only significant at the 10% level. The coefficient for the business size variable is not significant at the 10% level (in both subsectors), as in the case for the food industry model. Hence, in relation to the six hypotheses we tested

Table 6.3

Random Effects Probit Regression Results for (Overall) Innovation and APEs for Selected Key Business Characteristics, by Food Industry Subsector

Variables	AgriFF							non-AgriFF						
	Coefficient		*SE*	APE†		*SE*‡		Coefficient		*SE*	APE†		*SE*
Innovation (Response variable)													
Business size (Nonemploying)	0.09		*0.22*	0.020		*.045*		0.32		*0.22*	0.079		*0.043*
With collaboration	0.71	***	*0.16*	0.179	***	*.044*		0.70	***	*0.23*	0.177	***	*0.053*
Market competition													
Minimal	0.30	*	*0.18*	0.063		*.045*		0.71	**	*0.35*	0.17	*	*0.10*
Moderate	0.89	***	*0.14*	0.211	***	*.046*		0.85	***	*0.30*	0.210	***	*0.083*
Strong	0.72	***	*0.17*	0.165	***	*.038*		0.61	**	*0.31*	0.150	*	*0.086*
ICT Intensity (High to most intense	0.50	**	*0.24*	0.123	**	*.052*		0.62	***	*0.16*	0.161	***	*0.050*
Used STEM skills	0.63	***	*0.15*	0.157	***	*.040*		0.51	***	*0.15*	0.127	***	*0.046*
Export capability (Local only)	–0.30		*0.20*	-0.074		*.048*		–0.32		*0.20*	-0.080		*0.056*
With flexible working arrangements	0.71	***	*0.20*	0.174	***	*.037*		0.63	***	*0.11*	0.163	***	*0.039*
Sought debt and/or equity finance	0.19		*0.20*	0.046		*.042*		0.27		*0.21*	0.067	*	*0.036*
Financial year													
2008–2009	–0.33	*	*0.18*	-0.079	***	*.028*		–0.52	***	*0.15*	-0.128	***	*0.038*
2009–2010	–0.44	**	*0.22*	-0.104	***	*.037*		–0.52	***	*0.18*	-0.128	***	*0.029*
2010–2011	–0.40	***	*0.14*	-0.094	***	*.041*		–0.58	**	*0.23*	-0.143	***	*0.044*
Intercept	–1.22	***	*0.33*					– 1.02	***	*0.28*			
Log-likelihood	–465.18							–378.14					
AIC	948.35							774.27					
BIC	992.04							815.49					
Sigma	0.853		*0.058*					0.94		*0.16*			
rho (ρ)	0.421	***	*0.033*					0.469	***	*0.085*			
Number of observations (n)	948							720					

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

†APEs for selected key drivers of innovation.

for the subsector models, only Hypothesis 6, that small food businesses with export capability are more likely to innovate, was clearly rejected at the 5% significance level.

The estimated proportions of the total variance contributed by the panel-level variance component ($\hat{\rho}$) for both subsectors are found significantly different from zero (using the likelihood ratio test, i.e., test statistics *p*-values=0.000). The models for the AgriFF and the non-AgriFF subsectors accounted for more than 42 per cent and 47 per cent of the variability of the composite error, respectively. These results indicate that accounting for unobserved effects is also important in the subsector analyses, which again is consistent with the findings of Triguero et al. (2013) and Vancauteren (2016). The log-likelihood, AIC and BIC results also confirmed the goodness of fit of the subsector models compared with the pooled probit models, as exhibited in Table 6.7 in section 6.2.3. The likelihood ratio tests statistics (56.58 and 58.32 for the AgriFF and the non-AgriFF subsectors, respectively, were highly significant) further confirmed preference for the use of the random effects probit model.

The five key factors (collaboration, ICT intensity, flexible working arrangements, facing market competition and use of STEM skills) again were highly significant in contributing to increased innovation among small food businesses in both subsectors. These findings are consistent with the international empirical studies cited in our earlier discussions of the food industry results. Year effects, in general, remained negative and statistically significant. The global financial crisis had greater effect on the likelihood to innovate for small food businesses in the non-AgriFF subsector than for small food businesses in the AgriFF subsector. These results imply that even within businesses in each subsector, the importance of these factors was quite evident. Most APEs in the AgriFF model were found to be statistically significant. One exception is the APE of minimal market competition, which is smaller in magnitude than the rest. Two of the APEs (minimal and strong market competition) in the non-AgriFF model were significant at the 5% level, whereas the rest were found highly statistically significant (at the 1% level). After averaging across all small food businesses in each subsector and time periods, and assuming all other variables constant, the degree of association between having intense ICT and innovation was stronger in the non-AgriFF subsector whereas the effect on innovation propensity was stronger in the AgriFF subsector when small food businesses use STEM skills and provide flexible working arrangements for employees. The impact of collaboration was similar in both subsectors, which is approximately 18 per cent. The distributions of the APEs for the subsector modelling are presented in Tables 6.4 and 6.5 below.

Table 6.4

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Random Effects Probit Model)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Business size (Nonemploying)	0.009	0.017	0.021	0.025	0.026	0.000028	-0.726	2.355
With collaboration	0.092	0.169	0.190	0.207	0.211	0.0011	-1.095	3.079
Market competition								
Minimal	0.047	0.026	0.042	0.067	0.215	0.00061	0.270	1.766
Moderate	0.067	0.109	0.162	0.227	0.266	0.0044	-0.057	1.658
Strong	0.014	0.079	0.122	0.180	0.090	0.0031	0.038	1.664
ICT Intensity (High to most intense)	0.065	0.113	0.130	0.146	0.151	0.00068	-0.895	2.628
Used STEM skills	0.068	0.146	0.165	0.183	0.188	0.00094	-0.944	2.760
Export capability (Local only)	-0.092	-0.088	-0.078	-0.065	-0.032	0.00029	0.844	2.574
With flexible working arrangements	0.102	0.152	0.184	0.205	0.211	0.0012	-0.798	2.364
Sought debt and/or equity finance	0.021	0.040	0.048	0.055	0.058	0.00013	-0.781	2.465
Financial year								
2008/09	-0.100	-0.096	-0.083	-0.072	-0.034	0.00033	0.756	2.346
2009/10	-0.132	-0.127	-0.108	-0.094	-0.048	0.00062	0.713	2.294
2010/11	-0.120	-0.115	-0.099	-0.085	-0.042	0.00050	0.730	2.313

Table 6.5

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Random Effects Probit Model)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Business size (Nonemploying)	0.025	0.071	0.085	0.091	0.093	0.00023	-1.265	3.919
With collaboration	0.092	0.164	0.187	0.198	0.202	0.00070	-1.152	3.439
Market competition								
Minimal	0.060	0.133	0.168	0.197	0.204	0.0017	-0.767	2.487
Moderate	0.078	0.167	0.207	0.237	0.244	0.0022	-0.815	2.610
Strong	0.049	0.112	0.144	0.170	0.177	0.0014	-0.732	2.403
ICT Intensity (High to most intense)	0.078	0.153	0.170	0.176	0.179	0.00049	-1.695	5.305
Used STEM skills	0.036	0.116	0.136	0.144	0.146	0.00048	-1.533	5.017
Export capability (Local only)	-0.092	-0.091	-0.085	-0.074	-0.034	0.00018	1.374	4.244
With flexible working arrangements	0.080	0.152	0.171	0.179	0.182	0.00046	-1.516	4.923
Sought debt and/or equity finance	0.021	0.062	0.071	0.076	0.078	0.00013	-1.406	4.521
Financial year								
2008/09	-0.150	-0.147	-0.137	-0.117	-0.034	0.00056	1.414	4.582
2009/10	-0.150	-0.147	-0.137	-0.116	-0.034	0.00056	1.414	4.583
2010/11	-0.167	-0.163	-0.152	-0.128	-0.039	0.00068	1.406	4.571

6.2.3 Sensitivity analyses using Pooled Probit Model Estimation

The pooled probit panel model, which does not directly deal with the unobserved business-specific effects α_i, was also estimated to check the sensitivity of the random effects probit results in the previous subsection. The model is relatively simple to estimate, and there was no need to impose distributional assumptions of business-specific effects. Because this model ignores the unobserved heterogeneity, one can make adjustment in the estimation by computing panel-robust standard errors for all the model parameters. For the pooled probit empirical model, we used a similar dependent variable and covariates, as defined in section 6.2.1.

Comparing with the estimates for the random effects probit model, we see from Table 6.6 that the coefficient estimates in the pooled model for the food industry are consistent in terms of signs for all the explanatory variables. The levels of significance are almost similar, except for the business size, which was positive and significant at the 5% level. With regard to the estimated APEs, the magnitudes are higher in the pooled probit, which was expected, and the levels of significance are similar, except for the moderate ICT intensity, which is marginally significant. The highest effect remains in the small food businesses facing moderate market competition.

Looking at the findings for the food industry subsectors in Table 6.7, the results of the pooled probit model are again consistent with our expectations. The signs of the estimated coefficients for both dummy variables for the AgriFF and the non-AgriFF subsectors are consistent with the subsector results of the random effects probit models. Specifically, the estimated coefficients for export capability and finance variables are not significant in AgriFF samples. In terms of differences, business size and sought debt/equity finance were found significant at the 5% level in the pooled probit for non-AgriFF; these were not significant in the random effects probit model for non-AgriFF. The highest effect remains in the small food businesses facing moderate market competition for AgriFF while for non-AgriFF the effects are high and approximately the same for small food businesses facing minimal-to-moderate market competition.

Table 6.6

Pooled Probit Regression Results for (Overall) Innovation and Average Partial Effects for Selected Key Drivers of Innovation

Variables	Coefficient	*Bootstrap SE*	APE†	*SE*
Innovation (Response variable)				
Sub-industry (non-AgriFF)	0.05	*0.10*	0.015	*0.035*
Business size (Nonemploying)	0.22 **	*0.10*	0.067 **	*0.032*
With collaboration	0.62 ***	*0.11*	0.202 ***	*0.045*
Market competition				
Minimal	0.48 ***	*0.15*	0.141 ***	*0.042*
Moderate	0.75 ***	*0.13*	0.229 ***	*0.041*
Strong	0.61 ***	*0.12*	0.184 ***	*0.035*
ICT Intensity				
Moderate	0.21 **	*0.10*	0.064 **	*0.036*
High	0.66 ***	*0.18*	0.214 ***	*0.069*
Most intense	0.57 ***	*0.14*	0.184 ***	*0.051*
Used STEM skills	0.554 ***	*0.097*	0.180 ***	*0.036*
Export capability (Local only)	–0.26 **	*0.13*	-0.081 *	*0.044*
With flexible working arrangements	0.560 ***	*0.086*	0.182 ***	*0.028*
Sought debt and/or equity finance	0.194 **	*0.088*	0.061 **	*0.028*
Financial year				
2008/09	–0.382 ***	*0.087*	-0.119 ***	*0.030*
2009/10	–0.420 ***	*0.088*	-0.131 ***	*0.029*
2010/11	–0.438 ***	*0.099*	-0.136 ***	*0.034*
Intercept	–1.13 ***	*0.19*		
Log-likelihood	–904.17			
AIC	1842.34			
BIC	1934.48			
Number of observations (n)	1668			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

†APEs for selected key drivers of innovation.

Table 6.7

Pooled Probit Regression Results for (Overall) Innovation and Average Partial Effects for Selected Key Drivers of Innovation, by Food Industry Subsector

Variables	AgriFF				Non-AgriFF			
	Coefficient	*Bootstrap SE*	APE†	*SE‡*	Coefficient	*Bootstrap SE*	APE†	*SE*
Innovation (Response variable)								
Business size (nonemploying)	0.11	*0.14*	0.033	*0.045*	0.30**	*0.15*	0.095 **	*0.039*
With collaboration	0.69 ***	*0.14*	0.225 ***	*0.050*	0.58***	*0.16*	0.191 ***	*0.052*
Market competition								
Minimal	0.25	*0.17*	0.066	*0.044*	0.79**	*0.33*	0.250 ***	*0.094*
Moderate	0.77 ***	*0.16*	0.230 ***	*0.047*	0.78**	*0.31*	0.245 ***	*0.079*
Strong	0.65 ***	*0.14*	0.190 ***	*0.040*	0.64**	*0.29*	0.197 **	*0.078*
ICT Intensity (High to Most intense)	0.48 ***	*0.16*	0.151 ***	*0.053*	0.47***	*0.14*	0.159 ***	*0.052*
Used STEM skills	0.56 ***	*0.13*	0.179 ***	*0.046*	0.56***	*0.14*	0.185 ***	*0.049*
Export capability (Local only)	–0.14	*0.18*	-0.043	*0.052*	–0.31*	*0.19*	-0.103 *	*0.059*
With flexible working arrangements	0.60 ***	*0.12*	0.188 ***	*0.034*	0.48***	*0.12*	0.162 ***	*0.041*
Sought debt and/or equity finance	0.11	*0.12*	0.033	*0.041*	0.32**	*0.13*	0.104 ***	*0.031*
Financial year								
2008/09	–0.29 **	*0.12*	-0.088 ***	*0.028*	–0.43***	*0.12*	-0.139 ***	*0.040*
2009/10	–0.37 ***	*0.12*	-0.111 ***	*0.038*	–0.45***	*0.13*	-0.145 ***	*0.030*
2010/11	–0.34 **	*0.14*	-0.103 ***	*0.041*	–0.49***	*0.14*	-0.157 ***	*0.042*
Intercept	–1.12 ***	*0.23*			–0.93 ***	*0.35*		
Log-likelihood	–493.47				–407.30			
AIC	1014.95				842.60			
BIC	1082.91				842.60			
Number of observations (n)	948				720			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

†APEs for selected key drivers of innovation.

The sensitivity analysis conducted here attests that: collaboration, the use of resources with STEM skills, use of ICT, competitiveness and having flexible working arrangements play important roles in explaining the innovation behaviour of small businesses in the food industry. Moreover, some unobserved factors that may have been captured by the time dummies might also have affected the likelihood of innovation for the small businesses.

6.3 Understanding the extent of innovation (innovation intensity)

6.3.1 Empirical model specification

In the previous section, we examined the key determinants that drive the propensity of overall innovation for small food businesses in Australia. In this section, we investigate and focus on the role of the determinants in the intensity of the businesses to engage in the four types of innovation. The intensity of innovation is measured as the number of types of innovation that a particular small food business has undertaken in a given year t as the dependent variable y_{it}. This count dependent variable has two unique properties: it is nonnegative and has integer values (i.e., $y_{it} = 0,1,2,3,4$ for $i = 1,2,\ldots,417$; $t = 1,2,3,4$), which are necessary for Poisson regression analysis. The innovation intensity dependent variable is defined as follows:

$$y_{intensity} = \begin{cases} 0 & \textit{if the business did not engage in any of the four types of innovation} \\ 1 & \textit{if the business engaged in only one type of innovation} \\ 2 & \textit{if the business engaged in only two types of innovation} \\ 3 & \textit{if the business engaged in only three types of innovation} \\ 4 & \textit{if the business engaged in all four types of innovation} \end{cases} \tag{6.5}$$

For our explanatory variables, we included the same covariates used in the random effects probit modelling in section 6.2, with the exception of the constant term in the negative binomial model. The reason behind the exclusion of this variable was the non-convergence of the likelihood estimation procedure for that model with random effects if this variable is not omitted. Preliminary modelling using the fixed effects Poisson model showed that this variable was not significant; hence, its exclusion will not affect the robustness of our findings.

Based on the empirical findings in subsection 6.2.2, there is a basis to account for the unobserved heterogeneity in the count model. Using the above dependent variable and covariates specification, we employed the panel data Poisson regression model with random effects, and also implemented the Hausman, Hall and Griliches (HHG) (1984) specification with random effects which is equivalent to the HHG random effects negative binomial (Greene, 2007). The latter specification is favoured to remedy the issue of overdispersion. The *xtpoisson* (with standard error bootstrapping) and *xtnbreg* procedures in STATA 15 MP were employed for the statistical estimation. Interpreting the coefficients of the Poisson model regression in logged form (i.e., the difference between the logarithms of expected counts) is difficult; hence, the incidence-rate ratios[34] are calculated instead for easiness of interpretation. The average marginal effects are also calculated to determine the effect of each determinant on the extent of innovation. The empirical results are presented in the next subsection.

6.3.2 Empirical results

Table 6.8 presents the estimates for the parameters of the random effects Poisson and negative binomial models for the small food businesses with innovation intensity as the dependent variable. The relationships of each determinant to the intensity of innovation are observed to be characterised by the statistical significance in each model. Based on the likelihood ratio test statistics, the negative binomial model is favoured over the Poisson model to avoid overdispersion. Although the random effects estimates are quite similar between the Poisson and negative binomial models, all of the covariates in the negative binomial model are found to have statistically significant coefficients, implying that all of them influence the extent to which small food businesses engage in the four types of innovation.

Estimates for the random effects Poisson and negative binomial models for the AgriFF and non-AgriFF subsectors appear in Table 6.9. They are again consistent with our expectations and the food industry results. Small food businesses that collaborate, use STEM skills, face market competition, use high to most-intense ICT, and have labour market flexibility are significantly more likely to engage in an intensive form of innovation.

[34] The incidence rate ratio (IRR) is the ratio of the incidence rate among the exposed portion of the population and the incidence rate of the unexposed portion of the population, where incidence rate is defined as the number of events divided by the population-time at risk (Delfini, 2018).

Table 6.8

Count Models with Random Effects Regression Results for Small Food Businesses

Item	Poisson Random Effects				Negative Binomial Random Effects			
	Coefficient (IRR) †		*Bootstrap SE*	AME ‡	Coefficient (IRR) †		*Bootstrap SE*	AME ‡
Number of types of innovation (Response variable)								
Sub-industry (non-AgriFF)	1.23	*	*0.15*	0.2080	1.26	**	*0.15*	0.2306
Business size (Nonemploying)	1.11		*0.14*	0.1085	1.20	*	*0.13*	0.1146
With collaboration	1.52	***	*0.11*	0.4159	1.47	***	*0.12*	0.3858
Market competition								
Minimal	1.98	***	*0.32*	0.6817	1.87	***	*0.30*	0.6238
Moderate	2.68	***	*0.41*	0.9842	2.52	***	*0.37*	0.9234
Strong	2.23	***	*0.32*	0.8023	2.11	***	*0.30*	0.7448
ICT Intensity								
Moderate	1.31	**	*0.15*	0.2678	1.27	**	*0.15*	0.2405
High	1.62	***	*0.26*	0.4820	1.52	**	*0.27*	0.4179
Most intense	1.87	***	*0.26*	0.6277	1.76	***	*0.25*	0.5638
Used STEM skills	1.62	***	*0.13*	0.4841	1.59	***	*0.13*	0.4645
Market location (Local only)	0.755	***	*0.079*	-0.2807	0.775	**	*0.092*	-0.2549
With flexible working arrangements	1.65	***	*0.14*	0.4985	1.58	***	*0.13*	0.4580
Sought debt and/or equity finance	1.198	***	*0.084*	0.1809	1.175	**	*0.090*	0.1613
Financial year								
2008/09	0.652	***	*0.057*	-0.4276	0.661	***	*0.058*	-0.4144
2009/10	0.656	***	*0.059*	-0.4216	0.667	***	*0.059*	-0.4057
2010/11	0.602	***	*0.059*	-0.5075	0.612	***	*0.057*	-0.4911
Intercept	0.164	***	*0.035*					
Log-likelihood	-1721.99				-1714.73			
AIC	3479.99				3465.45			
BIC	3577.54				3563.00			
Sigma	0.840	**	*0.057*					
Wald χ^2	308.45	***			225.85	***		
a					13.95		*2.37*	
b					1.66		*0.30*	
Number of observations (n)	1668				1668			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.
†Incidence rate ratio; ‡Average marginal effect; *a* and *b* are parameters of the Beta distribution

Table 6.9

Count Models with Random Effects Regression Results for the AgriFF and non-AgriFF Subsectors

Variables	Poisson Random Effects						Negative Binomial Random Effects					
	AgriFF			Non-AgriFF			AgriFF			Non-AgriFF		
	Coefficient (IRR)[(a)]	*SE*	AME [(b)]	Coefficient (IRR)[(a)]	*SE*	AME [(b)]	Coefficient (IRR)[(a)]	*SE*	AME [(b)]	Coefficient (IRR)[(a)]	*SE*	AME [(b)]
Number of types of innovation (Response variable)												
Business size (Nonemploying)	1.05	*0.20*	*0.0463*	1.14	*0.21*	*0.0567*	1.15	*0.19*	*0.1404*	1.29 *	*0.18*	*0.1516*
With collaboration	1.74 ***	*0.22*	*0.5546*	1.64 ***	*0.24*	*0.4919*	1.41 ***	*0.13*	*0.3458*	1.39 ***	*0.15*	*0.3316*
Market competition												
Minimal	1.50 *	*0.32*	*0.4051*	1.42	*0.31*	*0.3497*	2.39 **	*0.84*	*0.8704*	2.28 **	*0.74*	*0.8239*
Moderate	2.76 ***	*0.53*	*1.0163*	2.60 ***	*0.47*	*0.9570*	2.76 ***	*0.90*	*1.0149*	2.64 ***	*0.83*	*0.9719*
Strong	2.32 ***	*0.38*	*0.8395*	2.17 ***	*0.36*	*0.7731*	2.24 **	*0.73*	*0.8057*	2.18 **	*0.68*	*0.7773*
ICT Intensity (High to most intense)	1.43 **	*0.23*	*0.3578*	1.33	*0.25*	*0.2889*	1.54 ***	*0.16*	*0.4297*	1.50 ***	*0.18*	*0.4048*
Used STEM skills	1.84 ***	*0.25*	*0.6082*	1.81 ***	*0.24*	*0.5933*	1.49 ***	*0.15*	*0.4003*	1.46 ***	*0.16*	*0.3800*
Market location (Local only)	0.78	*0.12*	*-0.2440*	0.76	*0.13*	*-0.2752*	0.74 **	*0.11*	*-0.3064*	0.80	*0.13*	*-0.2178*
With flexible working arrangements	1.65 ***	*0.24*	*0.5032*	1.58 ***	*0.21*	*0.4584*	1.65 ***	*0.17*	*0.4987*	1.58 ***	*0.17*	*0.4576*
Sought debt and/or equity finance	1.29 **	*0.15*	*0.2555*	1.28 **	*0.16*	*0.2431*	1.15	*0.10*	*0.1381*	1.12	*0.11*	*0.1123*
Financial year												
2008/09	0.630 ***	*0.086*	*-0.4624*	0.637 ***	*0.089*	*-0.4508*	0.685 ***	*0.074*	*-0.3777*	0.691 ***	*0.078*	*-0.3698*
2009/10	0.652 ***	*0.098*	*-0.4278*	0.658 ***	*0.092*	*-0.4188*	0.673 ***	*0.071*	*-0.3959*	0.681 ***	*0.078*	*-0.3844*
2010/11	0.60 ***	*0.10*	*-0.5075*	0.61 ***	*0.09*	*-0.4964*	0.629 ***	*0.070*	*-0.4636*	0.64 ***	*0.08*	*-0.4510*
Intercept	0.181 ***	*0.047*					0.246 ***	*0.090*				
Log Likelihood	-840.9			-836.69			-878.88			-875.276		
AIC	1711.79			1703.39			1787.76			1780.55		
BIC	1784.61			1776.21			1856.44			1849.24		
Sigma	0.855 **	*0.086*					0.82 **	*0.074*				
Wald x^2	140.65 ***			95.81 ***			120.14 ***			85.83 ***		
a				11.15						17.87		
b				1.69						1.74		
Number of observations (n)	948			948			720			720		

coefficients are given to the same number of digits behind the decimal points as their SEs.

†Incidence rate ratio; ‡Average marginal effect; *a* and *b* are parameters of the Beta distribution

6.4 Understanding the correlations between innovation dimensions

6.4.1 Empirical model specification

As mentioned in section 4.3, we complement the analysis for the random effects probit model results for overall innovation by undertaking multivariate probit modelling. Also, we assume that business engagements between each type of innovation are independent. Here, we consider the possible correlations between the different types of innovation. We employed a multivariate probit to further scrutinise the correlation structure between the four types of innovation, and to estimate simultaneously the effect of the drivers for all innovation outcomes. The multivariate probit (equation (4.10)) allows the prediction of all possible combinations of innovation outcomes from the system of binary probits. It is also possible to compute the predicted probability of a given innovation outcome, conditional upon any other specified innovation outcome. These prediction processes are computationally intensive due to the derivation of multivariate normal distribution. Hence, in this study we only predicted the following probabilities: (i) the probability of being an innovator; (ii) the probability of innovating exactly four types of innovation; (iii) the probability of innovating between one to three types of innovation; and (iv) the probability of being a noninnovator for a reference business belonging to the AgriFF subsector (for the food industry sample only). This illustrative business is small, does not collaborate, has low ICT intensity, has no effective competition, does not use STEM skills, has no debt or equity finance, has export capability, and does not have any flexible working arrangements, during the period 2007/08 (i.e., the base year). The other probabilities can easily be computed using the empirical results presented here.

The indicators for the dependent variable in the four-equation multivariate process in equation (4.10) are as follows:

$$
\begin{aligned}
y_{(1)} &= \begin{cases} 1 & \textit{if business is a goods and services innovator} \\ 0 & \textit{otherwise} \end{cases} \\
y_{(2)} &= \begin{cases} 1 & \textit{if business is an organisational or managerial process innovator} \\ 0 & \textit{otherwise} \end{cases} \\
y_{(3)} &= \begin{cases} 1 & \textit{if business is an operational process innovator} \\ 0 & \textit{otherwise} \end{cases} \\
y_{(4)} &= \begin{cases} 1 & \textit{if business is a marketing methods innovator} \\ 0 & \textit{otherwise} \end{cases}
\end{aligned}
\tag{6.6}
$$

Again, we used all the covariates as defined in the empirical model in section 6.2.1 and estimated the above multivariate probit process using simulated maximum likelihood (see Capellari and Jenkins 2003; Greene 2012; and Wooldridge 2010, 2013). The empirical results of the multivariate panel probit modelling for the small food businesses in the AgriFF and non-AgriFF subsectors are presented in the next subsection.

6.4.2 Empirical results

Table 6.10 presents the results for the multivariate probit modelling for small food businesses. The estimated coefficients for collaboration, the use of resources with STEM skills, high intense use of ICT, and flexible working arrangements in all of the types of innovation models are in line with our expectations (i.e., positive and highly significant). The association between nonemploying small food business and products innovation is positive and highly significant. Similar relationships for products innovation are also exhibited for businesses belonging to the non-AgriFF subsector.

All the degrees of market competition had positive and significant associations with the propensity to innovate goods and services, and marketing methods. In addition, the more competitors that small businesses face (i.e., moderate to strong) the more likely they are to innovate in all four types of innovation. It seems that business use of ICT plays an important role in both organisational and operational processes innovations. Export capability was found significant in marketing method innovation whereas access to finance through debt and equity was only significant for operational process innovation.

We also examine graphically the results of the multivariate probit modelling by looking at the probability density functions for each innovation dimension using equation (6.6). The kernel density function for organisational and managerial process innovation is similar to the marketing methods and very much skewed to the right peaking at around 0.1. Though the peak may seem to be similar for the other two types of innovation (i.e., goods and services, and operational process innovation), the latter two types have flatter density distribution. This implies that, overall, a typical (or reference) small food business is more likely to undertake the product and operational process innovations.

Table 6.10

Multivariate Probit Regression Results for Small Food Businesses by Type of Innovation as the Dependent Variable

Variables	Goods and services			Organisational and Managerial			Operational Process			Marketing Methods		
	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*
Sub-industry (non-AgriFF)	0.316	***	*0.086*	0.011		*0.088*	0.014		*0.081*	0.192	**	*0.088*
Business size (Nonemploying)	0.344	***	*0.090*	-0.004		*0.094*	0.031		*0.085*	0.148		*0.094*
With collaboration	0.365	***	*0.097*	0.543	***	*0.094*	0.431	***	*0.092*	0.463	***	*0.096*
Market competition												
Minimal	0.63	***	*0.16*	0.18		*0.16*	0.25	*	*0.14*	0.53	***	*0.18*
Moderate	0.59	***	*0.15*	0.52	***	*0.14*	0.56	***	*0.12*	0.80	***	*0.16*
Strong	0.57	***	*0.14*	0.31	**	*0.13*	0.47	***	*0.11*	0.78	***	*0.15*
ICT Intensity												
Moderate	0.02		*0.11*	0.29	**	*0.12*	0.30	***	*0.10*	0.08		*0.12*
High	0.54	***	*0.18*	0.67	***	*0.19*	0.44	**	*0.18*	0.37	*	*0.19*
Most intense	0.50	***	*0.13*	0.46	***	*0.14*	0.37	***	*0.13*	0.71	***	*0.13*
Used STEM skills	0.503	***	*0.096*	0.579	***	*0.095*	0.509	***	*0.089*	0.411	***	*0.097*
Export capability (Local only)	-0.07		*0.11*	-0.11		*0.11*	-0.02		*0.11*	-0.32	***	*0.11*
With flexible working arrangements	0.396	***	*0.084*	0.435	***	*0.084*	0.503	***	*0.077*	0.337	***	*0.085*
Sought debt and/or equity finance	0.089		*0.093*	0.159	*	*0.091*	0.223	***	*0.085*	0.196	**	*0.093*
Financial year												
2008/09	-0.40	***	*0.11*	-0.34	***	*0.12*	-0.31	***	*0.10*	-0.36	***	*0.12*
2009/10	-0.55	***	*0.12*	-0.18		*0.12*	-0.44	***	*0.11*	-0.32	***	*0.12*
2010/11	-0.46	***	*0.12*	-0.28	**	*0.12*	-0.45	***	*0.11*	-0.38	***	*0.12*
Intercept	-1.85	***	*0.19*	-1.79	***	*0.19*	-1.59	***	*0.18*	-1.83	***	*0.21*
ρ_{2k}†	0.460	***	*0.045*									
ρ_{3k}	0.574	***	*0.038*	0.627	***	*0.036*						
ρ_{4k}	0.529	***	*0.042*	0.533	***	*0.043*	0.495	***	*0.043*			
Log-likelihood	-2501.32											
AIC	5150.64											
BIC	5551.67											
Wald Chi-Squared	610.61	***										
Number of observations (n)	1668											

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs. †Correlations between the residuals in the four equations, k=1, 2, 3.

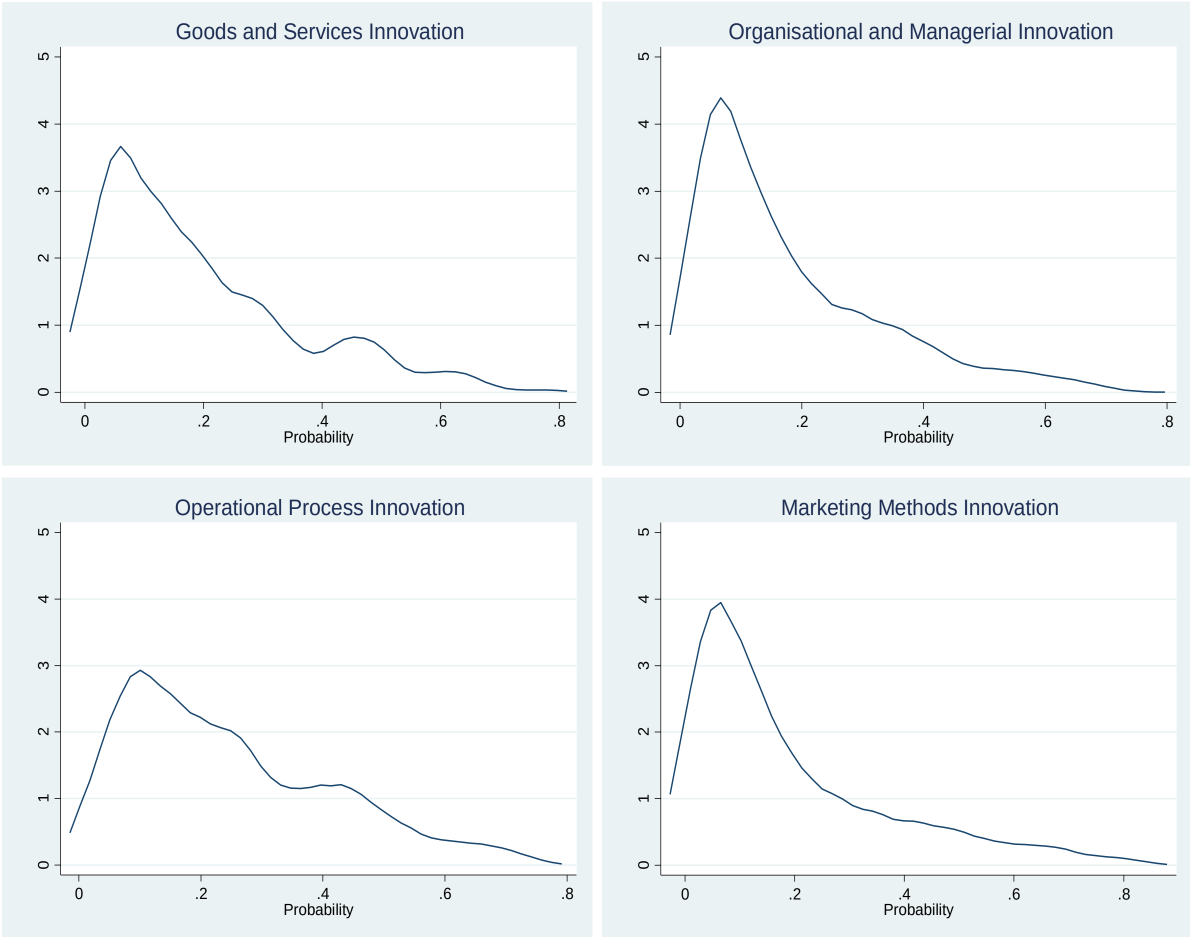


Figure 6.1. Probability density functions for the four types of innovation in the food industry using multivariate probit.

Figure 6.2. reveals the impact, again on a typical (reference business) small food business, of the following five significant key determinants (i.e., use of STEM skills, with moderate to strong competition, with collaboration, with high to most intense ICT, and having flexible arrangement) on the likelihood of innovation in the four types of innovation. Having intense ICT, use of STEM skills and engaging in collaboration have greater impact on the likelihood for a typical small food business to undertake each of the four types of innovation. The effect of having flexible working arrangement is more pronounced for the operational process innovation.

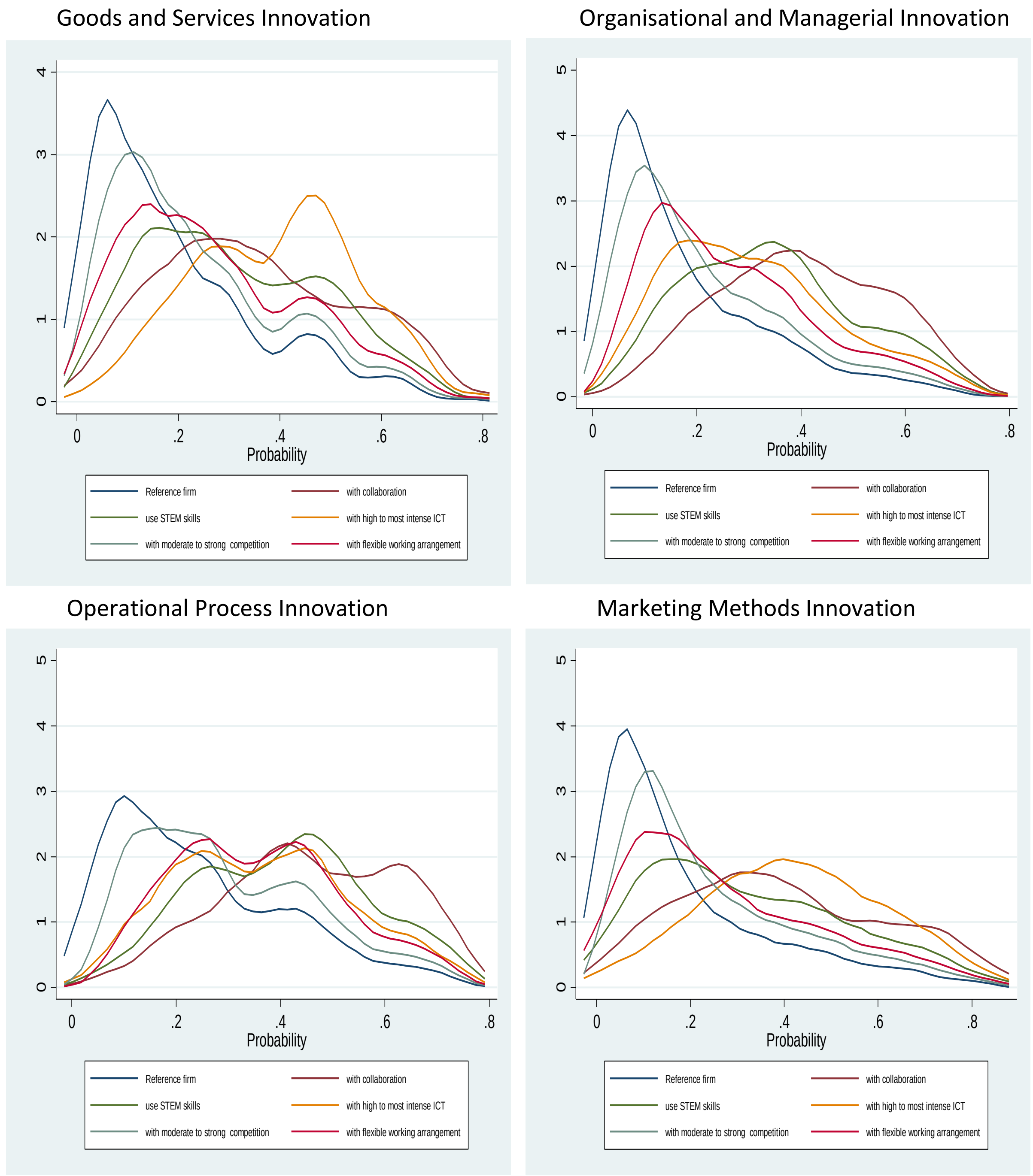


Figure 6.2. Impact of drivers on the probability density function innovation in the food industry using multivariate probit.

Another key result of the multivariate probit model is in the lower part of Table 6.10 where correlations defined in equation (4.11) (i.e., $\rho_{kl} = \rho_{lk},\ l \neq k,\ l,k = 1,2,3,4$) as between the residuals in the four equations (equation 6.6) are reported. All of the estimated correlations are significantly positive, which indicates that small food businesses do combine different types of innovation. The significance might be associated with possible omitted variables (e.g., R&D

intensity, business age). The highest correlation of 0.63 implies that business engagement in both organisational and operational processes innovations is popular among small food businesses.

The overall results of the multivariate probit modelling for the two subsectors are consistent with the food industry results (see Tables 6.11–6.12). Correlations between the disturbances for all the innovation outcomes are also positive and significant implying that small food businesses even at the subsector level do combine different types of innovation when innovating.

To complement the results of the multivariate probit, we predicted the innovation outcome probabilities (see Table 6.13) for the reference small food business. By looking at the estimated coefficients for all the multivariate models, it is easy to get other predicted probabilities when a particular key determinant/driver/business characteristic is changed from those of the reference small food business.

On average, the probability of being an overall innovator for the reference small food business in the food industry was found to be 40.5 per cent with a probability of innovating exactly four types of innovation of 5.23 per cent. The probability of innovating exactly four types of innovation is higher for small food businesses belonging to the non-AgriFF subsector (9.7 per cent). Businesses belonging to the AgriFF subsector have greater likelihood of noninnovating. The high innovation rate for the small food businesses in the non-AgriFF subsector might be due to the fact that businesses in the manufacturing sector are found to engage more in innovation activities than those in the AgriFF subsector.

The probability density functions for the AgriFF and non-AgriFF subsectors are exhibited in Figure 6.3 and 6.4, respectively. The probability density functions in the non-AgriFF subsector for all the innovation dimensions are nearly similar to each other. For the AgriFF, the kernel density is flatter for operational process innovation. The predicted density functions showing the impacts of the five key determinants on each of the four types of innovation for the subsectors are presented in Appendix C.

Table 6.11

Multivariate Probit Regression Results for the AgriFF Subsector by Type of Innovation as the Dependent Variable

Variables	Goods and services			Organisational and Managerial			Operational Process			Marketing Methods		
	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*
Business size (Nonemploying)	0.30	**	*0.14*	-0.03		*0.14*	0.01		*0.13*	0.00		*0.15*
With collaboration	0.48	***	*0.15*	0.57	***	*0.14*	0.42	***	*0.13*	0.56	***	*0.15*
Market competition												
Minimal	0.43	**	*0.20*	0.00		*0.21*	0.03		*0.19*	0.27		*0.24*
Moderate	0.48	***	*0.18*	0.49	***	*0.16*	0.68	***	*0.15*	0.89	***	*0.20*
Strong	0.56	***	*0.16*	0.31	**	*0.14*	0.56	***	*0.13*	0.83	***	*0.18*
ICT Intensity (High to most intense)	0.49	***	*0.16*	0.03		*0.17*	0.28	*	*0.16*	0.60	***	*0.16*
Used STEM skills	0.48	***	*0.15*	0.61	***	*0.13*	0.57	***	*0.13*	0.29	**	*0.15*
Export capability (Local only)	-0.12		*0.19*	-0.14		*0.18*	-0.16		*0.17*	-0.21		*0.18*
With flexible working arrangements	0.33	***	*0.13*	0.45	***	*0.12*	0.59	***	*0.11*	0.26	**	*0.13*
Sought debt and/or equity finance	-0.08		*0.14*	0.11		*0.13*	0.21	*	*0.12*	0.15		*0.14*
Financial year												
2008/09	-0.41	**	*0.17*	-0.30	*	*0.17*	-0.28	**	*0.14*	-0.23		*0.17*
2009/10	-0.68	***	*0.18*	-0.05		*0.16*	-0.41	***	*0.15*	-0.23		*0.17*
2010/11	-0.40	**	*0.17*	-0.21		*0.17*	-0.42	***	*0.15*	-0.29		*0.18*
Intercept	-1.66	***	*0.26*	-1.57	***	*0.25*	-1.38	***	*0.23*	-1.88	***	*0.27*
ρ_{2k}†	0.362	***	*0.072*									
ρ_{3k}	0.497	***	*0.063*	0.542	***	*0.057*						
ρ_{4k}	0.482	***	*0.069*	0.524	***	*0.064*	0.493	***	*0.066*			
Log-likelihood	-1224.42											
AIC	2572.83											
BIC	2873.80											
Wald Chi-Squared	282.11	***										
Number of observations (n)	948											

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.
†Correlations between the residuals in the four equations, k=1, 2, 3

Table 6.12
Multivariate Probit Regression Results for the Non-AgriFF Subsector by Type of Innovation as the Dependent Variable

	Goods and services			Organisational and Managerial			Operational Process			Marketing Methods		
Variables	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*	Coefficient		*SE*
Business size (Nonemploying)	0.41	***	*0.12*	0.00		*0.13*	0.03		*0.12*	0.28	**	*0.12*
With collaboration	0.27	**	*0.13*	0.52	***	*0.13*	0.47	***	*0.13*	0.43	***	*0.13*
Market competition												
Minimal	1.05	***	*0.33*	0.89	**	*0.42*	0.33		*0.27*	0.84	**	*0.34*
Moderate	0.90	***	*0.32*	1.07	***	*0.41*	0.36		*0.25*	0.83	**	*0.32*
Strong	0.83	***	*0.31*	0.81	**	*0.40*	0.28		*0.24*	0.80	***	*0.31*
ICT Intensity (High to most intense)	0.52	***	*0.12*	0.45	***	*0.12*	0.18		*0.12*	0.61	***	*0.12*
Used STEM skills	0.52	***	*0.13*	0.54	***	*0.14*	0.49	***	*0.13*	0.57	***	*0.13*
Export capability (Local only)	-0.04		*0.13*	-0.03		*0.14*	0.10		*0.13*	-0.36	***	*0.14*
With flexible working arrangements	0.42	***	*0.12*	0.37	***	*0.12*	0.41	***	*0.11*	0.40	***	*0.12*
Sought debt and/or equity finance	0.23	*	*0.13*	0.23	*	*0.13*	0.27	**	*0.12*	0.21		*0.13*
Financial year												
2008/09	-0.38	**	*0.15*	-0.31	*	*0.16*	-0.30	**	*0.15*	-0.48	***	*0.16*
2009/10	-0.49	***	*0.16*	-0.25		*0.17*	-0.44	***	*0.15*	-0.41	**	*0.16*
2010/11	-0.51	***	*0.16*	-0.24		*0.17*	-0.43	***	*0.15*	-0.48	***	*0.16*
Intercept	-1.91	***	*0.35*	-2.19	***	*0.44*	-1.26	***	*0.29*	-1.67	***	*0.35*
ρ_{2k}†	0.539	***	*0.057*									
ρ_{3k}	0.650	***	*0.047*	0.713	***	*0.044*						
ρ_{4k}	0.561	***	*0.054*	0.560	***	*0.056*	0.524	***	*0.056*			
Log-likelihood	-1253.64											
AIC	2631.27											
BIC	2915.19											
Wald Chi-Squared	248.93	***										
Number of observations (n)	720											

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.
†Correlations between the residuals in the four equations, k=1, 2, 3.

Table 6.13

Predicted Probabilities for Small Food Businesses Using Estimates from the Multivariate Models†

Outcome	FOOD %	AgriFF %	Non-AgriFF %
Innovator	40.46	33.27	49.25
Noninnovator	59.54	66.73	50.75
Innovating four types of innovation	5.29	2.39	9.66
Innovating at most 3 types of innovation	35.18	30.88	39.59

† The reference food business is small, does not collaborate, has low ICT intensity, has no effective competition, does not use STEM skills, has no debt or equity finance, has export capability, and does not have any flexible working arrangements in the reference year, 2007/08.

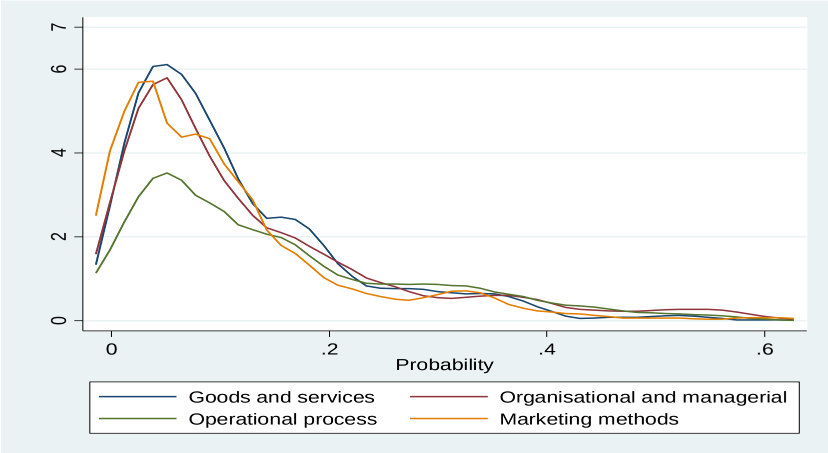


Figure 6.3. Probability density functions for the four types of innovation in the AgriFF subsector using multivariate probit.

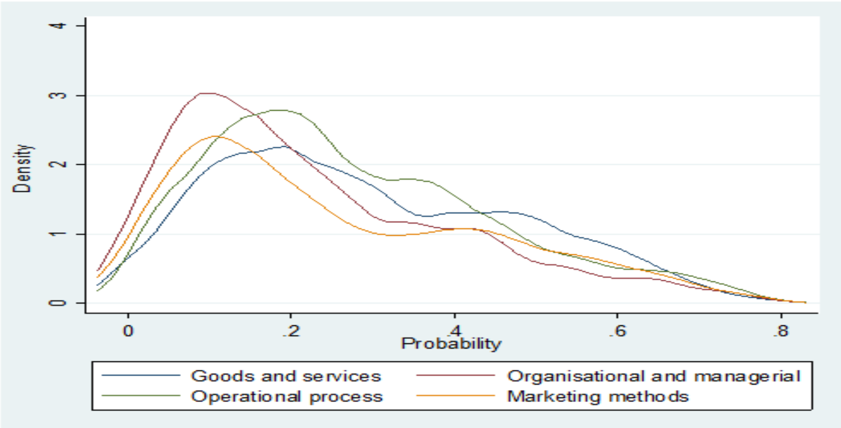


Figure 6.4. Probability density functions for the four types of innovation in the non-AgriFF subsector using multivariate probit.

6.5 Summary of findings

This study investigates the key drivers of innovation among small businesses in the Australian food industry, which is an important part of the country's regional economies. The modelling technique used to identify the factors that play important roles in influencing the innovation behaviour of small food businesses and their strength of association is well established in the literature. Estimating robust standard errors for impact summary measures called APEs simulation using modern bootstrapping procedures is a novelty in this work. We also employed five panel modelling procedures: random effects probit, pooled probit, Poisson with random effects, negative binomial with random effects, and multivariate probit. Results were used to verify and evaluate the set of key determinants of innovation for small food businesses in Australia.

In this chapter, we observed the connection between collaboration, the use of STEM skills, the use of ICT, having flexible working arrangements, degree of market competition and innovation among small businesses in the Australian food industry. The analyses focused on one aspect of innovation—the propensity of the businesses to innovate—though we also included innovation intensity. Other possible drivers of innovation, such as business size, export capability and finance sought, were also examined. Overall, we found that innovation is an essential element in activities of small food businesses (also in Avermaete et al. (2003), Baregheh, Rowley, Sambrook, and Davies (2012), Caiazza and Stanton (2016), De Martino and Magnotti (2017), and Wixe et al. (2017)) and the results about associations between the above drivers and innovation propensity were similar to most of the ABS cross-sectional studies on innovation.

One of the highlights in the analyses was the significant and positive association between collaboration and business innovation (both in overall innovation and intensity) among small food businesses, where we found that businesses engaging in any form of collaborative arrangements were more likely to innovate. This is similar to the results of most of the previous international studies. The adoption of OI practices in the small food industry in Australia is being supported by the findings. Our empirical results also indicate that small food businesses using STEM skills are significantly more likely to innovate. The above findings are supportive of the mission of the Food and Agribusiness Growth Centre—the FIAL—to build capability and encourage collaboration and innovation in the Australian food sector (FIAL, 2017).

The findings in this chapter also raise important policy implications for expanding the food industry in Australia. It is supporting both the Industry Innovation and Competitiveness Agenda as well as the National Innovation and Science Agenda for small businesses to grow and become competitive both nationally and internationally. Hence, it is imperative for the small food businesses to: have a favourable conditions and an environment to utilise the emerging ICT technologies in their business activities; offer flexible working arrangements to their employees; support access to new international markets; and increase industry competitiveness, to be innovative.

Moreover, the unique sample data for the Australian food industry have enabled us to undertake separate analyses for small businesses belonging to the AgriFF and the non-AgriFF subsectors of the food industry. Additional findings, obtained in these subsector analyses, indicate that the degree of association between having intense ICT and innovation is stronger in the non-AgriFF subsector. On the other hand, the impact on innovation is stronger in the AgriFF subsector when small businesses use STEM skills and provide flexible working arrangements to employees. The impact of collaboration is positive and statistically significant and is similar in magnitude in both subsectors. Further, OI has shown its importance at the subindustry level.

The analysis also finds that market competition is strongly and positively associated with an increase in the propensity to innovate, supporting the theory posited by Aghion et al. (2005) that greater levels of competition lead to more innovation. Amongst the Australian small food businesses, collaboration, use of STEM skills, market competition, use of high to most-intense ICT, and labour market flexibility are found to be significantly associated with small food businesses completing a greater number of different types of innovation (i.e., are strong determinants of innovation intensity).

The main output-based measure of innovation used in this analysis was overall innovation. However, using multivariate probit analysis we also found positive and significant correlation structures exist among the four types of innovation: new goods and services; new organisational processes; new operational processes; and new marketing methods. In Chapter 7, we extend the analyses of small food businesses by considering each type of innovation separately and examining how sensitive the impacts of the drivers are to the different types of innovation, as has been done by Smit et al. (2015), Zouaghi and Sanchez (2016) and Wixe et al. (2017). In addition, there is strong evidence suggesting that persistence of innovation is an important characteristic of successful businesses (Rotaru, 2013; Rotaru & Soriano, 2013; Triguero et al., 2013; Tavassoli & Karlsson, 2015) and this suggests that the causes of persistence in innovation in small food businesses are worthy of further investigation. This phenomenon is also investigated in Chapter 7 including the modelling of innovation persistence where we account for correlation between the business-specific effects and the regressors because there may exist time-varying regressors across the periods in the panel data.

6.6 Concluding remarks

Now that we have established what drives small food businesses to innovate, a next step is to determine whether the innovation behaviour of these businesses is becoming more persistent over time. If there is evidence of persistence of innovation, we would like to know if the degree of persistence varies between the different types of innovation. Whether this is the case for small food businesses in Australia is worth investigating to provide additional evidence to support the government's policies and investments in expanding Australian food businesses.

The next chapter presents the empirical work on the dynamics of innovation dimensions among small food businesses in Australia.

Chapter 7: Dynamics of Innovation Dimensions in Small Food Industry Businesses in Australia[35]

7.1 Introduction

In Chapter 3, we present the theoretical underpinnings on the concepts of innovation persistence and review empirical studies that provide the basis to formulate the hypotheses in section 4.4 of Chapter 4. Recall that the previous empirical works have indicated that the degree of persistence depends on the innovation output measures (Crepon & Duguet, 1997; Cefis & Orsenigo, 2001; Cefis, 2003; Duguet & Monjon, 2004; Rogers, 2004; Latham & Le Bas, 2006; Raymond et al., 2006; Peters, 2009; Clausen et al., 2012; Altuzarra, 2017). Most of the empirical studies on innovation persistence are applied using manufacturing industry data (e.g., Raymond et al., 2006; Antonelli et al., 2012; Tavassoli & Karlsson, 2015; Altuzarra, 2017). Analysing innovation persistence in food businesses is scarce and the current study is an important addition particularly in examining the dynamic patterns of persistence in the goods and services, organisational and managerial processes, operational processes, and marketing methods innovations. This chapter answers two fundamental research questions, namely:

- *Does innovation persist among small food businesses in Australia (Research Question 3)?*
- *Does the degree of innovation persistence vary between the different types of innovation (Research Question 4)?*

Using the methodological frameworks in section 4.4 of Chapter 4 and applying them to the ABS BLD CURF panel data compiled in Chapter 5, this chapter presents the empirical models and findings for understanding the dynamics of innovation dimensions among small food businesses in Australia. Section 7.2 presents evidence of innovation persistence using a transition probability matrix (TPM). Understanding the existence of state-dependence in each type of innovation follows in section 7.3 using a simple dynamic probit model. An empirical application of dynamic correlated random effects probit model that accounts for unobserved heterogeneity, α_i, as well as correlations between the unobserved heterogeneity α_i and the

[35] Some materials in this chapter focusing on the results in sections 7.2 and 7.4 were presented in the 63rd Annual Conference of the Australasian Agricultural and Resource Economics Society in Melbourne (Soriano, Villano, Fleming, & Battese, 2019), whereas the analysis in section 7.3 was presented as a contributed paper at the 2017 Australian Conference of Economists in Sydney (Soriano et al., 2017).

covariates, x_{it}, (i.e., equation (4.19)) are performed in section 7.4. Section 7.5 summarises the results, and section 7.6 concludes.

7.2 Empirical evidence of innovation persistence using a TPM

7.2.1 The TPM specifications

We begin by constructing the five TPMs to represent each of the above types or combination of innovations. Let a *state* be the innovation behaviour of businesses in a given time period *t*, i.e., being innovation-active in a *j*-th type of innovation (active innovator) or not being innovation-active at all (active noninnovator). Our sequence of *states* is modelled as a stochastic process approximated by a two-state Markov chain with transition probabilities formulated as:

$$P\left[Y_{j,t}=b \mid Y_{j,t-1}=c\right]=\begin{bmatrix} p_j & 1-p_j \\ 1-q_j & q_j \end{bmatrix}=\text{TPM}_j \tag{7.1}$$

where each term in the *j*-th TPM measures the probability of moving from *state c* in period *t-1* to *state b* in period *t* for the random variable Y_j. Note that the rows of the TPM above must sum to one.

In this empirical study, Y_j, refers to engaging in the *j*-th type of innovation (*j*=1,2,3,4,denote the states, new goods and services, new operational process, new organisational/managerial process, or new marketing methods innovations, respectively) or for any of the four types of innovation (*j*=5). Thus, five TPMs are constructed. For example, suppose we consider Y_1 as engaging in the new goods and services innovation. The TPM_1 measures the probability that a small food business moves from being a goods-and-services active innovator to a goods and services active noninnovator ($1-p_1$) or just remains a goods-and-services active innovator (p_1), while moving from one period to another for all the time periods examined in the data. On the other hand, q_1 measures the probability for a goods-and-services active noninnovator to remain as a noninnovator whereas ($1-q_1$) expresses the probability for noninnovating small food business to engage in innovating goods and services in the following year. Besides applying the TPM for the remaining types of innovation and overall innovation for the food industry sample, the calculation of the five transition matrices is repeated for the case of the AgriFF and the non-AgriFF subsector samples.

In a simple way, the TPM used in this study is just a matrix composed of one-step transition probabilities. These are the probabilities of moving from one state to another or to remain in the same state in a single step. The probabilities of the small food businesses to transition from: (1) being innovation-active to noninnovation-active or vice versa; and (2) remain either innovation-active or noninnovation-active, from one time period to the next time period. And the transitions are independent of time period.

As discussed in Chapter 4, the unknown probabilities in the TPM, say, for engaging in the goods-and-services innovation (j=1), are estimated using the first-order autoregressive (*AR(1))* process for the stochastic variable $Y_{1,t}$ given by:

$$Y_{1,t} = (1 - q_1) + \theta_1 Y_{1,t-1} + \upsilon_t, \tag{7.2}$$

where $\theta_1 = p_1 + q_1 - 1$ and υ_t is the error term assumed to be uncorrelated and normally distributed $(0, \sigma^2)$ random variables. The bootstrapping procedure using STATA MP 15 was used to estimate the standard errors associated with the transition probabilities.

Recall that the use of the above TPMs for our short panel information shows the inter-temporal stabilities in undertaking a particular type of innovation and adds to justifying if the three theoretical arguments discussed in section 3.9 are occurring in small food businesses in Australia. Furthermore, *weak persistence* in goods-and-services innovation is observed if the sum of the diagonal elements of the TPM_1 is equal to or greater than 100 per cent but not all terms in the diagonal are equal to or greater than 50 per cent. And, if all the elements in the diagonal of the TPM_1 are equal to or greater than 50 per cent then a case of *strong persistence* in goods-and-services innovation is evident. Lastly, if all the elements in the diagonal of the TPM_1 are less than 50 per cent then goods-and-services innovation persistence is not evident. For the TPM_1, an unconditional state-dependence measure (USD)[36] is estimated by:

$$\text{USD}_1 = P\left[Y_{1,t} = e \mid Y_{1,t-1} = e\right] - P\left[Y_{1,t} = e \mid Y_{1,t-1} = d\right], \tag{7.3}$$

where *state e* is the state of being a goods-and-services active innovator and *state d* is an active noninnovator state. It can be shown that the estimated value for USD_1 is equivalent to the

[36] See Peters (2005) and Tavasolli and Karlsson (2015) for more details.

estimate of the parameter θ_1 in equation (7.2). USD_j is also estimated for the rest of innovation dimensions (j=2,3,4) and for overall innovation (j=5).

We now empirically address Research Question 3 and evaluate its corresponding Hypotheses 7 for each type of innovation―new products, new operational process, new organisational or managerial process, or new marketing methods innovations―and for overall innovation, following the approach of Cefis and Orsenigo (2001) and Cefis (2003) by using the TPMs defined above.

7.2.2 Estimated transition probabilities for innovation dimensions

Table 7.1 presents the estimated TPMs in each type of innovation and overall innovation (as labelled in the first column) for small food businesses in the food industry as well as in the AgriFF and non-AgriFF subsectors. The table contains '*Yes*' and '*No*' subheadings which indicate the *state* of innovation behaviour of small food businesses in time period *t-1* and *t*.

7.2.2.1 TPM for the food industry

In the food industry, the transitional probabilities indicate an overall presence of innovation persistence over the whole period of study (2007/08–2010/11). Looking at the overall innovation, on average, 67 per cent of innovative businesses persist to remain innovative in the subsequent period, whereas only 33 per cent change their engagements. About 78 per cent of the noninnovators remain in the same state whereas 22 per cent change to innovative behaviour. This means that the probability of engaging in any type of innovation in year *t* is about 45 percentage points higher for innovators than noninnovators in year *t* (i.e., USD_5=45 per cent—state-dependence measure for overall innovation of small food businesses). From Table 7.1, we see that there are difficulties for small food businesses to engage in a particular type of innovation. Between 86 per cent and 90 per cent of the businesses remain noninnovators between period *t*-1 and *t*, for the different types of innovation. The persistency in innovation behaviour is found strong for new goods and services, new operational process and new marketing methods. Relative to the USD for overall innovation, similar percentage points can be seen for engagement in a new product, new operational process and new marketing methods innovation where the estimated USDs range from 42 per cent to 44 per cent.

In the new organisational or managerial process innovation, we find weak persistence of innovative behaviour with 55 per cent of innovative small businesses shifting from being innovative in year *t*-1 to noninnovative in year *t*. This result is very similar to the findings of

Tavassoli and Karlsson (2015) where goods-and-services active innovators showed higher persistency in staying innovative among other types of innovation, with operational process and marketing innovators following the persistent behaviours and the organisational process innovators being the least persistent active innovators.

7.2.2.2 TPM for AgriFF and non-AgriFF subsectors

Decomposing TPMs in small food businesses into the AgriFF and non-AgriFF subsectors, the results are somewhat different. Although we find strong unconditional innovation persistence behaviour for overall innovators in both subsectors, in the AgriFF subsector we find weak persistency in staying active innovators in the subsequent period for goods and services, organisational or managerial process, and marketing innovations. The persistent behaviour of organisational-process active innovators in the AgriFF subsector is weaker compared with the food industry. Among the various types of innovation, new operational-process innovators show strong persistency in innovative behaviour for small food businesses. This is because all the diagonal elements of its TPM were above 50 per cent. This result for process innovators is supported by the findings of Triguero et al. (2013) who found strong persistency in Spanish agri-food businesses. What is noticeable in the AgriFF subsector is the increased difficulties in accessing innovation for all types of innovation with both goods-and-services and marketing innovators having 93 per cent of non-innovative businesses not changing their innovative behaviour in the subsequent period. This implies that innovation behaviour among the small food businesses in the AgriFF subsector does not show significant learning and accumulation of knowledge that increases their probability of subsequent innovation. One possible reason is the low percentage of collaboration happening in the small food businesses (see Figure 5.7). The TPM results for the AgriFF do not support the success-breeds-success and sunk-cost-account hypotheses for the small food businesses in this subsector. This suggests that unless the noninnovating small businesses start engaging in any form of innovation, they will not able to increase their internal funding (or profit) to finance innovation. As shown in Figure 2.22, lower profit margins to remain competitive was the third highest barrier to business performance among the small food and agribusiness businesses in Australia in 2013/14. With regard to the sunk-cost perspective, small food businesses seem not really spending into R&D investment and human resources to perform innovation.

Table 7.1

Transition Probabilities by Types of Innovation and Industry/Subsector (t = 2007/08 to 2010/11)

Types of innovation	Innovator in time (*t-1*)	FOOD			AGRIFF			NON-AGRIFF		
		Innovator in time(*t*)		USD†	Innovator in time(*t*)		USD†	Innovator in time(*t*)		USD†
		No	Yes		No	Yes		No	Yes	
Any types (overall innovation)	No	78%	22%	45%	81%	19%	42%	72%	28%	44%
		0.012	*0.012*	*0.020*	*0.016*	*0.016*	*0.031*	*0.024*	*0.024*	*0.033*
	Yes	33%	67%		39%	61%		28%	72%	
		0.017	*0.017*		*0.028*	*0.028*		*0.023*	*0.023*	
New goods and services	No	90%	10%	44%	93%	7%	36%	84%	16%	46%
		0.0086	*0.0086*	*0.030*	*0.0090*	*0.0090*	*0.045*	*0.016*	*0.016*	*0.035*
	Yes	45%	55%		57%	43%		39%	61%	
		0.029	*0.029*		*0.045*	*0.045*		*0.031*	*0.031*	
New organisational or managerial process	No	88%	12%	33%	89%	11%	26%	86%	14%	40%
		0.0084	*0.0084*	*0.028*	*0.011*	*0.011*	*0.041*	*0.014*	*0.014*	*0.042*
	Yes	55%	45%		64%	36%		47%	53%	
		0.027	*0.027*		*0.040*	*0.040*		*0.038*	*0.038*	
New operational process	No	86%	14%	42%	88%	12%	39%	84%	16%	44%
		0.0089	*0.0089*	*0.025*	*0.012*	*0.012*	*0.038*	*0.018*	*0.018*	*0.039*
	Yes	44%	56%		49%	51%		40%	60%	
		0.023	*0.023*		*0.036*	*0.036*		*0.034*	*0.034*	
New marketing methods	No	89%	11%	42%	93%	7%	34%	84%	16%	43%
		0.0088	*0.0088*	*0.029*	*0.010*	*0.010*	*0.048*	*0.016*	*0.016*	*0.036*
	Yes	48%	52%		59%	41%		41%	59%	
		0.028	*0.028*		*0.047*	*0.047*		*0.032*	*0.032*	

†Estimated unconditional state-dependence measured in percentage points.
Note: SEs (i.e., italicised values below each transition probabilities) are computed using bootstrapping.

On the other hand, the findings for the non-AgriFF subsector show different patterns of innovation. The persistence is strong in all types of innovation including the overall innovation. The estimated USDs for all types of innovators are relatively similar, varying between 40 per cent and 46 per cent. These results align with Peters (2008) in a study of German manufacturing. The study of Triguero et al. (2013) found that USD is relatively higher for businesses in the manufacturing industry compared with the food and beverage industry.

In summary, the above results indicate that there are evidences of innovation persistence in small food business innovation behaviour among innovators as reflected in the estimated TPMs. Although they show solid evidence of unconditional persistence or state-dependence, the observed and unobserved characteristics of the small food businesses are not considered in the estimation of probabilities. Hence, from what we observe, it is uncertain as to whether this unconditional state-dependence is “true”. To address this concern, we reevaluate the state-dependence occurrences by accounting the observed business characteristics of the small food businesses in the next section.

7.3 Empirical evidence of state-dependence using simple dynamic probit modelling

7.3.1 Empirical model specification

We test the occurrence of state-dependence among small food businesses in Australia using the dynamic probit model for panel data outlined in section 4.4. Again, the following hypotheses are tested for each type of innovation—new goods and services, new operational process, new organisational or managerial process, or new marketing methods innovations—and for overall innovation:

- *Small food businesses that innovate in period t-1 are more likely to innovate in period t (Hypothesis 7); and*
- *The degrees of innovation persistence are the same for the different types of innovation (Hypothesis 8).*

The empirical model following equation (4.15) is specified as:

$$
\begin{aligned}
P\left(y_{it}=1 \middle| x_i, y_{i,t-1}\right) &= P\left(y_{it}^{*}>0 \middle| x_{it}, y_{i,t-1}\right) \\
&= P\left(\phi y_{i,t-1}+x_{it}'\beta+\varepsilon_{it}>0 \middle| x_{it}, y_{i,t-1}\right) \\
&= \Phi\left(\phi y_{i,t-1}+x_{it}'\beta\right),
\end{aligned} \tag{7.4}
$$

where y_{it} denote binary dependent variables for the different types of innovation; ϕ is a scalar state-dependence parameter for the lagged dependent variable, $y_{i,t-1}$; $\Phi(\cdot)$ is the normal cumulative distribution function for ε_{it} conditional on $x_i, y_{i,t-1}$; and ε_{it} is the idiosyncratic error that summarises the effect of other time-varying unobservable variables, where $\varepsilon_{it} | \, x_{it}, y_{i,t-1} \sim \, N(0,1)$.

The dynamic probit model is applied to the food industry using the balanced panel sample described in section 5.5. The same modelling procedure is also applied to the balanced panel samples created for businesses belonging to the AgriFF and the non-AgriFF subsectors. For the dependent variable, y_{it}, five binary response variables are created, one for overall innovation and one for each type of innovation. Overall, 15 simple dynamic probit models are estimated and analysed.

The indicator function is similar to equation (4.2) in section 4.2, i.e., the dependent variable, y_{it}, is a binary response variable taking the value 1, if the *i*-th business engaged in innovation in period *t*, and 0 otherwise. The latent variable is formulated as:

$$
y_{it}^{*}=\beta_0+\phi y_{i,t-1}+x_{1it}\beta_1+x_{2it}\beta_2+\ldots+x_{kit}\beta_k+\varepsilon_{it}, \quad k=16, i=1,2,\ldots,417 \,; t=1,2,3,4 \tag{7.5}
$$

The observed explanatory variables in equation (7.5) are similar to those presented in Chapter 6, where x_k, *k*=1,2,..16, which include whether the business belongs to the subsector non-AgriFF (x_1); the business is nonemploying (x_2); the business has collaboration arrangements (x_3); the business faces minimal competition (x_4), moderate competition (x_5), and strong competition (x_6); the business uses moderate ICT (x_7), high ICT (x_8), and the most-intense ICT (x_9); the business uses STEM skills (x_{10}); the business has export capability (x_{11}); the business has flexible working arrangements (x_{12}); the business seeks debt and/or equity financing (x_{13}); and there are three time-period dummies (x_{14}, x_{15}, x_{16}) for year effects. The definitions of these variables follow those definitions in Chapter 5, see Tables 5.3–5.8.

As in Chapters 5 and 6, in the subsector models, the categories in the ICT intensity variable were combined to form two binary dummy variables (i.e., business uses low-to-moderate and high-to-most-intense ICT). Hence, the empirical model applied for each of the subsector samples (i.e., n_s=237 for AgriFF and n_s=180 for non-AgriFF) is reduced in terms of the number of regressors (to include that the subsector dummy indicator) with the latent variable formulated as:

$$y_{it}^{*} = \beta_0 + \phi y_{i,t-1} + x_{1it}\beta_1 + x_{2it}\beta_2 + \ldots + x_{kit}\beta_{13} + \varepsilon_{it}, \quad i = 1, 2, \ldots, n_s \; ; t = 1, 2, 3, 4 \qquad (7.6)$$

Following equation (4.7), the average partial effects (APE) for a binary variable, z_k (to include that of lagged y_i), is estimated by:

$$APE_{z_k} = \frac{1}{n}\left[\sum_{i=1}^{n}\left[\Phi\left(\hat{\phi}_a y_{i,t-1} + x_{it}'\hat{\beta}_a \mid z_k = 1\right) - \Phi\left(\hat{\phi}_a y_{i,t-1} + x_{it}'\hat{\beta}_a \mid z_k = 0\right)\right]\right]. \qquad (7.7)$$

The subscript *a* in equation (7.7) denotes the model parameter estimates divided by $\sqrt{\hat{\sigma}_{\varepsilon}^{2}}$ and *n* is total number of businesses in the food industry (*n*=1,668) or subsector samples (*n*=948 and 720). Following Rotaru and Soriano (2013) and Rotaru (2013), the bootstrapping technique is implemented for robust statistical inferences of both equations (7.4) and (7.6) as well as in the corresponding estimations of the APEs for the covariates.

As discussed in Chapter 4, the simple dynamic probit modelling is an initial step that would empirically indicate the possible occurrence of true state-dependence among small food businesses in Australia after controlling for observed business characteristics. The issue of unobserved heterogeneity is addressed in the next section (section 7.4). Hence, the focus of the discussions below is on the estimates and APEs of the scalar state-dependence parameter ϕ in all models.

7.3.2 Results for the models accounting for observed business characteristics

This subsection presents the empirical results of the simple dynamic probit model, specified in equation (7.4), applied to the food industry panel of businesses and to the balanced panel samples created for businesses belonging to the AgriFF and non-AgriFF subsectors. These are the same panel of businesses used in Chapter 6. The empirical results are compared with those of other ABS and DIIS studies that used cross-sectional modelling and employed data collected in the same survey (i.e., BCS) as well as with the findings coming from previous international food industry studies.

7.3.2.1 Findings for the food industry

Table 7.2 shows the simple dynamic probit regression results for the different types of innovation and overall innovation (i.e., any type of innovation) for the food industry. The APEs for the key business characteristics and lagged innovation are also included. The APEs in all estimated models are to be interpreted with reference to a business belonging to the AgriFF subsector (for the food industry sample only), which is small, does not collaborate, has low ICT intensity, has no effective competition, does not use STEM skills, has no debt or equity finance, has export capability, and does not have any flexible working arrangements, during the base period (i.e., 2007/08).

The estimated coefficients (for the scalar state-dependence parameter, ϕ, in all models) for each type of innovation as well as for overall innovation are found highly significant (in Table 7.2). This implies that state-dependence was evident for all types of innovation, i.e., small food businesses that engage in goods and services or organisational/managerial process or operational process or marketing methods innovation in period *t*-1 are significantly more likely to innovate in period *t*. These findings further indicate that innovation persistence, after accounting for the observed business characteristics, exists among the small food businesses in Australia and that the three theoretical hypotheses (i.e., dynamic increasing-returns, success-breeds-success, sunk-cost-account) are being experienced by the small food businesses in the food industry.

Observing the degree of innovation persistence among the four types of innovation, the simple dynamic probit models show findings consistent with the TPM results, where the persistence in innovation behaviour was slightly larger for new goods and services, new operational process and new marketing methods compared with the persistence in organisational or managerial process innovation. Moreover, the APEs conditional on the observed covariates show that the degrees of innovation persistence are different in magnitude for the different types of innovation but each of them is found highly significant.

Further examination of the simple dynamic modelling results for overall innovation reveals statistical significance at the 1% level for collaboration, use of STEM skills, facing moderate-to-strong market competition, and having flexible working arrangements, which are consistent with our findings in Chapter 6. Having higher-to-most-intense use of ICT is also highly significant for overall innovation whereas their significances varied among the four innovation dimensions. With stronger market competition, the estimated APEs diminish for those that are found significant for goods and services innovation, whereas for new marketing methods the effects are the other way. The results for each type of innovation are also consistent in terms of direction and significance with the previous empirical findings in section 6.4 for the multivariate probit modelling in terms of significance, signs and direction of the estimated coefficients for the observed covariates. The log-likelihood, AIC and BIC results confirm the goodness-of-fit of the model compared with the pooled probit model, as exhibited in Table 6.6 in section 6.2.3. The log-likelihood for the overall innovation model is nearly similar to that of the log-likelihood value of the random effects probit model in Table 6.1 in section 6.2.2.

7.3.2.2 Findings for the food subsectors

Tables 7.3 and 7.4 present the simple dynamic probit regression results for the different types of innovation and overall innovation for the subsector models utilising the AgriFF panel (with 948 observations) and the non-AgriFF panel (with 720 observations), respectively. The findings are consistent with our expectations based on the earlier TPM results for the small food businesses in the two subsectors. The sign of the estimated coefficients for the lagged innovation for both the AgriFF and the non-AgriFF subsectors are still consistent with the food industry results. For the overall innovation and four innovation dimension models, all the state-dependence estimates of ϕ are found statistically significant at the 1% level, leading to the acceptance of Hypothesis 7, implying that small food businesses that innovate in period t-1 are more likely to innovate in period t.

The state dependences exhibited in Table 7.4 are evidently stronger for the non-AgriFF subsector, in all types of innovation including the overall innovation, compared with the AgriFF subsector as well as with the overall food industry, again consistent with the TPM findings. In terms of the corresponding APEs, conditional to the observed covariates, the subsector model results show that the degrees of persistency are different in magnitude for the different types of innovation but all of them are found highly significant.

Table 7.2

Simple Dynamic Probit Regression Results for Different Types of Innovation and Average Partial Effects for Selected Key Business Characteristics and Lagged Innovation: Food Industry

	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovation (overall)			
Variables	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡
Innovation (Response variable)																				
Innovation (t-1)	1.11 ***	*0.11*	0.305 ***	*0.032*	0.77 ***	*0.11*	0.200 ***	*0.036*	1.038 ***	*0.092*	0.312 ***	*0.034*	0.913 ***	*0.099*	0.232 ***	*0.030*	0.863 ***	*0.085*	0.281 ***	*0.028*
Sub-industry (non-AgriFF)	0.256 ***	*0.094*			0.021	*0.094*			-0.008	*0.088*			0.19 *	*0.10*			0.04	*0.08*		
Business size (Nonemploying)	0.224 **	*0.099*			-0.01	*0.11*			0.020	*0.095*			0.092	*0.097*			0.189 **	*0.085*		
With collaboration	0.31 ***	*0.11*	0.067 ***	*0.025*	0.42 ***	*0.10*	0.100 ***	*0.025*	0.31 ***	*0.10*	0.080 ***	*0.030*	0.37 ***	*0.11*	0.080 ***	*0.027*	0.48 ***	*0.10*	0.146 ***	*0.028*
Market competition																				
Minimal	0.51 ***	*0.16*	0.097 ***	*0.035*	0.22	*0.19*	0.039	*0.036*	0.16	*0.15*	0.032	*0.032*	0.44 **	*0.21*	0.067 **	*0.030*	0.37 ***	*0.14*	0.103 **	*0.044*
Moderate	0.45 ***	*0.15*	0.084 ***	*0.029*	0.56 ***	*0.16*	0.114 ***	*0.033*	0.52 ***	*0.13*	0.122 ***	*0.027*	0.71 ***	*0.19*	0.124 ***	*0.031*	0.62 ***	*0.12*	0.176 ***	*0.036*
Strong	0.40 ***	*0.13*	0.073 ***	*0.022*	0.33 **	*0.15*	0.062 **	*0.025*	0.40 ***	*0.11*	0.089 ***	*0.025*	0.67 ***	*0.18*	0.115 ***	*0.024*	0.49 ***	*0.11*	0.138 ***	*0.031*
ICT Intensity																				
Moderate	-0.04	*0.11*	-0.007	*0.025*	0.21 *	*0.12*	0.041 *	*0.025*	0.27 **	*0.11*	0.062 **	*0.026*	-0.02	*0.12*	-0.003	*0.025*	0.12	*0.10*	0.035	*0.029*
High	0.37 *	*0.20*	0.082 *	*0.049*	0.51 ***	*0.19*	0.112 **	*0.045*	0.37 **	*0.19*	0.088 *	*0.051*	0.18	*0.19*	0.037	*0.041*	0.56 ***	*0.16*	0.165 ***	*0.057*
Most intense	0.29 **	*0.14*	0.064 *	*0.035*	0.35 **	*0.15*	0.072 **	*0.030*	0.33 **	*0.14*	0.078 **	*0.032*	0.44 ***	*0.15*	0.098 ***	*0.037*	0.39 ***	*0.13*	0.114 ***	*0.042*
Used STEM skills	0.437 ***	*0.097*	0.096 ***	*0.022*	0.552 ***	*0.096*	0.131 ***	*0.030*	0.406 ***	*0.095*	0.105 ***	*0.027*	0.40 ***	*0.10*	0.086 ***	*0.023*	0.46 ***	*0.09*	0.138 ***	*0.032*
Market location (Local only)	-0.01	*0.14*			-0.07	*0.13*			0.02	*0.12*			-0.25 **	*0.12*			-0.15	*0.12*		
With flexible working arrangements	0.328 ***	*0.091*	0.067 ***	*0.021*	0.327 ***	*0.088*	0.069 ***	*0.020*	0.402 ***	*0.086*	0.099 ***	*0.022*	0.274 ***	*0.093*	0.055 ***	*0.020*	0.494 ***	*0.077*	0.147 ***	*0.024*
Sought debt and/or equity finance	0.067	*0.096*			0.131	*0.092*			0.233 **	*0.093*			0.166 *	*0.093*			0.172 **	*0.084*		
Financial year																				
2008/09	-0.45 ***	*0.12*	-0.098 ***	*0.027*	-0.31 ***	*0.12*	-0.066 **	*0.026*	-0.34 ***	*0.11*	-0.086 ***	*0.029*	-0.40 ***	*0.13*	-0.081 ***	*0.024*	-0.40 ***	*0.10*	-0.114 ***	*0.030*
2009/10	-0.52 ***	*0.12*	-0.111 ***	*0.028*	-0.13	*0.12*	-0.029	*0.026*	-0.42 ***	*0.10*	-0.105 ***	*0.027*	-0.27 **	*0.12*	-0.058 **	*0.026*	-0.39 ***	*0.09*	-0.111 ***	*0.027*
2010/11	-0.40 ***	*0.13*	-0.087 ***	*0.030*	-0.29 **	*0.13*	-0.063 **	*0.029*	-0.41 ***	*0.12*	-0.102 ***	*0.034*	-0.41 ***	*0.13*	-0.083 ***	*0.022*	-0.38 ***	*0.11*	-0.109 ***	*0.031*
Intercept	-1.86 ***	*0.20*			-1.90 ***	*0.22*			-1.78 ***	*0.18*			-1.86 ***	*0.24*			-1.34 ***	*0.17*		
Log Likelihood	-605.27				-628.56				-714.01				-592.71				-835.13			
AIC	1246.55				1293.13				1464.03				1221.43				1706.26			
BIC	1344.10				1390.67				1561.57				1318.98				1803.81			
Number of observations (n)	1668				1668				1668				1668				1668			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

† Average partial effects for selected key drivers of innovation.

‡ SEs for APEs are computed using bootstrapping.

For both the AgriFF and non-AgriFF subsectors, the degree of persistent innovation is higher for small food businesses engaging in goods and services and operational process innovation than for those engaging in marketing methods and organisational process innovations. However, for overall innovation, the impacts of lagged innovation are approximately similar in magnitudes between the two subsectors. This means a rejection of Hypothesis 8 when it comes to the small food businesses in the two subsectors.

Regarding the estimated coefficients for the selected key explanatory variables, we find statistical significance for collaboration, moderate-to-strong degrees of market competition and use of STEM skills covariates, for the AgriFF subsector in all types of innovation. Having high-to-most-intense use of ICT, using STEM skills as well as having flexible working arrangements are found significant for the non-AgriFF subsector whereas the rest of the covariates varied among the four innovation dimensions. These findings are consistent with the modelled results in Tables 6.11 and 6.12, for the Agriff and the non-AgriFF subsectors, respectively. They indicate that these covariates are important when examining the determinants of the nature and persistence of innovation.

For overall innovation and, in comparison, with the previous empirical findings in section 6.2 for the case of random effects probit modelling, the signs of the estimated coefficients for the observed covariates are consistent but the significance varies particularly for the business size, degree of market competition and sought debt and/or equity finance variables for the non-AgriFF subsector. This was expected because of the addition of the lagged dependent variables as well as the non-consideration of the unobserved heterogeneity in the simple dynamic probit model.

Summing up, we have empirically observed the nature of innovation persistence or state-dependence happening among the small food businesses in Australia when we account for the observed business characteristics in the model. The above results further indicate that a causal behavioural relationship or path-dependent process, where the decision to innovate in one period increases the likelihood to successfully innovate in the following period, is evident for these small food businesses, for both in the AgriFF and the non-AgriFF subsectors.

Table 7.3

Simple Dynamic Probit Regression Results for Different Types of Innovation and Average Partial Effects for Selected Key Business Characteristics and Lagged Innovation: AgriFF Subsector

	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovation (overall)			
Variables	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡
Innovation (Response variable)																				
Innovation (t-1)	1.12 ***	*0.15*	0.267 ***	*0.043*	0.61 ***	*0.17*	0.141 ***	*0.046*	0.98 ***	*0.12*	0.269 ***	*0.034*	0.92 ***	*0.16*	0.199 ***	*0.048*	0.87 ***	*0.11*	0.275 ***	*0.034*
Business size (Nonemploying)	0.24 *	*0.14*			-0.04	*0.16*			0.04	*0.13*			-0.01	*0.15*			0.13	*0.12*		
With collaboration	0.42 ***	*0.15*	0.076 **	*0.033*	0.45 ***	*0.16*	0.101 **	*0.042*	0.29 **	*0.14*	0.067 **	*0.033*	0.42 ***	*0.15*	0.075 ***	*0.029*	0.48 ***	*0.13*	0.143 ***	*0.042*
Market competition																				
Minimal	0.35 *	*0.20*	0.048	*0.029*	0.03	*0.23*	0.005	*0.036*	-0.11	*0.20*	-0.019	*0.031*	0.17	*0.27*	0.016	*0.027*	0.20	*0.17*	0.049	*0.040*
Moderate	0.38 **	*0.19*	0.054 *	*0.031*	0.51 ***	*0.19*	0.100 **	*0.040*	0.64 ***	*0.15*	0.144 ***	*0.038*	0.75 ***	*0.22*	0.106 ***	*0.027*	0.66 ***	*0.14*	0.182 ***	*0.042*
Strong	0.43 ***	*0.15*	0.062 ***	*0.024*	0.33 **	*0.17*	0.059 **	*0.028*	0.49 ***	*0.14*	0.104 ***	*0.029*	0.71 ***	*0.21*	0.098 ***	*0.023*	0.55 ***	*0.12*	0.150 ***	*0.035*
ICT Intensity (High to Most intense)	0.35 *	*0.18*	0.064	*0.039*	-0.01	*0.19*	-0.003	*0.033*	0.24	*0.15*	0.056 *	*0.033*	0.39 **	*0.20*	0.071 *	*0.038*	0.37 ***	*0.14*	0.106 **	*0.044*
Used STEM skills	0.42 ***	*0.14*	0.074 ***	*0.026*	0.60 ***	*0.14*	0.134 ***	*0.038*	0.50 ***	*0.13*	0.120 ***	*0.033*	0.28 *	*0.16*	0.046 *	*0.028*	0.48 ***	*0.12*	0.141 ***	*0.038*
Market location (Local only)	-0.06	*0.22*			-0.10	*0.19*			-0.09	*0.17*			-0.21	*0.20*			-0.10	*0.16*		
With flexible working arrangements	0.21	*0.13*	0.034	*0.023*	0.35 ***	*0.12*	0.069 ***	*0.024*	0.51 ***	*0.12*	0.116 ***	*0.029*	0.22 *	*0.13*	0.034	*0.022*	0.55 ***	*0.10*	0.159 ***	*0.029*
Sought debt and/or equity finance	-0.11	*0.14*			0.07	*0.12*			0.19	*0.13*			0.13	*0.14*			0.06	*0.11*		
Financial year																				
2008/09	-0.41 **	*0.17*	-0.072 **	*0.028*	-0.25	*0.17*	-0.048	*0.035*	-0.28 **	*0.14*	-0.066 *	*0.037*	-0.19	*0.18*	-0.031	*0.032*	-0.27 *	*0.14*	-0.074 *	*0.038*
2009/10	-0.62 ***	*0.20*	-0.098 ***	*0.029*	0.00	*0.16*	0.000	*0.031*	-0.42 ***	*0.14*	-0.095 ***	*0.036*	-0.17	*0.19*	-0.028	*0.034*	-0.35 ***	*0.13*	-0.097 ***	*0.034*
2010/11	-0.28	*0.20*	-0.052	*0.033*	-0.22	*0.18*	-0.043	*0.040*	-0.40 **	*0.16*	-0.089 ***	*0.033*	-0.27	*0.18*	-0.042	*0.030*	-0.26 *	*0.15*	-0.073 *	*0.040*
Intercept	-1.76 ***	*0.27*			-1.68 ***	*0.28*			-1.60 ***	*0.22*			-1.93 ***	*0.34*			-1.37 ***	*0.22*		
Log Likelihood	-269.20				-328.09				-368.36				-267.75				-455.03			
AIC	568.40				686.18				766.71				565.51				940.07			
BIC	641.22				759.00				839.53				638.32				1012.88			
Number of observations (n)	948				948				948				948				948			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

† Average partial effects for selected key drivers of innovation.

‡ SEs for APEs are computed using bootstrapping.

Table 7.4

Simple Dynamic Probit Regression Results for Different Types of Innovation and Average Partial Effects for Selected Key Business Characteristics and Lagged Innovation: Non-AgriFF Subsector

	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovation (overall)			
Variables	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡	Coefficient	*SE*	APE†	*SE*‡
Innovation (Response variable)																				
Innovation (t-1)	1.12 ***	*0.15*	0.354 ***	*0.051*	0.93 ***	*0.14*	0.267 ***	*0.046*	1.14 ***	*0.14*	0.373 ***	*0.044*	0.91 ***	*0.13*	0.273 ***	*0.043*	0.88 ***	*0.14*	0.296 ***	*0.053*
Business size (Nonemploying)	0.23 *	*0.13*			0.00	*0.16*			-0.05	*0.14*			0.20	*0.13*			0.22 *	*0.13*		
With collaboration	0.22	*0.14*	0.059	*0.041*	0.41 ***	*0.14*	0.102 **	*0.041*	0.38 **	*0.15*	0.107 **	*0.053*	0.36 **	*0.16*	0.095 **	*0.043*	0.50 ***	*0.15*	0.152 ***	*0.045*
Market competition																				
Minimal	0.78 ***	*0.31*	0.185 **	*0.074*	0.69 *	*0.37*	0.124 *	*0.067*	0.16	*0.27*	0.042	*0.073*	0.63	*0.46*	0.137	*0.097*	0.54 *	*0.30*	0.158 *	*0.091*
Moderate	0.65 **	*0.28*	0.148 **	*0.064*	0.89 ***	*0.31*	0.175 ***	*0.050*	0.18	*0.24*	0.048	*0.066*	0.67	*0.43*	0.148 *	*0.080*	0.54 *	*0.28*	0.158 **	*0.072*
Strong	0.56 **	*0.27*	0.124 **	*0.060*	0.64 **	*0.31*	0.112 **	*0.050*	0.12	*0.22*	0.031	*0.062*	0.63	*0.43*	0.137 *	*0.082*	0.41	*0.26*	0.121 *	*0.073*
ICT Intensity (High to Most intense)	0.33 **	*0.14*	0.088 **	*0.036*	0.37 ***	*0.13*	0.087 ***	*0.034*	0.14	*0.13*	0.036	*0.038*	0.44 ***	*0.13*	0.116 ***	*0.037*	0.36 ***	*0.12*	0.111 ***	*0.041*
Used STEM skills	0.44 ***	*0.14*	0.122 ***	*0.045*	0.50 ***	*0.13*	0.126 ***	*0.040*	0.32 **	*0.14*	0.088 **	*0.042*	0.54 ***	*0.14*	0.145 ***	*0.043*	0.44 ***	*0.13*	0.134 ***	*0.045*
Market location (Local only)	0.00	*0.17*			0.00	*0.16*			0.10	*0.16*			-0.27 *	*0.15*			-0.15	*0.17*		
With flexible working arrangements	0.41 ***	*0.12*	0.106 ***	*0.032*	0.28 **	*0.13*	0.064 **	*0.031*	0.28 **	*0.12*	0.076 **	*0.030*	0.32 **	*0.14*	0.081 **	*0.036*	0.40 ***	*0.11*	0.122 ***	*0.034*
Sought debt and/or equity finance	0.21	*0.14*			0.21	*0.15*			0.32 **	*0.14*			0.17	*0.13*			0.34 ***	*0.13*		
Financial year																				
2008/09	-0.50 ***	*0.17*	-0.134 **	*0.053*	-0.34 **	*0.17*	-0.080 **	*0.038*	-0.34 **	*0.16*	-0.095 **	*0.044*	-0.58 ***	*0.18*	-0.149 ***	*0.043*	-0.53 ***	*0.16*	-0.155 ***	*0.044*
2009/10	-0.50 ***	*0.15*	-0.135 ***	*0.043*	-0.26	*0.17*	-0.062	*0.041*	-0.41 ***	*0.15*	-0.111 **	*0.044*	-0.40 **	*0.16*	-0.106 **	*0.042*	-0.44 ***	*0.14*	-0.129 ***	*0.037*
2010/11	-0.53 ***	*0.16*	-0.142 ***	*0.043*	-0.32 **	*0.16*	-0.076 **	*0.039*	-0.34 **	*0.16*	-0.095 **	*0.047*	-0.54 ***	*0.17*	-0.140 ***	*0.042*	-0.49 ***	*0.15*	-0.144 ***	*0.047*
Intercept	-1.86 ***	*0.32*			-2.14 ***	*0.33*			-1.37 ***	*0.27*			-1.66 ***	*0.44*			-1.10 ***	*0.31*		
Log Likelihood	-331.36				-296.64				-340.55				-321.73				-375.70			
AIC	692.71				623.29				711.09				673.46				781.40			
BIC	761.40				691.98				779.78				742.15				850.09			
Number of observations (n)	720				720				720				720				720			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

† Average partial effects for selected key drivers of innovation.

‡ SEs for APEs are computed using bootstrapping.

The estimated TPMs in the previous section, as well as the applications of simple dynamic probit modelling for each type of innovation, are instrumental in drawing the patterns of innovation persistence. We also test Hypotheses 7 and 8 in a simple way and find acceptance of the former and rejection of the latter. Our general results that the degree of persistency among the different types of innovation varies are consistent and supported by the findings of Antonelli et al. (2012), Triguero et al. (2013),Tavassoli and Karlsson (2015) and Altuzarra (2017).

In the preceding section, we find sufficient evidence of the persistence of innovation by considering the observed characteristics of businesses. The unobserved characteristics (i.e., unobserved firm heterogeneity) as well as the serial correlations between the observed business characteristics and unobserved firm-specific effects were not being controlled for in the above measurement, which could result in possible spurious results. "Spurious" state-dependence exists when the determinants (observed and unobserved covariates) of innovation persistency are persistent themselves (Heckman 1981). In the above simple dynamic probit model, spurious state-dependence may still prevail because we were unable to account for the other unobserved determinants of innovation persistence (e.g., managerial skills) that make the small food businesses behave in a persistent manner. To address this concern, we employ the Wooldridge (2005) dynamic probit model to fully distinguish between the "true" and "spurious" state-dependence in innovation among small food businesses, giving way to what we call the true or conditional state-dependence. The results are presented in the next section.

7.4 Modelling the dynamics of innovation dimensions: state-dependence with unobserved heterogeneity due to covariates

We reexamined the persistence of different types of innovation, as well as the impact of various important drivers of innovation that we identified in Chapter 6. We again investigate whether the observed persistence is due to the underlying differences in business characteristics and/or due to a real causal effect of past on future innovations. In this section, we employ the Wooldridge (2005) dynamic random effects probit model (defined in equation (4.19)) that allows for any correlation between the unobserved heterogeneity, α_i, (treated as a random variable with a specified distribution) and the covariates, x_{it}, following Mundlak (1978) and Chamberlain (1984). Testing for the existence of true state-dependence, including the correlation between unobserved firm effects with the initial condition, y_{i0}, is also captured in this dynamic CRE probit model. The estimation and implementation of the above dynamic CRE model is much more complex than the random effects probit model in Chapter 6 and the simple dynamic probit model in the previous section. For the empirical modelling and following Wooldridge (2005), the conditional maximum likelihood estimation incorporates the Mundlak/Chamberlain approach which follows strict exogenous assumptions. Wooldridge (2010, 2012) designed this modelling approach to also correct for other explanatory variables that are not strictly exogenous in a nonlinear model, hence taking care of the issue of endogeneity. We use the group/cluster means of the observed time-varying covariates as some sort of instrumental variables for the dynamic CRE probit model.

7.4.1 Empirical model specification using the dynamic correlated random effects probit model

The empirical model following equation (4.19) is specified as:

$$P\left(y_{it}=1\middle|x_i, y_{i,t-1},\ldots,y_{i0},\bar{\mathrm{x}}_i,\alpha_i\right) = P\left(y_{it}^*>0\middle|x_{it}, y_{i,t-1}, y_{i0},\bar{\mathrm{x}}_i,\alpha_i\right) \tag{7.8}$$

where the dependent variable, y_{it}, is a binary response variable taking the value 1 if the i-th business engaged in a particular type of innovation (i.e., product innovation; organisational or managerial innovation; operational process innovation; or marketing methods innovation) and any type (i.e., overall innovation) in the t-th year, and 0 otherwise. Applying this to the three sets of panels (i.e., the food industry; the AgriFF; and the non-AgriFF samples) we specify 15 separate empirical models, each having the latent variable formulated as:

$$y_{it}^* = \phi y_{i,t-1} + \psi + \delta y_{i0} + \bar{\mathrm{x}}_i{}'\gamma + x_{1it}\beta_1 + x_{2it}\beta_2 + \ldots + x_{kit}\beta_k + u_i + \varepsilon_{it} , \tag{7.9}$$

where $k = 16,\ i = 1,2,\ldots,417\ ;\ t = 1,2,3,4$ for food industry sample

$k = 13,\ i = 1,2,\ldots,237\ ;\ t = 1,2,3,4$ for AgriFF subsector sample

$k = 13,\ i = 1,2,\ldots,180\ ;\ t = 1,2,3,4$ for non-AgriFF subsector sample

and $\alpha_i = \psi + \delta y_{i0} + \bar{\mathrm{x}}_i{}'\gamma + u_i,\quad u_i \sim N(0,\sigma_u^2)$, and u_i is independent of $\bar{\mathrm{x}}_i$ and y_{i0}.

Again, ε_{it} is the idiosyncratic error which summarises the effect of other time-varying unobservable variables, where $\varepsilon_{it} \sim N(0,1)$ and $\alpha_i \mid y_{i0}, \bar{\mathrm{x}}_i \sim N(\psi + \delta y_{i0} + \bar{\mathrm{x}}_i{}'\gamma, \sigma_\alpha^2)$. We use the covariates that apply, defined in sections 6.2.1 and 7.3.1. For the $\bar{\mathrm{x}}_i$, we use the group/cluster means of the observed time-varying covariates[37] in x_{it} across all time periods. The data used for the initial condition, y_{i0}, is extracted from the first period (i.e. 2006/07) innovation data of the ABS BLD for the food industry sample. For all the 15 dynamic models, the percentage of the total variance explained by the unobserved heterogeneity (ρ) is obtained using equation (4.6), and the significance of the estimate for ρ is tested using likelihood ratio test.

Following equation (4.20), we estimate the APE for the binary covariate variable, w_k, using:

$$APE_{w_k} = \frac{1}{n}\left[\sum_{i=1}^{n}\left[\begin{array}{l}\Phi\left(\hat{\phi}_a y_{i,t-1} + x_{it}'\hat{\beta}_a + \hat{\psi}_a + \hat{\delta}_a y_{i0} + \overline{\mathrm{x}}_i{}'\hat{\gamma}_a \mid w_k = 1\right) \\ -\Phi\left(\hat{\phi}_a y_{i,t-1} + x_{it}'\hat{\beta}_a + \hat{\psi}_a + \hat{\delta}_a y_{i0} + \overline{\mathrm{x}}_i{}'\hat{\gamma}_a \mid w_k = 0\right)\end{array}\right]\right] \tag{7.10}$$

where the subscript a denotes original parameter estimates from equation (7.8), divided by $\sqrt{1+\hat{\sigma}_u^2}$, and n is the total number of businesses in the food industry models (n=1668) or subsector models (n=948 and 720). Following Rotaru and Soriano (2013) and Rotaru (2013), the bootstrapping technique is implemented for robust statistical inferences of the 15 models defined by equation (7.8) as well as in the corresponding calculations of the APEs for the covariates. Just like what we did in Chapter 6, we again complement the empirical results of the dynamic CRE probit models by examining the distribution of the estimated APEs obtained through some descriptive summary statistics. The goodness-of-fit of the models is evaluated using the *F-test* statistics, AIC and BIC criteria. The empirical findings are presented in the next subsection.

7.4.2 Empirical results

This subsection presents the estimated coefficients and their bootstrapped standard errors (SEs) of the dynamic CRE probit modelling for the food industry and for the AgriFF and the non-AgriFF small food businesses, for the four types of innovation and overall innovation. We focus our attention on the lag innovation effect and analyse the level of persistence, particularly the impact on the degree of innovation persistence after accounting for the initial condition, observed business characteristics, unobserved heterogeneity and allowing for correlations between the business-specific effects and observed covariates in all four innovation dimensions.

[37] We exclude the time-period dummy variables and other time-invariant explanatory variables.

In interpreting the significance of the covariates, we examine the estimated APEs and not the estimated coefficients (see Wooldridge (2013)). To complement the estimated APEs in the modelled results, their distributions and summary statistics are also tabulated in the Appendix D.

7.4.2.1 Findings for the food industry

Table 7.5 presents the empirical results for the dynamic CRE probit model for the different types of innovation and the APEs for the food industry sample. After accounting for the initial condition, observed business characteristics, unobserved heterogeneity and allowing for correlations between the business-specific effects and the observed covariates, the past innovation (or lagged innovation) has a significant effect on future innovation for new marketing methods, and a marginally significant effect for operational process, confirming the hypothesis of true state-dependence (i.e., acceptance of Hypothesis 7) among small food businesses engaging in these two types of innovation. However, the significance of the lagged dependent variable, exhibited previously in the simple dynamic probit modelled results in Table 7.2, vanished for the overall, goods and services, and organisational or managerial process innovation models. This shows that, for the food industry, both the goods and services and organisational process innovation do not have true state-dependency of their future innovation behaviour and, hence, no causal inference can be drawn (i.e., rejection of Hypothesis 7).

Furthermore, we have confirmed that, for the food industry, the degrees of innovation persistence do vary for the different types of innovation with marketing methods having the most significant and strongest persistence. The corresponding APE result shows that, after averaging across all small food businesses and time periods, assuming all other variables are constant, past innovation is associated with an increase of more than eight per cent in the propensity to innovate marketing methods. The APEs for marketing methods for this state-dependency at the 25th and 75th percentiles are 4.2 per cent and 12.6 per cent, respectively. This indicates that, even after accounting for the initial condition, unobserved heterogeneity and allowing correlations between the business-specific effects and observed covariates, the significant effect of the past on future marketing methods innovation was a true state-dependency and this was not evident for the other types of innovation as well as for overall innovation.

Table 7.5

Dynamic Correlated Random Effects Probit Regression Results for Different Types of Innovation and Average Partial Effects: Food Industry

	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovations			
Variables	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]
Innovation (Response variable)																				
Innovation (t-1)	0.24	*0.18*	0.039	*0.034*	0.05	*0.18*	0.007	*0.027*	0.29 *	*0.15*	0.060 *	*0.034*	0.44 ***	*0.15*	0.082 **	*0.034*	0.16	*0.14*	0.038	*0.034*
Innovation (initial condition, t=0)	1.07 ***	*0.27*	0.207 ***	*0.046*	0.51 ***	*0.19*	0.092 **	*0.038*	0.84 ***	*0.19*	0.187 ***	*0.039*	0.33 *	*0.20*	0.059 *	*0.036*	0.81 ***	*0.17*	0.211 ***	*0.041*
Sub-industry (non-AgriFF)	0.34 **	*0.17*			0.12	*0.18*			0.01	*0.14*			0.13	*0.16*			0.11	*0.14*		
Business size (Nonemploying)	0.33 *	*0.19*			0.02	*0.17*			0.02	*0.18*			0.10	*0.12*			0.21	*0.13*		
With collaboration	0.49 **	*0.22*	0.030	*0.043*	0.35 **	*0.17*	0.140 **	*0.062*	0.20	*0.17*	0.096 **	*0.048*	0.23	*0.18*	0.131 ***	*0.050*	0.41 ***	*0.15*	0.164 ***	*0.060*
Market competition																				
Minimal	0.29	*0.27*	0.184 **	*0.076*	0.61 **	*0.24*	0.046	*0.070*	0.27	*0.27*	0.042	*0.061*	-0.06	*0.31*	0.175 **	*0.069*	0.31	*0.19*	0.208 **	*0.084*
Moderate	0.32	*0.23*	0.078	*0.051*	1.22 ***	*0.20*	0.061	*0.059*	0.64 ***	*0.23*	0.102 *	*0.055*	0.30	*0.28*	0.152 ***	*0.043*	0.66 ***	*0.18*	0.152 **	*0.069*
Strong	0.11	*0.26*	0.089 **	*0.040*	0.71 ***	*0.17*	0.052	*0.046*	0.34	*0.24*	0.129 ***	*0.038*	0.12	*0.29*	0.180 ***	*0.035*	0.36 **	*0.18*	0.182 ***	*0.047*
ICT Intensity																				
Moderate	0.05	*0.21*	-0.035	*0.039*	0.19	*0.23*	0.049	*0.031*	0.22	*0.16*	0.067 *	*0.035*	-0.02	*0.26*	-0.004	*0.032*	0.06	*0.16*	0.025	*0.046*
High	0.00	*0.37*	0.140	*0.092*	0.04	*0.39*	0.247 ***	*0.074*	0.26	*0.39*	0.062	*0.092*	-0.24	*0.34*	0.099	*0.083*	0.29	*0.27*	0.197 **	*0.096*
Most intense	-0.06	*0.28*	0.060	*0.058*	0.57 *	*0.33*	0.044	*0.036*	0.33	*0.31*	0.052	*0.048*	0.12	*0.31*	0.120 **	*0.050*	0.21	*0.27*	0.086	*0.063*
Used STEM skills	0.55 ***	*0.14*	0.142 ***	*0.049*	0.33 **	*0.17*	0.223 ***	*0.063*	0.18	*0.13*	0.209 ***	*0.066*	0.35 **	*0.14*	0.102 **	*0.044*	0.29 **	*0.14*	0.241 ***	*0.060*
Market location (Local only)	-0.13	*0.28*	-0.001	*0.047*	-0.26	*0.23*	-0.015	*0.041*	-0.16	*0.24*	0.007	*0.041*	-0.47 *	*0.27*	-0.052	*0.038*	-0.18	*0.25*	-0.027	*0.045*
With flexible working arrangements	0.29	*0.18*	0.076 **	*0.032*	0.22	*0.17*	0.082 ***	*0.029*	0.39 ***	*0.14*	0.126 ***	*0.038*	0.34 **	*0.16*	0.045	*0.028*	0.48 ***	*0.14*	0.151 ***	*0.038*
Sought debt and/or equity finance	-0.06	*0.12*	0.022	*0.038*	0.09	*0.14*	0.025	*0.040*	0.33 **	*0.13*	0.016	*0.046*	0.26 *	*0.14*	0.008	*0.034*	0.18	*0.12*	0.023	*0.048*
Financial year																				
2008/09	-0.52 ***	*0.17*	-0.089 ***	*0.029*	-0.25 *	*0.15*	-0.039 *	*0.023*	-0.25 **	*0.12*	-0.051 **	*0.026*	-0.40 **	*0.17*	-0.069 **	*0.027*	-0.32 **	*0.12*	-0.075 ***	*0.028*
2009/10	-0.70 ***	*0.16*	-0.115 ***	*0.025*	0.05	*0.19*	0.008	*0.029*	-0.37 ***	*0.14*	-0.074 ***	*0.028*	-0.28	*0.18*	-0.050 *	*0.029*	-0.35 ***	*0.12*	-0.084 ***	*0.028*
2010/11	-0.60 ***	*0.17*	-0.101 ***	*0.028*	-0.11	*0.17*	-0.018	*0.027*	-0.38 ***	*0.13*	-0.075 ***	*0.026*	-0.41 **	*0.16*	-0.071 ***	*0.027*	-0.36 ***	*0.12*	-0.084 ***	*0.030*
Intercept	-2.53 ***	*0.56*			-2.70 ***	*0.48*			-2.54 ***	*0.39*			-2.69 ***	*0.42*			-1.95 ***	*0.32*		
Time-averaged variables																				
With collaboration (Average)	-0.30	*0.36*			0.40	*0.38*			0.26	*0.23*			0.45	*0.29*			0.25	*0.31*		
Market competition (Average)																				
Minimal	0.88 *	*0.53*			-0.30	*0.42*			-0.01	*0.43*			1.44 ***	*0.47*			0.58	*0.39*		
Moderate	0.27	*0.46*			-0.82 **	*0.37*			-0.07	*0.35*			0.97 **	*0.44*			0.02	*0.33*		
Strong	0.55	*0.37*			-0.36	*0.32*			0.36	*0.32*			1.28 ***	*0.40*			0.43 *	*0.26*		
ICT Intensity (Average)																				
Moderate	-0.28	*0.35*			0.14	*0.33*			0.14	*0.24*			-0.01	*0.31*			0.04	*0.26*		
High	0.73	*0.63*			1.25 **	*0.56*			0.08	*0.61*			0.77	*0.53*			0.52	*0.48*		
Most intense	0.40	*0.46*			-0.27	*0.48*			-0.05	*0.38*			0.50	*0.39*			0.15	*0.36*		
Used STEM skills (Average)	0.25	*0.31*			0.81 **	*0.36*			0.77 **	*0.31*			0.21	*0.27*			0.67 ***	*0.26*		
Market location (Average)	0.12	*0.41*			0.17	*0.31*			0.20	*0.32*			0.18	*0.38*			0.07	*0.29*		
With flexible working arrangements (Average)	0.19	*0.25*			0.28	*0.24*			0.24	*0.24*			-0.08	*0.23*			0.13	*0.19*		
Sought debt and/or equity finance (Average)	0.19	*0.26*			0.06	*0.28*			-0.25	*0.28*			-0.21	*0.28*			-0.08	*0.27*		
Log Likelihood	-574.96				-597.39				-684.49				-574.93				-800.87			
AIC	1211.91				1256.78				1430.98				1211.86				1663.74			
BIC	1379.91				1424.78				1598.98				1379.86				1831.74			
Sigma	0.88	*0.14*			0.85	*0.15*			0.77	*0.15*			0.63	*0.14*			0.70	*0.13*		
rho (ρ)	0.435 ***	*0.079*			0.421 ***	*0.083*			0.374 ***	*0.089*			0.285 ***	*0.089*			0.331 ***	*0.081*		
Number of observations (n)	1668				1668				1668				1668				1668			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

(a) Average partial effects for selected key drivers of innovation and other covariates

(b) SEs for APEs are computed using bootstrapping.

Another important finding here is that the estimated coefficient for the initial condition is positive and highly significant for new goods and services, new organisational process, and new operational process. This means that for there is selection into innovating any of the three dimensions that is correlated with unobserved business fixed effect, such as managerial or owner capability. The highest significant impact was in the estimated APE for goods and services, which is an increase of 20.7 per cent, followed by operational process with 18.7 per cent increase in the probability for small businesses to innovate. The APEs at the 25th and 75th percentiles are also higher for these two types of innovation at 14.3 per cent and 28.3 per cent, and 13.9 per cent and 24.7 per cent, respectively. The estimated APE for new organisational process is only 9.2 per cent. This implies a substantial correlation between small food businesses' initial innovation status and the unobserved heterogeneity for these three innovation dimensions. This is also evident for any innovations, but it is only marginally significant for new marketing methods. This means that small businesses in the food industry value greatly the past marketing methods innovation behaviour considering the existence of true state-dependence for this innovation dimension.

It also emerges that, in addition to the significant effect of past innovation experience, the degree of market competition (i.e., from being minimal to strong) has a vital influence on generating more marketing methods innovation among small food businesses over time. Two of the APEs (moderate and strong market competition) in the marketing methods innovation model are significant at the 1% level, whereas for the minimal degree of market competition, it is found to be statistically significant at the 5% level. For the organisational and operational processes as well as for any innovations, the time-averaged effect of the use of STEM-skilled employees is found significant at the 5% level. Having high ICT intensity across time is positive and significant for organisational or managerial innovation.

Regarding the observed covariates, particularly the identified key determinants of innovation in Chapter 6, we find them to be significant key factors in explaining innovation behaviour after allowing for unobserved heterogeneity, the initial condition and lagged innovation outcome. Small food businesses that engaged in any form of collaboration are significantly more likely to engage in the four types of innovation, with the probability being high for implementing any innovations. Businesses facing any degree of marketing competition exhibit a significant propensity to perform organisational or managerial process innovation. In contrast, the subsector indicator is only important for goods and services innovation. The use of STEM skills remains an important driver of innovation behaviour for goods and services, organisational or managerial process, marketing methods and overall innovations with corresponding estimated APEs of 14.2 per cent, 22.3 per cent, 10.2 per cent and 24.1 per cent, respectively. Despite the insignificance of the estimated coefficient, the degree of association between use of STEM skills and operational process innovation is found stronger at 20.9 per cent because of the time-averaged effect of this determinant, as mentioned earlier. Having flexible working arrangements also matters for new operational process and new marketing methods. We also find that the impact of flexible working arrangements on operational process innovation is significantly higher at 12.6 per cent. Moreover, the year effects are also found important for the unexpected variation or special events that may affect engagement in any of the four innovation dimensions. In terms of the year effects, the results indicate that, all other things being held constant, the association is negative and significant moving onwards from 2007/08, particularly for goods and services, operational process and overall innovation.

The results further provide evidence that the unobserved heterogeneity is a key factor for innovation persistence. This can be gauged from the estimated rho ($\hat{\rho}$). Comparing with the random effects probit model results in Table 6.1 for overall innovation (i.e., any innovations), Table 7.5 shows that introducing the lagged dependent variable and the initial condition manifest a clear reduction of the importance of the unobserved heterogeneity. The estimated proportion of the total variance contributed by the panel-level variance component ($\hat{\rho}$) is found significantly different from zero (using the likelihood ratio test) and indicates that this component accounts for more than 33 per cent of the variance of the composite error, which is a reduction from the 44 per cent in the random effects probit model. Unobserved heterogeneity explains between 28 per cent and 43 per cent of the variation in the four types of innovation in the food industry, which is similar to the findings of Peters (2005, 2009) but for the manufacturing sector. The lowest $\hat{\rho}$ came from the marketing methods whereas the highest is for goods and services innovation. All estimates are found highly significant; hence, it is important to address unobserved heterogeneity for the dynamic modelling of innovation dimensions in establishing state-dependence. The log-likelihood, AIC and BIC results for overall innovation also confirm the goodness-of-fit of the dynamic CRE probit model compared with the standard random effect probit model, as exhibited in Table 6.1.

After empirically investigating the conditional state-dependence using the dynamic CRE probit modelling, the five key determinants (collaboration, ICT intensity, flexible working arrangements, facing market competition and use of STEM skills) remained important in contributing to increased overall innovation among small food businesses in the Australian food industry. These findings are again consistent with the international empirical studies cited in our discussion of the food industry results in Chapter 6.

7.4.2.2 Findings for the food subsectors

Tables 7.6 and 7.7 present results for the dynamic correlated random effects probit model for different types of innovation and APEs for the AgriFF and non-AgriFF samples. After allowing for the initial condition, observed business characteristics, unobserved heterogeneity and correlations between the business-specific effects and observed covariates, past goods and services and marketing methods innovations among small food businesses show significant effects at the 5% significance level on future innovation for the AgriFF subsector. In the non-AgriFF subsector, we find only marginal significance for organisational or managerial process, operational process and marketing methods past innovations. These results led to the acceptance of the true state-dependence hypothesis that small food businesses that innovate in period *t-1* are more likely to innovate in period *t* engaging in these types of innovation.

Moreover, the significant effects at the 1% level of the lagged dependent variable exhibited previously in the simple dynamic probit modelled results in both Tables 7.3 and 7.4 disappear for subsectors' overall innovation model. This shows that, for the subsectors, true state-dependencies are not evident after controlling for initial condition, and for observed and unobserved heterogeneity.

Considering the magnitudes of those significant effects, the degrees of innovation persistence do vary between types of innovation and even between the two subsectors, but they are found to be only marginally significant. The APEs for past marketing methods innovation are associated with an increase of 8.4 per cent and 7.2 per cent in the propensity to innovate for the AgriFF and non-AgriFF subsectors, respectively. The APEs of the marketing methods for this true state-dependency at the 25th and 75th percentiles are 3.5 per cent and 12.2 per cent for the AgriFF subsector and 4.9 per cent and 10.1 per cent for the non-AgriFF subsector. Recall that the significant effect of the past on future marketing methods innovation is also evident for the food industry.

Table 7.6

Dynamic Correlated Random Effects Probit Regression Results for Different Types of Innovation and Average Partial Effects: AgriFF Subsector

Variables	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovations			
	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE [(a)]	*SE* [(b)]
Innovation (Response variable)																				
Innovation (t-1)	0.55 **	*0.22*	0.091 *	*0.051*	-0.24	*0.31*	-0.032	*0.035*	0.25 *	*0.14*	0.048	*0.033*	0.54 **	*0.23*	0.084 *	*0.044*	0.21	*0.19*	0.050	*0.048*
Innovation (initial condition, t=0)	0.82 ***	*0.31*	0.162 **	*0.078*	0.50 **	*0.24*	0.111 **	*0.056*	1.04 ***	*0.15*	0.276 ***	*0.057*	0.06	*0.27*	-0.008	*0.052*	0.76 ***	*0.17*	0.194 ***	*0.041*
Business size (Nonemploying)	0.25	*0.18*			-0.10	*0.29*			0.12	*0.22*			-0.06	*0.18*			0.16	*0.18*		
With collaboration	0.60	*0.38*	0.066	*0.049*	0.43	*0.27*	0.109	*0.082*	-0.18	*0.35*	0.144 ***	*0.050*	0.31	*0.28*	0.115 **	*0.050*	0.27	*0.24*	0.211 ***	*0.061*
Market competition																				
Minimal	0.30	*0.38*	0.016	*0.046*	0.58 *	*0.31*	-0.065	*0.054*	0.01	*0.28*	-0.064	*0.053*	-0.09	*0.41*	0.030	*0.044*	0.25	*0.22*	-0.002	*0.098*
Moderate	0.12	*0.34*	0.062	*0.063*	1.04 ***	*0.32*	0.084	*0.075*	0.72 ***	*0.24*	0.119 *	*0.069*	0.32	*0.31*	0.153 ***	*0.048*	0.66 ***	*0.21*	0.181 **	*0.087*
Strong	0.11	*0.27*	0.074 **	*0.037*	0.70 ***	*0.21*	0.037	*0.056*	0.41	*0.26*	0.151 ***	*0.049*	0.13	*0.31*	0.160 ***	*0.045*	0.42 **	*0.19*	0.185 ***	*0.057*
ICT Intensity (High to most intense)	0.05	*0.48*	0.059	*0.045*	-0.36	*0.36*	-0.002	*0.050*	0.23	*0.45*	0.032	*0.039*	-0.16	*0.42*	0.109 *	*0.058*	0.06	*0.29*	0.123 **	*0.062*
Used STEM skills	0.56 ***	*0.17*	0.084	*0.052*	0.32	*0.23*	0.253 ***	*0.074*	0.40	*0.27*	0.092 *	*0.055*	0.20	*0.23*	0.071	*0.054*	0.37 *	*0.22*	0.195 **	*0.076*
Market location (Local only)	0.05	*0.30*	-0.038	*0.050*	-0.41	*0.35*	0.019	*0.058*	-0.34	*0.35*	0.001	*0.056*	-0.54 *	*0.33*	0.006	*0.049*	-0.51 *	*0.27*	0.068	*0.069*
With flexible working arrangements	0.46	*0.30*	0.009	*0.032*	-0.07	*0.20*	0.083 **	*0.041*	0.29	*0.35*	0.170 ***	*0.046*	0.10	*0.30*	0.037	*0.029*	0.47 **	*0.21*	0.166 ***	*0.054*
Sought debt and/or equity finance	0.09	*0.18*	-0.053 *	*0.029*	0.02	*0.12*	0.005	*0.038*	0.47 **	*0.23*	-0.035	*0.035*	0.52 **	*0.22*	-0.037	*0.038*	0.22	*0.19*	-0.038	*0.047*
Financial year																				
2008/09	-0.47 ***	*0.18*	-0.074 ***	*0.028*	-0.17	*0.22*	-0.023	*0.028*	-0.21	*0.16*	-0.040	*0.029*	-0.17	*0.24*	-0.025	*0.028*	-0.22 *	*0.12*	-0.052 *	*0.027*
2009/10	-0.76 ***	*0.21*	-0.106 ***	*0.027*	0.19	*0.25*	0.029	*0.037*	-0.35 **	*0.16*	-0.064 **	*0.028*	-0.17	*0.26*	-0.024	*0.033*	-0.33 **	*0.16*	-0.076 **	*0.033*
2010/11	-0.45 *	*0.25*	-0.072 **	*0.034*	-0.01	*0.23*	-0.002	*0.037*	-0.37	*0.25*	-0.067 *	*0.039*	-0.30	*0.26*	-0.040	*0.031*	-0.27	*0.18*	-0.061	*0.040*
Intercept	-1.71 ***	*0.51*			-2.56 ***	*0.56*			-2.22 ***	*0.39*			-2.85 ***	*0.84*			-2.16 ***	*0.45*		
Time-averaged variables																				
With collaboration (Average)	-0.18	*0.62*			0.22	*0.45*			0.87 *	*0.46*			0.40	*0.48*			0.56 *	*0.34*		
Market competition (Average)																				
Minimal	-0.15	*0.57*			-1.22 *	*0.65*			-0.56	*0.47*			0.60	*0.75*			-0.26	*0.55*		
Moderate	0.38	*0.61*			-0.50	*0.65*			-0.05	*0.43*			1.09	*0.73*			0.12	*0.42*		
Strong	0.46	*0.42*			-0.43	*0.43*			0.41	*0.35*			1.32 **	*0.66*			0.38	*0.35*		
ICT Intensity (Average)	0.33	*0.49*			0.35	*0.49*			-0.06	*0.51*			0.82 *	*0.47*			0.44	*0.39*		
Used STEM skills (Average)	-0.02	*0.35*			1.06 **	*0.41*			0.07	*0.41*			0.28	*0.37*			0.41	*0.41*		
Market location (Average)	-0.30	*0.39*			0.55	*0.55*			0.35	*0.52*			0.58	*0.70*			0.83 *	*0.48*		
With flexible working arrangements (Average)	-0.39	*0.45*			0.63	*0.44*			0.60	*0.41*			0.17	*0.47*			0.22	*0.31*		
Sought debt and/or equity finance (Average)	-0.54	*0.33*			0.01	*0.30*			-0.67 **	*0.32*			-0.82 *	*0.43*			-0.39	*0.25*		
Log Likelihood	-259.23				-310.20				-345.41				-256.96				-436.67			
AIC	556.46				658.40				728.81				551.91				925.34			
BIC	648.70				750.63				821.04				644.14				1051.56			
Sigma	0.53	*0.30*			0.88	*0.16*			0.59	*0.15*			0.55	*0.96*			0.63	*0.15*		
rho (ρ)	0.22 **	*0.19*			0.438 **	*0.088*			0.255 ***	*0.097*			0.23 **	*0.62*			0.286 ***	*0.096*		
Number of observations (n)	948				948				948				948				948			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

(a) Average partial effects for selected key drivers of innovation and other covariates

(b) SEs for APEs are computed using bootstrapping.

Table 7.7

Dynamic Correlated Random Effects Probit Regression Results for Different Types of Innovation and Average Partial Effects: Non-AgriFF Subsector

	Goods and Services				Organisational or Managerial Process				Operational Process				Marketing Methods				Any Innovations			
Variables	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]	Coefficient	*SE*	APE[(a)]	*SE*[(b)]
Innovation (Response variable)																				
Innovation (t-1)	-0.08	*0.29*	-0.014	*0.034*	0.28 *	*0.17*	0.053	*0.036*	0.37 *	*0.21*	0.079	*0.050*	0.33 *	*0.18*	0.072 *	*0.043*	0.09	*0.24*	0.023	*0.056*
Innovation (initial condition, t=0)	1.46 ***	*0.48*	0.377 ***	*0.068*	0.51 *	*0.29*	0.111	*0.073*	0.80 ***	*0.30*	0.217 ***	*0.079*	0.62 ***	*0.20*	0.165 **	*0.070*	1.00 ***	*0.27*	0.265 ***	*0.057*
Business size (Nonemploying)	0.58	*0.47*			0.00	*0.27*			-0.01	*0.18*			0.24	*0.19*			0.25 *	*0.15*		
With collaboration	0.37	*0.34*	-0.053	*0.063*	0.29	*0.23*	0.172 *	*0.097*	0.53	*0.38*	0.06	*0.11*	0.16	*0.26*	0.161 *	*0.097*	0.53 *	*0.29*	0.111	*0.078*
Market competition																				
Minimal	0.63	*1.55*	0.50 ***	*0.14*	0.82	*2.27*	0.33 **	*0.16*	0.18	*0.48*	0.16	*0.15*	-0.07	*2.25*	0.49 ***	*0.10*	0.19	*0.51*	0.54 ***	*0.13*
Moderate	0.94	*1.36*	0.091	*0.083*	1.57	*2.25*	0.118 *	*0.067*	0.23	*0.54*	0.03	*0.11*	0.27	*2.23*	0.171 **	*0.085*	0.46	*0.52*	0.15	*0.11*
Strong	0.47	*1.37*	0.152 *	*0.078*	0.90	*2.24*	0.154 ***	*0.053*	-0.12	*0.47*	0.09	*0.10*	0.10	*2.18*	0.222 ***	*0.068*	0.11	*0.49*	0.241 **	*0.097*
ICT Intensity (High to Most intense)	-0.11	*0.21*	0.153 ***	*0.053*	0.53 *	*0.28*	0.071	*0.060*	0.05	*0.33*	0.006	*0.066*	0.11	*0.24*	0.157 **	*0.064*	0.29	*0.32*	0.088	*0.062*
Used STEM skills	0.52 *	*0.30*	0.220 ***	*0.079*	0.35	*0.27*	0.23 **	*0.11*	0.00	*0.24*	0.32 ***	*0.11*	0.50 **	*0.20*	0.185 **	*0.088*	0.20	*0.22*	0.313 ***	*0.087*
Market location (Local only)	-0.28	*0.58*	0.039	*0.050*	-0.13	*0.40*	-0.008	*0.057*	0.15	*0.40*	0.013	*0.061*	-0.33	*0.37*	-0.090	*0.065*	0.19	*0.40*	-0.069	*0.067*
With flexible working arrangements	0.15	*0.27*	0.162 **	*0.066*	0.49 *	*0.26*	0.052	*0.046*	0.54 **	*0.23*	0.075	*0.062*	0.52 **	*0.24*	0.020	*0.049*	0.49 **	*0.20*	0.091	*0.067*
Sought debt and/or equity finance	-0.24	*0.24*	0.177 **	*0.078*	0.10	*0.23*	0.061	*0.068*	0.21	*0.25*	0.14	*0.10*	0.04	*0.19*	0.080	*0.078*	0.10	*0.19*	0.128 *	*0.069*
Financial year																				
2008/09	-0.57 **	*0.23*	-0.103 **	*0.041*	-0.31	*0.27*	-0.055	*0.042*	-0.24	*0.17*	-0.051	*0.037*	-0.58 ***	*0.22*	-0.124 ***	*0.041*	-0.43 ***	*0.17*	-0.101 ***	*0.038*
2009/10	-0.57 ***	*0.17*	-0.103 ***	*0.029*	-0.12	*0.21*	-0.022	*0.033*	-0.39 **	*0.19*	-0.081 **	*0.036*	-0.38 **	*0.18*	-0.083 **	*0.038*	-0.40 ***	*0.12*	-0.094 ***	*0.028*
2010/11	-0.70 **	*0.28*	-0.125 ***	*0.043*	-0.19	*0.29*	-0.035	*0.043*	-0.33 **	*0.15*	-0.069 *	*0.041*	-0.53 **	*0.22*	-0.113 ***	*0.043*	-0.45 **	*0.21*	-0.106 **	*0.047*
Intercept	-3.79 *	*2.11*			-3.26	*2.54*			-2.18 ***	*0.66*			-2.86	*2.44*			-2.00 ***	*0.68*		
Time-averaged variables																				
With collaboration (Average)	-0.69	*0.44*			0.55	*0.44*			-0.23	*0.64*			0.53	*0.51*			-0.07	*0.41*		
Market competition (Average)																				
Minimal	2.22	*2.35*			1.26	*0.92*			0.61	*1.00*			2.74 ***	*0.96*			2.27 **	*0.99*		
Moderate	-0.23	*1.66*			-0.54	*0.57*			-0.06	*0.87*			1.04	*0.97*			0.24	*0.82*		
Strong	0.62	*1.87*			0.34	*0.62*			0.56	*0.79*			1.47	*0.91*			0.98	*0.75*		
ICT Intensity (Average)	0.94 **	*0.38*			-0.15	*0.58*			-0.03	*0.52*			0.60	*0.38*			0.07	*0.41*		
Used STEM skills (Average)	0.63	*0.40*			0.77	*0.62*			1.34 **	*0.59*			0.31	*0.39*			1.09 **	*0.44*		
Market location (Average)	0.51	*0.58*			0.09	*0.60*			-0.08	*0.63*			-0.07	*0.51*			-0.48	*0.54*		
With flexible working arrangements (Average)	0.78	*0.55*			-0.20	*0.23*			-0.18	*0.40*			-0.42	*0.32*			-0.12	*0.37*		
Sought debt and/or equity finance (Average)	1.18 **	*0.55*			0.22	*0.47*			0.41	*0.67*			0.33	*0.43*			0.43	*0.37*		
Log Likelihood	-297.62				-281.53				-323.10				-305.58				-350.38			
AIC	617.25				601.06				684.20				663.16				752.77			
BIC	667.62				688.07				771.21				782.22				871.83			
Sigma	1.10	*0.22*			0.84	*0.16*			0.90	*0.17*			0.64	*0.15*			0.71	*0.16*		
rho (ρ)	0.546 ***	*0.099*			0.411 ***	*0.091*			0.449 ***	*0.095*			0.289 ***	*0.098*			0.33 ***	*0.10*		
Number of observations (n)	720				720				720				720				720			

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.
(a) Average partial effects for selected key drivers of innovation and other covariates
(b) SEs for APEs are computed using bootstrapping.

One more important finding here is that the initial condition in new goods and services, new operational process and overall innovation models for both the AgriFF and non-AgriFF subsectors are found to be significant at the 1% level, where the highest significant impact is reflected in the AgriFF subsector estimated ATE for operational process innovation (27.6 per cent) and for goods and services innovation in the non-AgriFF subsector (37.7 per cent). The APEs at the 25th and 75th percentiles are also higher for these two types of innovation at 17.1 per cent and 34.1 per cent for the AgriFF subsector, and 26.3 per cent and 50.2 per cent for the non-AgriFF subsector, respectively. These results indicate a substantial correlation between small food businesses' initial innovation status and the unobserved heterogeneity for these innovation dimensions. Additional results concerning the effect of the initial condition are that, for the AgriFF subsector, organisational or managerial innovation, and for the non-AgriFF subsector, marketing methods innovation, the parameter estimates are found to be significant at the 5% and 1% levels, respectively.

The results for the AgriFF and non-AgriFF sector models also indicate that the allowance for correlation between unobserved heterogeneity and the regressors is important for the current small food businesses data. The group means for the AgriFF sector for the degree of market competition (i.e., moderate-to-strong) have a vital influence on generating more marketing methods innovation; the use of STEM skills is significant for organisational process innovation; and seeking debt and equity (though negative) is also important for operational process innovation. For the non-AgriFF subsector, the time-averaged effects of ICT intensity and seeking debt and equity for goods and services innovation; use of STEM skills for operational process and overall innovations; and minimal degree of market competition for marketing methods and any innovations were all significant. Furthermore, all the estimated APEs for the covariates corresponding to these group-means are found significant at the 1% level.

For the remaining association between the observed covariates and the propensity to innovate, after allowing for unobserved heterogeneity and its correlation with covariates, initial condition and lagged innovation outcome, we find significant effects in collaboration, market competition, use of STEM skills, having flexible working arrangement and seeking financial assistance through debt and equity in the various form of innovations for the AgriFF subsector. For the non-AgriFF subsector, use of ICT, use of STEM skills and having flexible working arrangements are found important determinants of innovation. The year effects, as expected, were also found to be vital in analysing innovation persistence for the four types of innovation.

As with the food industry results, the estimated rho ($\hat{\rho}$) for all the models in both the AgriFF and non-AgriFF subsectors provide evidence that the unobserved heterogeneity is a key factor for innovation persistence. Tables 7.5 and 7.6 also reveal that introducing the lagged dependent variable and initial condition manifest a clear reduction in the importance of the unobserved heterogeneity in each type of innovation. This finding is similar to the Swedish findings of Tavassoli and Karlsson (2015). For the AgriFF subsector, the lowest $\hat{\rho}$ is for the new goods and services, whereas the highest is for the organisational process innovation. For the non-AgriFF subsector, the lowest $\hat{\rho}$ is for new marketing methods, whereas the highest is for the goods and services innovation. All estimates are found significant; hence the importance of addressing unobserved heterogeneity for the dynamic modelling of innovation dimensions in establishing state-dependence. The log-likelihood, AIC and BIC results for overall innovation also confirm the goodness-of-fit of the dynamic random effects probit model compared with the random effect probit model, as exhibited in Table 6.3.

After empirically investigating the conditional state-dependence using the dynamic CRE probit modelling, the five key determinants (collaboration, ICT intensity, flexible working arrangements, facing market competition and use of STEM skills) remain important in contributing to increased overall innovation among small businesses in the AgriFF subsector, whereas, for the non-AgriFF subsector, we find only three significant determinants (ICT intensity, facing market competition and seeking debt and/or equity).

7.5 Summary of findings

In this chapter, we empirically examine the persistence behaviour of small food businesses in the goods and services, organisational or managerial processes, operational processes, and marketing methods innovations, in the Australian setting. We utilise ABS BLD CURF panel data from the food industry and the AgriFF and non-AgriFF subsector samples compiled in Chapter 5. We address Research Questions 3 and 4, and test their corresponding Hypotheses 7 and 8, using three approaches: transition probability matrix, simple dynamic probit modelling and dynamic CRE probit modelling.

For the food industry, the transitional probabilities indicate an overall presence of innovation persistence among small food businesses despite their difficulties to engage in a particular type of innovation. An earlier indication of strong persistency in innovation behaviour was revealed for new goods and services, new operational process and new marketing methods and a weak persistence for organisational or managerial process innovation. Employing the simple dynamic probit modelling, the existence of state-dependence is again revealed for all types of innovation and for any innovations. Then, after accounting for the initial condition, observed business characteristics, unobserved heterogeneity and allowing correlations between the business-specific effects and observed covariates, true state-dependence remains evident for new marketing methods and new operational process. Furthermore, the degrees of innovation persistence do vary for the different types of innovation with the marketing methods having the strongest persistence. The summary of these results is presented in Table 7.8.

These findings imply that the three theoretical hypotheses (i.e., dynamic increasing-returns, success-breeds-success, sunk-cost-account) supporting the concept of innovation persistence, discussed in Chapter 3, are being experienced by the small businesses in the Australian food industry. After investigating the conditional state-dependence using the dynamic CRE probit modelling, the five key determinants (collaboration, ICT intensity, flexible working arrangements, facing market competition and use of STEM skills) remain important in contributing to increased overall innovation among small businesses in the Australian food industry.

We find persistence of innovation in all innovation dimensions for both the AgriFF and non-AgriFF subsectors using the TPM and simple dynamic probit modelling approaches. But for only goods and services and marketing methods innovations are there true state-dependency in the AgriFF subsector whereas we find that, for the non-AgriFF subsector, operational process and marketing methods innovations are important. Once again, the degree of innovation persistence is not equal among various types of innovation.

The fact that innovation behaviour among small food businesses exhibits true state-dependence implies that innovation-stimulating policy measures (e.g., establishing Industry Growth Centres; promoting STEM skills for a more skilled workforce, better economic infrastructure; provision of R&D funding; etc.) contained in the IICA, NISA, FIAL and CRC programmes have the potential of long-lasting effects because they do not only impact the current innovation activities but are also likely to induce a favourable change in favour of innovation.

Table 7.8

Summary of Results for Innovation Persistence and Initial Condition, by Types of Innovation, by Industry/Subsector for the Three Methods

		Goods and services			Organisational and Managerial Process			Operational Process			Marketing Methods			Overall Innovation		
		TPM	SDPM	DCREPM	TPM	SDPM	DCREPM	TPM	SDPM	DCREPM	TPM	SDPM	DCREPM	TPM	SDPM	DCREPM
Innovation persistence	Food	Strong	***	ns	weak	***	ns	strong	***	*	strong	***	**	strong	***	***
	AgriFF	weak	***	**	weak	***	ns	strong	***	*	weak	***	*	strong	***	**
	non-AgriFF	strong	***	ns	strong	***	*	strong	***	*	strong	***	*	strong	***	*
Initial condition	Food			***			***			***			*			***
	AgriFF			***			**			***			ns			***
	non-AgriFF			***			*			***			***			***

Note: TPM—Transition probability matrix; SDPM—Simple dynamic probit model; DCREPM—Dynamic correlated random effects probit model
The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively, and *ns* refer to non-significance

7.6 Concluding remarks

We confirm the hypothesis of true state-dependence, the variation in the degree of innovation persistency among the four types of innovation, and the important role of unobserved heterogeneity in explaining the persistence of innovation behaviour. Now, the next step is to determine whether these persistent innovation behaviours influence productivity growth in small food businesses.

The next chapter provides empirical evidence about the existing relationships between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia.

Chapter 8: Innovation Persistence, Business Performance and Productivity Dispersion in the Small Food Businesses in Australia

8.1 Introduction

In the previous chapter, we empirically examined the persistence behaviour of small food businesses in goods and services, organisational and managerial processes, operational processes, and marketing methods innovations, using the TPM and dynamic modelling approaches. We confirmed the hypothesis of true state-dependence, the variation in the degree of innovation persistence among the four types of innovation, and the important role of unobserved heterogeneity in explaining the persistence of innovation behaviour. In this chapter, we reinvestigate persistence of innovation in the context of the observed continuity of innovation activity undertaken by businesses over the period of study and determine its impact on business growth. Analysing the causal relationship between innovation persistence and business growth performance among Australian small food businesses using PSM is a significant addition to the empirical literature. In addition, this study establishes the linkage between innovation behaviour and productivity dispersion in the four types of innovation, which is a novelty to the growing Australian literature on firm-level productivity dynamics. The findings of this study provide useful empirical evidence to support the Government's innovation policies, investments and initiatives to grow the Australian food industry.

The methodological approach outlined in section 4.5 is applied to a subset of the ABS BLD CURF panel sample data compiled in section 5.7 (i.e., a reduced[38] balanced panel of 240 small food businesses, 133 belonging to the AgriFF sector and 107 coming from the non-AgriFF sector). This chapter presents the empirical models and empirical results that address the following research questions:

- *Do the Australian small food industry businesses sustain productivity growth if they engaged in any form of innovation?(Research Question 5)*
- *What is the relationship between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia? (Research Question 6)*

[38] Reduced balanced panel data are compiled from the original food industry panel observations. The reduction in the sample size is due to missing and incomplete ATO financial information required for business performance measurement.

Section 8.2 starts with a descriptive data analysis of the innovation persistence variables and business performance measures. This analysis is complemented with some ANOVA results that test for the differences in various categories. Section 8.3 presents evidence on the impact of persistent innovation on business growth performance using propensity score matching. Using panel data regression modelling, further investigation follows in section 8.4 to understand the significant association between innovation persistence and business growth performance among small food businesses in each type of innovation. Productivity dispersion analyses are performed in section 8.5. Section 8.6 summarises the results for this chapter and concludes in section 8.7.

8.2 Innovation persistence and business performance: A descriptive analysis

8.2.1 Innovation persistence measures

The innovation-persistence variables are compiled following the definition in Hendrickson et al. (2018). Innovation persistence describes the extent of continuity of innovation activity over the four periods for this study (i.e., 2007/08 to 2010/11). Hence, we operationally created innovation-persistence variables according to the number of times a business in the four-year panel reported that it introduced or implemented any new or significantly improved innovation. That is, a small food business that introduced an innovation in one, two, three or four out of the four years is classified as an *intermittent, regular, persistent, and highly persistent innovator,* respectively. If a business is non-innovation active for four consecutive years, it is classified as a *persistent noninnovator*. Innovation-persistence variables are also compiled for each type of innovation—new goods and services, new operational process, new organisational or managerial process, and new marketing methods innovations—and for overall innovation. We analyse these in each of three balanced panels of small food businesses belonging to the food industry, the AgriFF and the non-AgriFF subsectors, respectively. For the purpose of this study, an overall innovation variable is important so that we can see the overall impact of innovating any type of innovation on business growth performance. Again, caution should be taken when interpreting findings under each innovation dimension because a business in this study may report/undertake more than one type of innovation in a certain period.

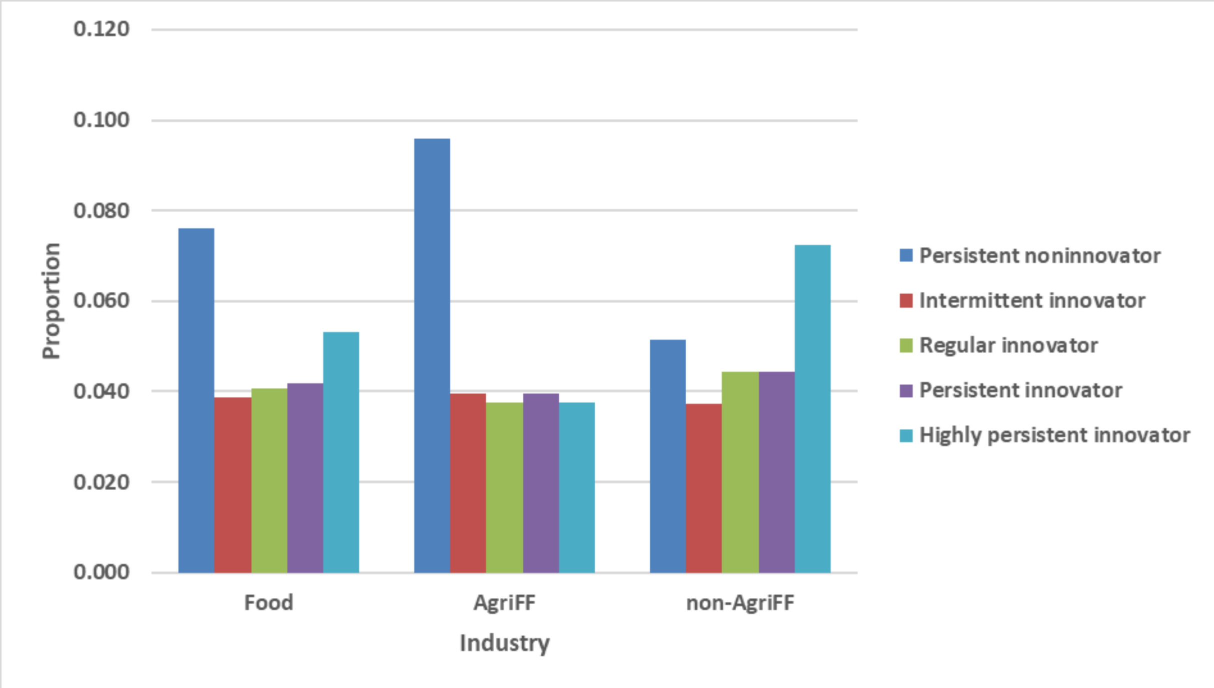


Figure 8.1 Proportion of innovation persistence measures by industry.

Figure 8.1 depicts the sample proportions of small food businesses that persist to undertake and not undertake any type of innovation within the four years involved. Despite a higher proportion of persistent noninnovators in the food industry, the presence of highly persistent innovators is evident. When it comes to the AgriFF sample, the proportion of persistent noninnovators peaks at nearly 10 per cent, whereas in the non-AgriFF sample, highly persistent innovators are notable.

Differentiating the innovation activities undertaken by the small food businesses by type, an increased proportion of persistent noninnovators are in all the innovation dimensions, between 12.0 and 15.0 per cent (Figure 8.2). The proportion pattern among the four innovation persistence variables is relatively the same for goods and services, organisational and managerial processes, and marketing methods innovation, with intermittent innovators having a higher proportion than the highly persistent innovator. For operational process innovation, regular and intermittent innovators have similar proportions, as do persistent and highly persistent innovators. The innovation persistence behaviours are more pronounced in the non-AgriFF subsector than in the AgriFF subsector (Figure 8.3). These findings are consistent with the results using the TPM where the unconditional state-dependent estimates are higher for non-AgriFF than for AgriFF for all types of innovation. We also found in the previous chapter that the degree of persistence is not equal among different types of innovation.

Overall, as shown in Figures 8.1–8.3, we observe lower proportions of small food businesses that persist to implement innovation activity within the four years.

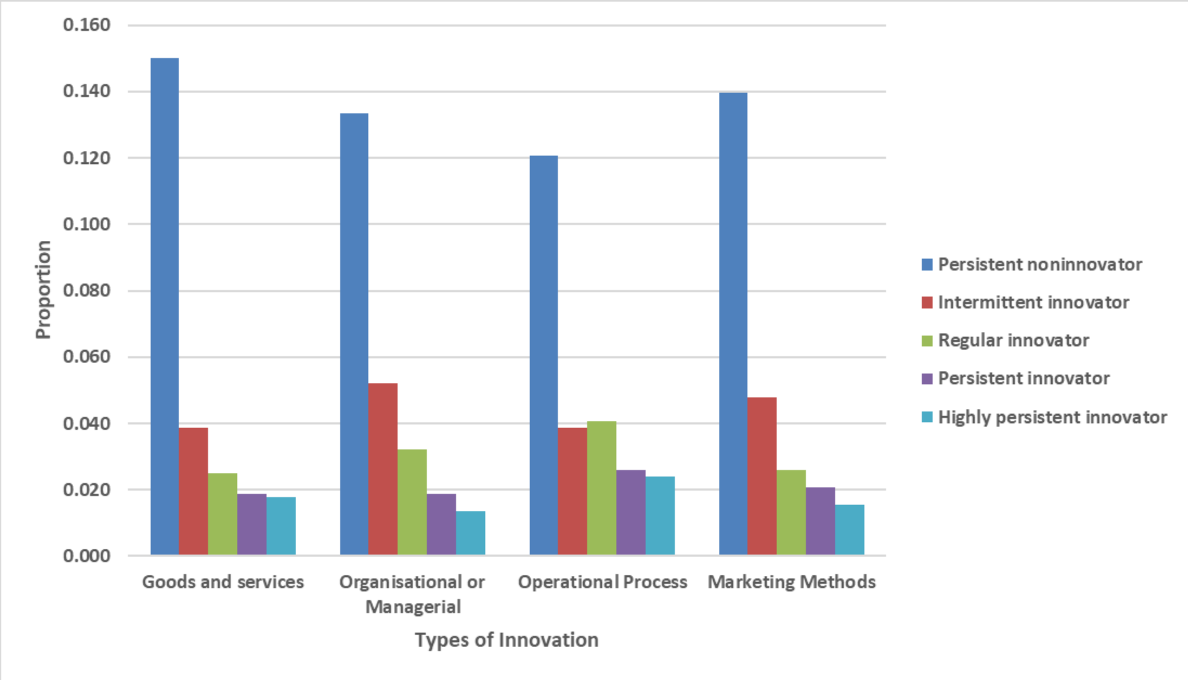


Figure 8.2 Proportion of innovation persistence measures by types of innovation, food industry

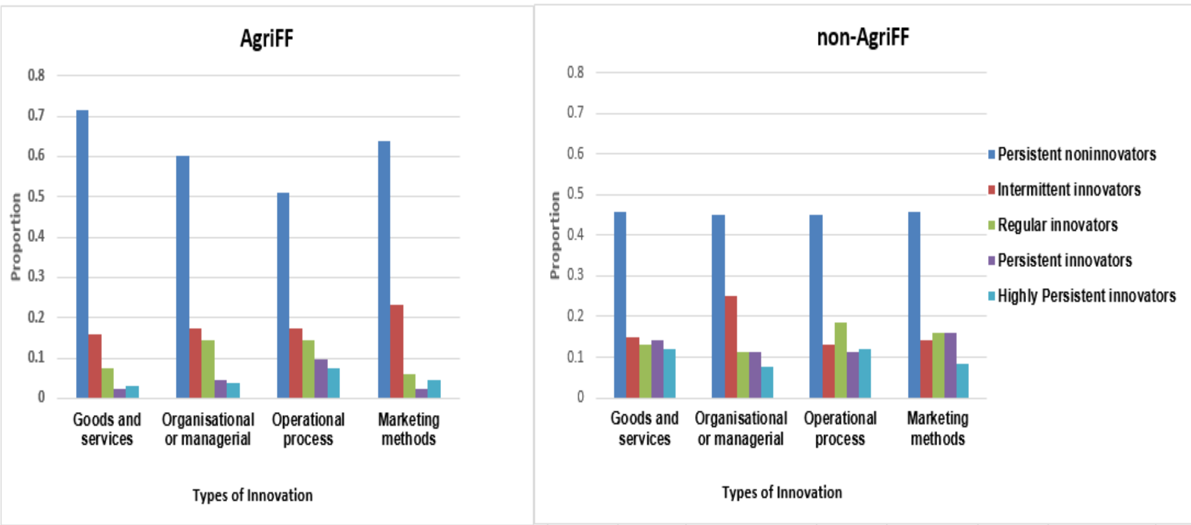


Figure 8.3: Mean of innovation persistence measures by types of innovation and subsector

Table 8.1 shows the summary statistics calculated for all the innovation-persistence variables including overall innovation in the samples of the food industry and AgriFF and non-AgriFF subsectors. Table 8.2 reveals the summary statistics for the four types of innovation.

These tables are another way of summarising all the above graphical illustrations with inclusion of other summary information.

Table 8.1

Summary Statistics for the Innovation Persistence Panel Data Variables, 2007/08–2010/11

	Mean	Standard Deviation	Min	Max
Food industry sample (n=960)				
Persistent noninnovator	0.0760	*0.2652*	0	1
Intermittent innovator	0.0385	*0.1926*	0	1
Regular innovator	0.0406	*0.1975*	0	1
Persistent innovator	0.0417	*0.1999*	0	1
Highly persistent innovator	0.0531	*0.2244*	0	1
Overall innovator	0.6125	*0.4874*	0	1
AgriFF subsector sample (n=532)				
Persistent noninnovator	0.0959	*0.2947*	0	1
Intermittent innovator	0.0395	*0.1949*	0	1
Regular innovator	0.0376	*0.1904*	0	1
Persistent innovator	0.0395	*0.1949*	0	1
Highly persistent innovator	0.0376	*0.1904*	0	1
Overall innovator	0.5226	*0.5000*	0	1
non-AgriFF subsector sample (n = 428)				
Persistent noninnovator	0.0514	*0.2211*	0	1
Intermittent innovator	0.0374	*0.1899*	0	1
Regular innovator	0.0444	*0.2062*	0	1
Persistent innovator	0.0444	*0.2062*	0	1
Highly persistent innovator	0.0724	*0.2595*	0	1
Overall innovator	0.7243	*0.4474*	0	1

8.2.2 Business performance measures

We use three business growth performance measures associated with two business outcome measures (i.e., GO and VA) and an LP measure, which are derived following the methodologies described in section 4.5 and presented in Table 5.14. The LP measure is calculated following equation (4.21) with either GO and VA as the numerator (i.e., output variable) with salary and wages (W) as the input variable. Following Hendrickson et al. (2018), individual business GO or VA growth measures are calculated by simply taking the difference between the business GO or VA data reported in 2010/11 and 2007/08. The growth in LP is measured by taking the ratio between the estimated individual business LP in 2010/11 and 2007/08, again for both GO- and VA-based LPs.

Table 8.2

Summary Statistics for the Innovation Persistence Panel Data Variables, by Type of Innovation, 2007/08–2010/11

	Mean	Standard Deviation	Min	Max
Goods and services innovation (n=960)				
Persistent noninnovator	0.1500	*0.3573*	0	1
Intermittent innovator	0.0385	*0.1926*	0	1
Regular innovator	0.0250	*0.1562*	0	1
Persistent innovator	0.0188	*0.1357*	0	1
Highly persistent innovator	0.0177	*0.1320*	0	1
Overall innovator	0.3417	*0.4745*	0	1
Organisational and managerial innovation (n=960)				
Persistent noninnovator	0.1333	*0.3401*	0	1
Intermittent innovator	0.0521	*0.2223*	0	1
Regular innovator	0.0323	*0.1769*	0	1
Persistent innovator	0.0188	*0.1357*	0	1
Highly persistent innovator	0.0135	*0.1156*	0	1
Overall innovator	0.3500	*0.4772*	0	1
Operational process innovation (n=960)				
Non-persistent innovator	0.1208	*0.3261*	0	1
Intermittent innovator	0.0385	*0.1926*	0	1
Regular innovator	0.0406	*0.1975*	0	1
Persistent innovator	0.0260	*0.1593*	0	1
Highly persistent innovator	0.0240	*0.1530*	0	1
Overall innovator	0.4302	*0.4954*	0	1
Marketing methods innovation (n=960)				
Persistent noninnovator	0.1396	*0.3467*	0	1
Intermittent innovator	0.0479	*0.2137*	0	1
Regular innovator	0.0260	*0.1593*	0	1
Persistent innovator	0.0208	*0.1429*	0	1
Highly persistent innovator	0.0156	*0.1241*	0	1
Overall innovator	0.3615	*0.4807*	0	1

The calculated sample means for the business performance measures (both in level and in growth) are presented in Table 8.3. It is observed that non-AgriFF exhibits highest mean GO of around AU$ 5.7 million, whereas, overall, the food industry has a mean GO of around AU$ 2.9 million. Based on the estimated sample mean for the VA, on average, small food businesses spent around 80 per cent of their income on intermediate input expenses. In the same manner, small food businesses belonging to the AgriFF subsector show higher LP than the small food businesses belonging to the non-AgriFF subsector during the study period. The average growth measures for the three samples are all positive with LP based on GO (LP-GO) and are similar. The AgriFF sample reveals the highest mean growth for LP based on VA (LP-VA). Overall, the results are consistent with the industry business performance behaviour when compared with the published figures in ABS (2018).

Table 8.3

Mean of the Performance Measures by Industry (For Level: 2007/08–2010/11)

Performance Measures	Food	AgriFF	non-AgriFF
Level			
Gross output (GO) $	2,889,184	575,131	5,765,530
Value added (VA) $	599,920	190,108	1,109,312
Labour productivity (LP-GO)	24.87	31.92	16.11
Labour productivity (LP-VA)	7.14	9.92	3.68
Growth			
GO growth (2007/08–2010/11) $	447,245	120,175	853,790
VA growth (2007/08–2010/11) $	129,134	69,958	202,689
LP-GO growth (2007/08–2010/11) Ratio	2.17	2.13	2.21
LP-VA growth (2007/08–2010/11) Ratio	2.46	3.44	1.48

Table 8.4 presents the summary statistics calculated for all the business performance measures including wages and salaries (i.e., our measure of labour input) in the food, AgriFF and non-AgriFF samples. It is noted that there is reduction in the number of observations for LP-VA growth measures as it excludes small food businesses with negative VA.

Table 8.4

Summary Statistics for the Business Performance Measures, (For Level: 2007/08–2010/11)

Performance Measures	Mean	Standard Deviation	Observations (N)
Food Industry Sample			
Level			
Gross output (GO) $	2,889,184	*8,980,740*	960
Value added (VA) $	599,920	*1,685,953*	960
Wages and salaries (W) $	223,012	*353,768*	960
Labour productivity (LP-GO)	24.87	*82.23*	960
Labour productivity (LP-VA)	7.14	*35.28*	960
Growth			
GO growth (2007/08–2010/11) $	447,245	*2,873,227*	240
VA growth (2007/08–2010/11) $	129,134	*1,232,852*	240
LP-GO growth (2007/08–2010/11) Ratio	2.17	*8.91*	240
LP-VA growth (2007/08–2010/11) Ratio	2.46	*7.35*	186
AgriFF subsector sample			
Level			
Gross output (GO) $	575,131	*657,077*	532
Value added (VA) $	190,108	*309,114*	532
Wages and salaries (W) $	72,894	*86,242*	532
Labour productivity (LP-GO)	31.92	*107.03*	532
Labour productivity (LP-VA)	9.92	*46.33*	532
Growth			
GO growth (2007/08–2010/11) $	120,175	*350,330*	133
VA growth (2007/08–2010/11) $	69,958	*266,663*	133
LP-GO growth (2007/08–2010/11) Ratio	2.13	*5.13*	133
LP-VA growth (2007/08–2010/11) Ratio	3.44	*10.03*	93
non-AgriFF subsector sample			
Level			
Gross output (GO) $	5,765,530	*12,900,000*	428
Value added (VA) $	1,109,312	*2,407,422*	428
Wages and salaries (W) $	409,608	*457,004*	428
Labour productivity (LP-GO)	16.11	*28.28*	428
Labour productivity (LP-VA)	3.68	*10.20*	428
Growth			
GO growth (2007/08–2010/11) $	853,790	*4,261,428*	107
VA growth (2007/08–2010/11) $	202,689	*1,824,443*	107
LP-GO growth (2007/08–2010/11) Ratio	2.21	*12.09*	107
LP-VA growth (2007/08–2010/11) Ratio	1.48	*2.43*	93

Note: Maximum and minimum values are excluded to maintain confidentiality.

8.2.3 Analysing variations in business performances and growth measures

We employ one-way ANOVA to investigate if there is a significant difference in the mean business performance measures (i.e., GO, VA, LP-GO and LP-VA) for the small food businesses in the food industry and the AgriFF/non-AgriFF subsector samples according to (i) the key drivers of innovation; (ii) between innovation-active and non-innovation-active businesses; and (iii) the four types of innovation. Accordingly, one year of business data is used to test if there is a significant difference in the mean of the performance growth measures (i.e., GO growth, VA growth, LP-GO growth and LP-VA growth) between (i) innovation-active and non-innovation-active businesses; and (ii) four degrees of innovation persistence (i.e., intermittent, regular, persistent and highly persistent innovators). Finally, we test if there is evidence to support significant mean differences in the business growth performance between small food businesses of varying innovation persistence in each type of innovation.

Table 8.5 presents the ANOVA results for testing the equality of mean business performance measures by drivers of innovation using the food industry balanced sample. We note from the table that business performance (in all four measures) differed significantly at 1% level of significance based on the subsector where small food businesses belong. The mean business performance measures are significantly higher for businesses belonging to non-AgriFF compared with AgriFF. The mean difference between collaborators and non-collaborators LP-VA measures are found significant. Significant differences are also found for GO and VA compared with LP-GO and LP-VA between market competitions and between ICT intensities. The LP-VA measures differ significantly between businesses having flexible working arrangements.

For the AgriFF balanced sample in Table 8.6, we found several significant associations between the GO performance measure and key drivers of innovation (i.e., having market competition, using STEM skills, having high to most-intense ICT, export capability, having flexible arrangements and sought debt & equity). The LP-VA measures differ significantly between small food businesses engaging and not engaging in collaboration whereas the VA measures differ significantly between businesses having high to most and moderate to none ICT intensity as well as between businesses having export capability and none. On the other hand, for the non-AgriFF balanced sample in Table 8.7, we obtain few key drivers that are significantly associated with GO, VA and LP-VA. These have high to most-intense ICT, use of STEM skills and have export capability. The GO measures differ marginally between collaborators and non-collaborators.

Table 8.8 shows the test results for the difference in mean business performance between innovation-active and non-innovation-active businesses as well as between the four types of innovation. For the VA and LP-GO measures, we found no significant F-statistic. For the food industry sample, both the mean GO and LP-VA differ significantly between the four types of innovation. Innovating small food businesses are significantly more likely to perform well in terms of LP-VA. Similar results are found for small food businesses in the AgriFF sample but for the non-AgriFF sample it was only marginally significant. Between the four types of innovation, the GO measures differ significantly in the AgriFF subsector whereas the LP-VA measures differ significantly in the non-AgriFF subsector. Overall, we found significant associations between the GO, LP-VA, innovation and types of innovation for the food industry.

After implementing ANOVA to test if there are significant differences in the mean of the four performance growth measures between innovation-active and non-innovation-active businesses, as well as between the four degrees of innovation persistence, by industry and subsector (for overall innovation), we found no significant variability (see Table 8.9). This may be due to the fact that we have only one year of information to perform the test. However, when we changed overall innovation and analysed the innovation dynamics by type of innovation, significant differences in the mean business performance growth were observed. For the food industry, Table 8.10 displays the ANOVA test results for the persistence of innovation in each type of innovation. The VA growth measure varies significantly between the four degrees of innovation persistence for all types of innovation and is highly significant for small food businesses undertaking organisational and managerial process innovation. The corresponding LP-VA growth measure significantly varied in terms of innovation persistence for operational process and marketing methods innovation but was only marginally significant for organisational and managerial innovation. The latter results for LP-VA are somehow mimicked in Table 8.11 by the small food businesses in the AgriFF subsector. It was found highly significant for marketing methods and significant for operational and organisational processes innovation. Small food businesses adopting new marketing methods indicate highly significant differences in the mean LP-GO growth measure when they persistently innovate. Marginal significance was also found in the VA growth measure. In the case of the non-AgriFF (as shown in Table 8.12), among persistent small food business innovators, significant differences at the 5% level are found only in the organisational and managerial innovation.

8.3 Impact of innovation on business performance: A propensity score matching approach

In this subsection, we empirically address the first research question stated earlier in this chapter and test the corresponding *Hypotheses 9* and *10* below using propensity score matching (PSM).

- *The Australian small food businesses that engage in any/a particular form of innovation are more likely to be productive than those of non-innovation-active businesses (Hypothesis 9)*
- *Persistent innovation-active small food businesses have higher performance growth (in terms of gross output, value added and labour productivity) than persistent noninnovation-active businesses (Hypothesis 10)*

The PSM approach simulates a randomised controlled experiment for the small food businesses using their observed characteristics coming from the ABS BCS questionnaire. This approach reduces the selection bias by matching each innovating business with one or more noninnovating businesses that have similar observed characteristics. Through the PSM we investigate the causal influence of innovation behaviour on business performance outcomes such as the growths in GO, VA and LP.

8.3.1 Empirical application

We adopt the four-step PSM procedures described in section 4.5, following Caliendo and Kopeinig (2008) and Heinrich et al. (2010). To implement the steps, we used three separate balanced panels of small food businesses from 2007/08 to 2010/11, i.e., the food industry panel (n=240 businesses), the AgriFF subsector panel (n=133 businesses) and the non-AgriFF subsector panel (n=107 businesses)[39]. We used the Stata MP 16 program for each PSM procedure.

[39] As before, we have excluded small food businesses that have negative VA values. Hence, the sample is slightly smaller than the panels used in Chapters 6 and 7 in the analysis involving VA and LP-VA growth measures.

Table 8.5

ANOVA Results for Testing the Equality of Mean Business Performance Measures by Drivers of Innovation, Food industry (2007/08–2010/11)

	Business performance measures (Level)											
	Gross output			Value added			LP-GO			LP-VA		
	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*
Sub-industry (non-AgriFF)	86.27	***	*0.000*	76.02	***	*0.000*	8.83	***	*0.003*	7.46	***	*0.006*
With collaboration	3.52	*	*0.061*	0.02		*0.900*	0.11		*0.740*	5.46	**	*0.020*
Market competition	5.15	***	*0.002*	5.67	***	*0.000*	1.00		*0.393*	2.20	*	*0.086*
Minimal	0.46		*0.496*	0.45		*0.505*	0.17		*0.684*	2.35		*0.126*
Moderate	0.00		*0.972*	1.06		*0.304*	1.23		*0.269*	1.44		*0.230*
Strong	9.40	***	*0.002*	13.76	***	*0.000*	0.18		*0.672*	1.63		*0.202*
ICT Intensity	18.78	***	*0.000*	19.74	***	*0.000*	1.87		*0.133*	1.55		*0.201*
Moderate	17.38	***	*0.000*	20.33	***	*0.000*	2.09		*0.149*	1.33		*0.248*
High	11.65	***	*0.001*	0.12		*0.730*	0.40		*0.527*	1.01		*0.315*
Most intense	35.41	***	*0.000*	56.99	***	*0.000*	4.68	**	*0.031*	2.91	*	*0.088*
Used STEM skills	12.57	***	*0.000*	14.71	***	*0.000*	1.44		*0.230*	2.24		*0.135*
Export capability	0.00		*0.953*	0.07		*0.795*	1.89		*0.170*	3.45	*	*0.064*
With flexible working arrangements	4.35		*0.037*	3.15	*	*0.076*	0.92		*0.337*	5.58	**	*0.018*
Sought debt and/or equity finance	1.89		*0.170*	1.89		*0.170*	1.56		*0.213*	0.43		*0.512*

Note: The asterisks, ***,** and *, denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8.6

ANOVA Results for Testing the Equality of Mean Business Performance Measures by Drivers of Innovation, AgriFF subsector (2007/08–2010/11)

	Business performance measures (Level)											
	Gross output			Value added			LP-GO			LP-VA		
	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*
With collaboration	0.41		*0.522*	1.12		*0.289*	0.14		*0.713*	4.15	**	*0.042*
Market competition	2.33	*	*0.074*	0.64		*0.589*	0.59		*0.623*	1.47		*0.223*
Minimal	4.13	**	*0.043*	1.41		*0.236*	0.44		*0.507*	3.00	*	*0.084*
Moderate	1.50		*0.221*	0.24		*0.625*	1.49		*0.222*	0.76		*0.383*
Strong	3.04	*	*0.082*	0.55		*0.459*	0.01		*0.913*	1.21		*0.272*
ICT Intensity (high to most intense)	3.90	**	*0.049*	4.37	**	*0.037*	1.16		*0.282*	0.45		*0.501*
Used STEM skills	9.22	***	*0.003*	1.17		*0.279*	1.34		*0.248*	1.45		*0.229*
Export capability	7.25	***	*0.007*	5.37	**	*0.021*	0.84		*0.359*	1.06		*0.303*
With flexible working arrangements	9.80	***	*0.002*	3.24	*	*0.073*	0.36		*0.547*	3.72	*	*0.054*
Sought debt and/or equity finance	6.22	**	*0.013*	1.03		*0.310*	1.26		*0.263*	0.17		*0.677*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.7

ANOVA Results for Testing the Equality of Mean Business Performance Measures by Drivers of Innovation, Non-AgriFF (2007/08–2010/11)

	Business performance measures (Level)											
	Gross output			Value added			LP-GO			LP-VA		
	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*
With collaboration	2.77	*	*0.097*	0.00		*0.949*	0.05		*0.817*	2.52		*0.113*
Market competition	1.12		*0.342*	1.93		*0.123*	0.81		*0.490*	0.56		*0.643*
Minimal	0.51		*0.475*	0.42		*0.520*	0.62		*0.431*	0.23		*0.630*
Moderate	0.50		*0.482*	2.75	*	*0.098*	1.18		*0.278*	0.65		*0.421*
Strong	2.35		*0.126*	5.30	**	*0.022*	0.01		*0.909*	1.56		*0.213*
ICT Intensity (high to most intense)	9.91	***	*0.002*	10.90	***	*0.001*	1.45		*0.230*	4.34	**	*0.038*
Used STEM skills	10.36	***	*0.001*	12.74	***	*0.000*	0.00		*0.975*	1.64		*0.201*
Export capability	1.63		*0.202*	1.35		*0.246*	0.43		*0.514*	7.32	***	*0.007*
With flexible working arrangements	0.80		*0.371*	0.29		*0.590*	0.00		*0.999*	0.28		*0.599*
Sought debt and/or equity finance	1.36		*0.245*	1.44		*0.231*	0.98		*0.978*	0.33		*0.569*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.8

ANOVA Results for Testing the Equality of Mean Business Performance Measures for Innovation, by Industry (2007/08–2010/11)

	Business performance measures (Level)											
	Gross output			Value added		LP-GO		LP-VA				
	F-statistic		*p-value*	F-statistic	*p-value*	F-statistic	*p-value*	F-statistic		*p-value*		
FOOD												
Innovator vs. noninnovator	2.99	*	*0.084*	0.76	*0.382*	2.10	*0.156*	14.53	***	*0.000*		
Between types of innovation	2.29	**	*0.026*	1.51	*0.197*	0.25	*0.912*	2.60	**	*0.035*		
AgriFF												
Innovator vs. noninnovator	4.88	**	*0.028*	0.52	*0.472*	1.43	*0.233*	9.80	***	*0.002*		
Between types of innovation	3.15	**	*0.014*	0.42	*0.792*	0.68	*0.605*	1.45		*0.216*		
non-AgriFF												
Innovator vs. noninnovator	0.02		*0.884*	0.19	*0.662*	0.76	*0.383*	3.74	*	*0.054*		
Between types of innovation	2.31	*	*0.057*	0.71	*0.586*	1.34	*0.254*	3.05	**	*0.017*		

Note: The asterisks, ***,** and *, denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8.9

ANOVA Results for Testing the Equality of Mean Business Performance Measures for Innovation Persistence, by Industry (2007/08–010/11)

	Business performance measures (Growth)							
	Gross output		Value added		LP-GO		LP-VA	
	F-statistic	*p-value*	F-statistic	*p-value*	F-statistic	*p-value*	F-statistic	*p-value*
Food industry								
Between innovation persistence	1.21	*0.354*	0.96	*0.431*	0.98	*0.422*	1.28	*0.280*
Innovator vs. noninnovator	0.86	*0.354*	0.10	*0.756*	0.35	*0.554*	0.62	*0.432*
AgriFF								
Between innovation persistence	0.08	*0.988*	0.63	*0.643*	1.36	*0.255*	0.96	*0.432*
Innovator vs. noninnovator	0.24	*0.622*	0.04	*0.839*	0.15	*0.699*	0.91	*0.343*
non-AgriFF								
Between innovation persistence	0.93	*0.450*	0.54	*0.706*	1.00	*0.413*	1.54	*0.196*
Innovator vs. noninnovator	0.33	*0.565*	0.05	*0.831*	0.26	*0.613*	0.68	*0.413*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.10

ANOVA Results for Testing the Equality of Mean Business Performance Measures for Innovation Persistence, by Type of Innovation, Food industry (2007/08–2010/11)

	Business performance measures (Growth)											
	Gross output			Value added			LP-GO			LP-VA		
	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*
Goods and services												
Between innovation persistence	1.96	*	*0.100*	2.37	*	*0.054*	0.31		*0.874*	1.19		*0.317*
Innovator vs. noninnovator	0.16		*0.694*	1.36		*0.245*	0.35		*0.555*	0.06		*0.800*
Organisational and Managerial Process												
Between innovation persistence	3.17	**	*0.015*	4.72	***	*0.001*	0.98		*0.418*	2.07	*	*0.087*
Innovator vs. noninnovator	5.67	**	*0.018*	2.24		*0.136*	0.43		*0.511*	1.89		*0.171*
Operational Process												
Between innovation persistence	1.96		*0.102*	3.10	**	*0.016*	0.22		*0.927*	2.86	**	*0.025*
Innovator vs. noninnovator	1.53		*0.217*	0.42		*0.518*	0.20		*0.658*	2.49		*0.116*
Marketing Methods												
Between innovation persistence	0.80		*0.523*	3.04	**	*0.018*	1.01		*0.462*	3.13	**	*0.016*
Innovator vs. noninnovator	1.09		*0.298*	0.20		*0.654*	0.15		*0.700*	2.21		*0.139*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.11

ANOVA Results for Testing the Equality of Mean Business Performance Measures for Innovation Persistence, by Type of Innovation, AgriFF subsector (2007/08–2010/11)

	Business performance measures (Growth)											
	Gross output			Value added			LP-GO			LP-VA		
	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*	F-statistic		*p-value*
Goods and services												
Between innovation persistence	0.65		*0.631*	0.39		*0.813*	2.19	*	*0.074*	1.51		*0.206*
Innovator vs. noninnovator	0.16		*0.694*	1.36		*0.245*	0.35		*0.555*	0.06		*0.800*
Organisational and Managerial Process												
Between innovation persistence	0.54		*0.706*	2.39	*	*0.054*	0.89		*0.472*	2.67	**	*0.037*
Innovator vs. noninnovator	3.30	*	*0.072*	0.01		*0.912*	0.83		*0.363*	1.22		*0.271*
Operational Process												
Between innovation persistence	0.41		*0.802*	2.38	*	*0.055*	0.74		*0.569*	2.90	**	*0.026*
Innovator vs. noninnovator	1.75		*0.188*	0.51		*0.477*	0.17		*0.682*	1.81		*0.181*
Marketing Methods												
Between innovation persistence	0.28		*0.890*	0.52		*0.725*	3.80	***	*0.006*	8.19	***	*0.000*
Innovator vs. noninnovator	0.28		*0.599*	0.72		*0.399*	0.55		*0.460*	1.42		*0.236*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.12

ANOVA Results for Testing the Equality of Mean Business Performance Measures for Innovation Persistence, by Type of Innovation, Non-AgriFF subsector (2007/08–2010/11)

	Business performance measures (Growth)											
	Gross output			Value added			LP-GO)			LP-VA		
	F_statistic		*p-value*	*F_statistic*		*p-value*	*F_statistic*		*p-value*	*F_statistic*		*p-value*
Goods and services												
Between innovation persistence	1.14		*0.344*	1.43		*0.230*	0.34		*0.849*	0.32		*0.863*
Innovator vs. noninnovator	0.02		*0.894*	0.63		*0.428*	1.40		*0.239*	0.87		*0.352*
Organisational and Managerial Process												
Between innovation persistence	2.05	*	*0.093*	3.00	**	*0.022*	0.81		*0.520*	0.64		*0.632*
Innovator vs. noninnovator	2.76	*	*0.100*	0.71		*0.400*	0.10		*0.756*	1.00		*0.320*
Operational Process												
Between innovation persistence	1.57		*0.187*	2.12	*	*0.084*	0.28		*0.889*	0.96		*0.436*
Innovator vs. noninnovator	0.85		*0.358*	0.26		*0.610*	1.09		*0.299*	3.22	*	*0.076*
Marketing Methods												
Between innovation persistence	0.74		*0.570*	1.54		*0.197*	1.45		*0.222*	2.37	*	*0.059*
Innovator vs. noninnovator	0.04		*0.837*	0.06		*0.812*	0.00		*0.978*	1.13		*0.291*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

8.3.1.1 Estimating the propensity scores

There are two important choices that need to be made in estimating the propensity scores: the correct specification propensity model and the correct identification of the covariates to be included in the propensity model. A logit or probit model is used in most PSM applications. The current study employs a standard linear probit model consistent with the previous ABS and DIIS works of Rotaru et al. (2013) and Hendrickson et al. (2018). The choice of adopting the binary probit model for PSM application to the food industry and the two subsector panels follows from the empirical work in Chapters 6 and 7.

With the binary probit model chosen, we next get a clear and comprehensive list of relevant covariates that would assure that the matching produces an unbiased estimate of the innovation (or other innovation treatment) impact. It is also important to include in our probit model, not only carefully chosen and appropriate conditioning variables, but also their correct functional form because estimates of treatment effects are sensitive to the specifications of the covariates. The inclusion and creation of the key business characteristics for propensity modelling in this study are based on previous innovation studies and analysis conducted/published at the ABS by Todhunter & Abello (2011), Tiy et al. (2013), Rotaru et al. (2013), Rotaru & Soriano (2013), and Soriano & Abello (2015).

The empirical probit model is specified by:

$$P(y_{it} = 1|x_i) \quad = \quad P(y_{it}^* > 0|x_{it}) = \emptyset(x_i\beta) \tag{8.1}$$

where the dependent variable, y_{it} , is a binary response variable taking the value 1, if the *i*-th business engaged in innovation in period *t*, and 0 otherwise; and $\emptyset(x_i\beta)$ is a standard normal cumulative distribution function. Because we are interested in innovation persistence, the dependent variable is defined in any of the five ways:

- Business is innovation-active in all four years (highly persistent innovator) when in period *t* , and 0 otherwise;
- Business is innovation-active in three years only (persistent innovator) when in period *t*, and 0 otherwise;
- Business is innovation-active in two years only (regular innovator) when in period *t*, and 0 otherwise;

- Business is innovation-active in one year only (intermittent innovator) when in period t, and 0 otherwise; or,
- Business engage in any of the four types of innovation (overall innovation) during the four-year period, and 0 otherwise.

Note that a business can engage in more than one type of innovation.

The latent variable is formulated as:

$$y_{it}^{*} = \beta_0 + x_{1it}\beta_1 + x_{2it}\beta_2 + \cdots + x_{kit}\beta_{1k}, \quad i = 1,2,\ldots,n, \;\; t = 2010/11 \qquad (8.2)$$

The observed explanatory variables in equation (8.2) are estimated for the food industry sample (n=240) where x_k, k=1,2,..12, which include whether: the business belongs to the subsector Non-AgriFF (x_1); the business has collaboration arrangements (x_2); the business faces minimal competition (x_3), moderate competition (x_4), and strong competition (x_5); the business uses moderate ICT (x_6), high ICT (x_7), and the most intense ICT (x_8); the business uses STEM skills (x_9); the business has export capability (x_{10}); the business has flexible working arrangements (x_{11}); and the business seeks debt and/or equity financing (x_{12}). For the subsector models, (i.e., n=133 for the AgriFF sample and n=107 for the Non-AgriFF sample), as usual the categories in the ICT intensity variable were combined to form two binary dummy variables (i.e., the business uses low-to-moderate or high-to-most-intense ICT). Hence, the number of covariates is reduced to k=9. We note that the business size variable (i.e., the business is non-employing) that was previously used in Chapters 6 and 7 probit modelling was excluded due to strong collinearity with other covariates.

8.3.1.2 Matching algorithm implementation

After the propensity scores are estimated, we examine different algorithms to match the treated (innovator) to control (noninnovators) participants (or businesses) based on the estimated propensity scores. We define the five treatments following the dependent variables described in equation (8.1). Although there are many matching algorithms in the literature (Caliendo & Kopeinig 2008; Heinrich et al. 2010; Gou & Fraser 2015), we tested three of the most commonly employed matching algorithms: nearest neighbour (NN) matching; caliper or radius (R) matching; and kernel (K) matching. For the NN and R matching procedures, we applied a caliper of 0.05 to rule out getting some bad matches. This is a bit tighter than the caliper usually set in practice (i.e., 0.2 or 0.25 standard deviations of the propensity score) (see Rosenbaum & Rubin, 1985).

8.3.1.3 Evaluating the assumptions and the quality of matching (bias tests)

We assessed the performance of matching by examining the standardised bias reduction, mean tests and pseudo R-squared. Table 8.13 shows that there is a large reduction in bias (i.e., difference in the covariance means) after matching. There is also a higher reduction in bias for kernel matching than for the NN, but the same reduction for R matching. The R matching paired well with K matching in their performances in the PSM.

Table 8.13

Comparison of the Three Algorithms' Matching Performance

Sample	Pseudo R-squared	LR Chi-square	(*p-value*)	Mean Bias (%)
Raw	0.202	50.16	*(0.000)*	37.2
Nearest Neighbour	0.036	4.94	*(0.934)*	6.6
Radius	0.004	0.57	*(1.000)*	4.8
Kernel	0.004	0.55	*(1.000)*	4.8

We plotted the standardised bias for all the covariates before and after matching to check whether the algorithm was able to balance the distribution of the relevant covariates. Figure 8.4 shows how the bias reduction works for all the covariates with K matching (this particular example is for highly persistent innovators in the food industry as the treatment group).

We note in Chapter 4 that the validity of the PSM depends on whether the key assumptions are satisfied: the conditional independence and the common support conditions. The conditional independence assumption cannot be directly tested; however, we used a transparent and well-controlled/justified selection process for the covariates. We also used a set of covariates that were stable over time. Our control and treatment datasets come from the same source (BLD). Whereas the deterministic nature of some of the covariates included is debatable, most of them have shown to significantly drive business innovation (based on findings in Chapters 6). We tested the common support by visual analysis of the kernel density of propensity scores for treated and control business groups, before and after matching. Where the impacts were found significant, the kernel density of propensity scores was more alike between the two groups after matching, which clearly shows an overlapping of distributions (for the highly persistent innovators case, see Figure 8.5).

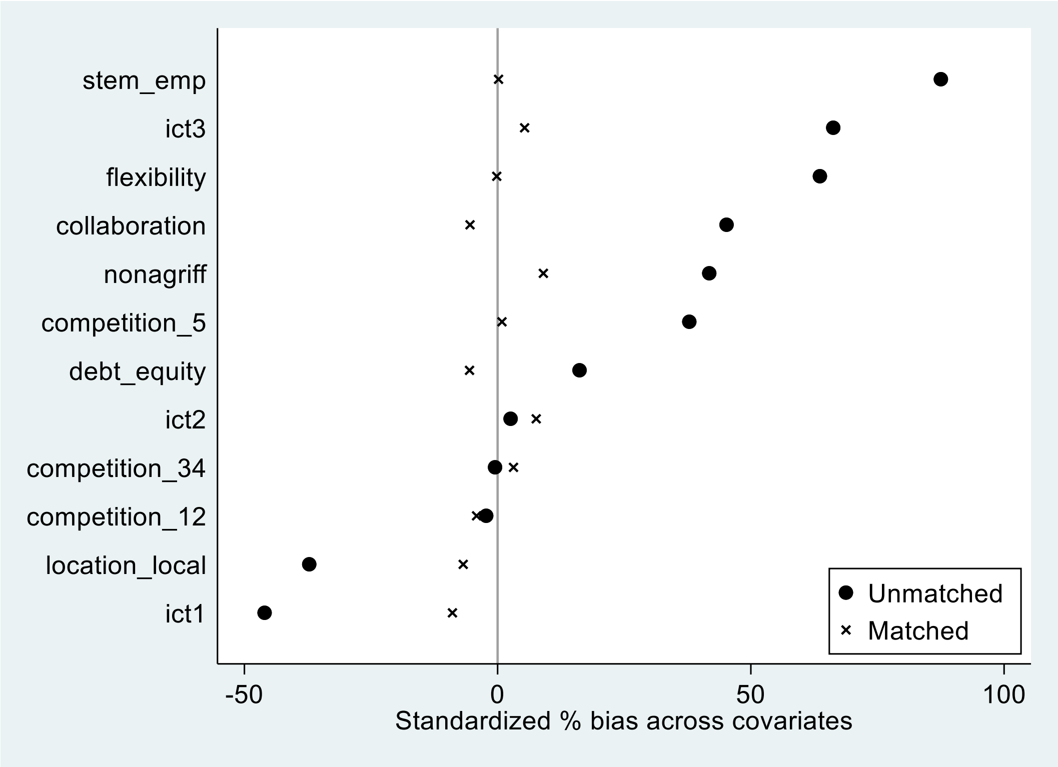


Figure 8.4. Standardised bias graph before and after matching (Kernel)[40]

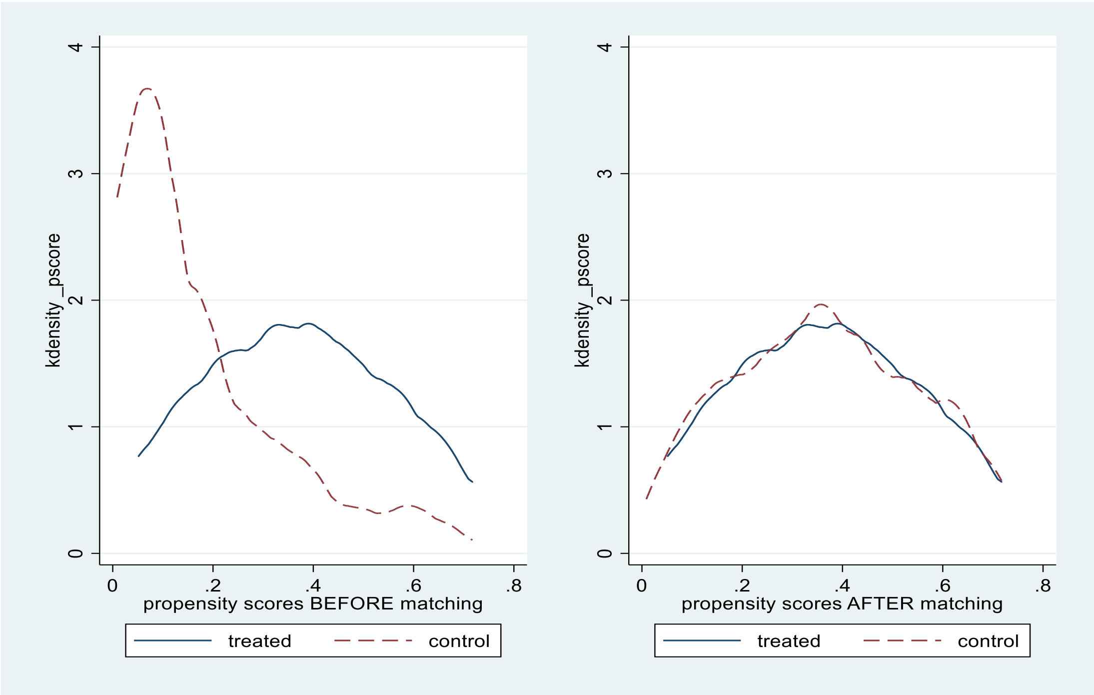


Figure 8.5. Propensity scores distributions before and after matching (Kernel).

[40] Graph of the standardized bias is directly capture from the Stata output. The coded variables in vertical axis corresponds to the explanatory variables defined in equation 8.2.

8.3.2 Impact analysis: Any form of innovation

After evaluating the quality of the matching results, we chose to focus on the kernel algorithm findings in the impact analysis because we found K superior in the reduction of bias. Moreover, kernel matching has the nice property that it constructs matches using all the small food businesses in the potential control sample, hence taking more information from those businesses with propensity scores closest to the treated business. The findings for the NN and R matching were also included for sensitivity analysis and results are presented in Appendix E

We estimated the ATT following Wooldridge (2010) and using Stata *Psmatch2* software. The ATT is of substantive interest in this study because, in deciding whether innovation persistence (or any innovation program) is beneficial, our interest is whether, on average, innovation persistence is beneficial for those noninnovating small food businesses had they engaged and persisted to innovate any type of innovations. The ATT estimations were done using the four business growth performance measures (discussed in section 8.2.2) as outcome variables. The standard errors for the ATT were conventionally calculated using the bootstrapping method and the associated t-tests were obtained to determine the significance of each of the treatment effects.

8.3.2.1 Kernel matching results (treatment effects)

Table 8.14 provides evidence on the impact of innovation persistence among small food businesses on a range of growth outcomes using kernel matching. An example to interpret a particular results in the table is provided here—let us consider the VA growth ($) with the treatment highly persistent innovators (where ATT is found positive and significant), we can infer that, had the small food business who is persistently noninnovator, actually engaged in innovation and become highly persistent innovator, on average the business VA will increase by AU$909,600.

For the food industry, the PSM found significant positive impacts on both the GO and VA growth measures for highly persistent innovators, and a marginally significant impact by overall innovators on VA growth. We found no significance in LP growth for any of the innovation persistence treatments. However, we see from the table that innovating small food businesses improved the LP-VA by 1.2 per cent, on average, and it doubled to around 3 per cent for highly persistent innovators which is estimated to be equivalent to approximately AU$4–7 billion infusion into the Australian economy. The results here depict similarity with those of Hendrickson et al. (2018) where significance at the 5% level was achieved in the GO growth for persistent innovating Australian businesses and non-significance in the LP growth.

For the AgriFF sample, the PSM found significant positive impacts on both the LP-VA growth measures for persistent innovators (1.37). For the non-AgriFF sample, the PSM confirmed a marginally significant effect on both the VA and LP-VA growth measures for innovating small food businesses. The results imply that there was no significant additional average treatment effect of innovation persistence in the non-AgriFF subsector.

Table 8.14

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Kernel Matching

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Food industry					
Gross output growth ($)	1,535,509**	32,985	41,037	-225,752	540,358
Value added growth ($)	909,600**	7,499	162,512	-150,543	307,407*
LP-GO growth (ratio)	0.39	-0.18	1.24	3.56	1.30
LP-VA growth (ratio)	3.34	0.32	2.50	-0.20	1.22
AgriFF					
Gross output growth ($)	149,419	-102,783	107,211	63,501	50,652
Value added growth ($)	28,179	-137,823	-25,734	-63,649	-42,310
LP-GO growth (ratio)	1.08	0.28	3.39	-0.36	1.11
LP-VA growth (ratio)	0.67	1.37*	6.39	-0.85	2.90
non-AgriFF					
Gross output growth ($)	3,654,827	588,483	724,702	-918,310	1,081,948
Value added growth ($)	504,642	95,523	247,281	84,361	765,095*
LP-GO growth (ratio)	0.27	0.15	-0.12	9.16	1.74
LP-VA growth (ratio)	2.86	-0.19	0.16	0.39	0.80*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

NN & Radius matching results (sensitivity analysis)

The PSM results using the NN and R matching for the food, the AgriFF and the non-AgriFF samples are exhibited in Tables 8.15 and 8.16. As expected, we find consistency in the PSM results using R matching with the kernel matching in terms of significance and directions of the impacts on a range of business performance growths because both algorithms performed well in the reduction of bias. This also confirms the robustness of the results produced by the

K matching. With the PSM using NN matching, we found a few significant results but they were not consistent with the K matching results.

Table 8.15
Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Nearest Neighbour Matching

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Food industry					
Gross output growth ($)	1,302,221	74,790	60,549	-311,556	566,938
Value added growth ($)	856,189*	1,007	202,852	-194,297	247,215
LP-GO growth (ratio)	0.29	-0.25	1.42	0.60	1.35
LP-VA growth (ratio)	3.46	0.47	2.66	-0.20	1.47
AgriFF					
Gross output growth ($)	106,063	-356,096	118,461	107,263	-61,587
Value added growth ($)	-12,479	-402,108	-43,910	-12,211	-134,000
LP-GO growth (ratio)	1.07	-0.12	3.71	-0.90	1.14
LP-VA growth (ratio)	0.77	1.46	7.21	0.28	3.27
non-AgriFF					
Gross output growth ($)	3,375,998	1,288,976	1,216,806**	-1,602,378	999,799
Value added growth ($)	502,879	298,620	229,308	37,262	851,982*
LP-GO growth (ratio)	0.32	0.27	-0.04	8.91	1.73
LP-VA growth (ratio)	3.17	-0.41	0.08	0.39	0.76

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

8.3.3 Impact analysis: Innovation Dimension

Here, we are interested in the persistence in each type of innovation. The PSM was carried out where the dependent variable for the probit model was defined in one of the five ways, say, for example, for goods and services innovation:

- Business is goods and services innovator in all four years (highly persistent innovator) when in period *t*, and 0 otherwise;
- Business is goods and services innovator in three years only (persistent innovator) when in period *t*, and 0 otherwise;
- Business is goods and services innovator in two years only (regular innovator) when in period *t*, and 0 otherwise;
- Business is goods and services innovator in one year only (intermittent innovator) when in period *t*, and 0 otherwise; or

- Business is goods and services innovator (overall goods and services innovation) during the four-year period, and 0 otherwise.

Similar approaches were conducted for the other types of innovation when doing the PS

Table 8.16

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Radius Matching

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Food industry					
Gross output growth ($)	1,541,354**	26,426	97,576	-225,444	547,896
Value added growth ($)	939,450**	7,499	154,197	-145,251	306,495*
LP-GO growth (ratio)	0.40	-0.09	1.30	0.20	1.32
LP-VA growth (ratio)	3.31	0.19	2.57	-0.13	1.23
AgriFF					
Gross output growth ($)	157,223	-88,162	92,822	55,299	55,090
Value added growth ($)	36,907	-115,331	-30,510	-68,194	-27,352
LP-GO growth (ratio)	1.13	0.22	3.42	-0.33	1.18
LP-VA growth (ratio)	0.68	1.39*	6.31	-0.82	2.94
non-AgriFF					
Gross output growth ($)	3,643,155	254,288	552,596	-948,474	1,075,701
Value added growth ($)	514,512	21,212	234,999	71,942	729,305*
LP-GO growth (ratio)	0.26	0.07	-0.18	9.17	1.76
LP-VA growth (ratio)	2.76	-0.29	0.15	0.37	0.79*

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

8.3.3.1 Findings for the food industry

Table 8.17 presents evidence on the impact of innovation persistence on a particular type of innovation among small food businesses for a range of growth outcomes using kernel matching for the food industry sample. Looking at the goods and services innovation, the PSM found significant positive impact on VA growth for persistent innovators. An interesting result is a negative and significant impact of being an intermittent innovator only of goods and services innovation. For organisational and managerial process innovation, being an overall innovator had a significant impact on LP-VA growth. For the operational process, we find four marginally significant effects–being highly persistent and overall innovators on GO growth; being an overall innovator for LP-VA and a negative impact on VA growth for intermittent innovators.

Table 8.17

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Kernel Matching: Food Industry by Type of Innovation

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Goods and services					
Gross output growth ($)	1,969,246	-244,469	-707,721	-41,521	-184,504
Value added growth ($)	1,136,585	440,839**	-179,758	-114,643	231,829
LP-GO growth (ratio)	-2.35	-0.57	1.32	-2.75**	-1.08
LP-VA growth (ratio)	-0.04	-0.25	4.73	-0.25	1.26
Organisational and managerial process					
Gross output growth ($)	2,923,929	258,156	136,122	557,842	183,817
Value added growth ($)	1,795,553	244,414	-32,145	-106,648	190,888
LP-GO growth (ratio)	-0.16	-0.16	1.72	3.41	2.03
LP-VA growth (ratio)	6.54	0.79	3.33	1.26	2.73**
Operational Process					
Gross output growth ($)	2,492,814*	344,584	152,801	753,538	731,436*
Value added growth ($)	1,179,088	51,909	13,975	-304,728*	69,297
LP-GO growth (ratio)	-0.21	0.01	-2.05	-1.05	-1.57
LP-VA growth (ratio)	0.90	0.69	5.66	0.43	1.90*
Marketing Methods					
Gross output growth ($)	-615,746	391,044	927,555	777,310	260,561
Value added growth ($)	310,888	1,605,508	167,349	-86,656	112,379
LP-GO growth (ratio)	0.14	0.63	2.55	3.12	1.80
LP-VA growth (ratio)	-0.30	2.61	7.43	0.44	2.00

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Findings for the AgriFF and the non-AgriFF subsectors

In the AgriFF sample in Table 8.18, the stories are different in terms of the observed significant impacts. Most of the significant effects are the result of high innovation persistence among the small food businesses. More notable are the positive and significant effects on LP-VA for innovating goods and services as well as on the GO growth for innovating operational process. In the case of the non-AgriFF subsector, the PSM findings in Table 8.19 show significant positive impacts on the VA and GO growth measures for highly persistent and persistent innovators of organisational and operational process. There are some odd results for the goods and services innovation having negative and highly significant effects.

The PSM results using the NN and R matching algorithms for the food, AgriFF and non-AgriFF samples by types of innovation are exhibited in the Appendix E.

Table 8.18

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Kernel Matching: AgriFF Subsector by Type of Innovation

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	-239,224*	57,409	-97,208	8,331	-3,577
Value added growth ($)	23,953	35,590	42,977	55,387	59,470
LP-GO growth (ratio)	1.45	0.39	5.19	-0.12	1.54
LP-VA growth (ratio)	2.48**	-0.45	13.08	-2.30	3.27
Organisational and managerial process					
Gross output growth ($)	-85,051	-11,102	-13,151	-81,480	26,612
Value added growth ($)	41,859	-48,971	-49,606	-134,667	3,050
LP-GO growth (ratio)	0.19	-0.41	3.02	0.80	1.34
LP-VA growth (ratio)	19.98	0.42	5.79	-0.08	5.12
Operational Process					
Gross output growth ($)	539,023**	36,762	-26,364	58,935	-19,774
Value added growth ($)	474,788*	-64,852	-20,794	-97,299	-68,606
LP-GO growth (ratio)	0.71	0.79	4.23	0.42	1.22
LP-VA growth (ratio)	0.16	-0.88	12.75	0.64	4.10
Marketing Methods					
Gross output growth ($)	210,191	-359,564	-3,592	86,313	52,371
Value added growth ($)	246,194*	278,456	-110,706	-10,543	4,976
LP-GO growth (ratio)	0.24	0.69	10.80	0.39	1.85
LP-VA growth (ratio)	-0.09	1.03	32.50*	0.56	5.31

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.19

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Kernel Matching: Non-AgriFF Subsector by Type of Innovation

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	2,342,362	451,222	-3,397,279***	-2,735,117*	4,383
Value added growth ($)	1,532,385	308,613	623,716	135,828	487,615
LP-GO growth (ratio)	-2.60	-0.61	-0.70	-1.54	-1.70
LP-VA growth (ratio)	-0.05	-0.33	-0.21	-0.75***	-0.11
Organisational and managerial process					
Gross output growth ($)	4,831,442**	1,591,299*	1,932,958	949,867	1,659,065*
Value added growth ($)	5,233,868	803,628***	808,903	-185,038	465,720
LP-GO growth (ratio)	-0.04	0.35	0.16	5.73	3.02
LP-VA growth (ratio)	1.37	0.80	0.64	0.91	0.58
Operational Process					
Gross output growth ($)	3,773,773	340,952	408,072	1,744,211	1,527,176*
Value added growth ($)	1,687,777	126,775	142,943	-510,167	275,737
LP-GO growth (ratio)	0.29	-1.73	-3.95	-3.67	-2.71
LP-VA growth (ratio)	0.61	-0.06	1.39	0.16	0.64
Marketing Methods					
Gross output growth ($)	1,388,295	-1,523,749	1,893,662	2,647,244	790,379
Value added growth ($)	682,221	916,917	369,444	-240,369	132,812
LP-GO growth (ratio)	-0.31	0.53	0.00	8.73	2.27
LP-VA growth (ratio)	0.45	3.01	-0.53	-0.55**	0.60

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

8.4 Panel data regression modelling of business performance and innovation persistence

This empirical section complements the results of the PSM analysis to confirm the established relationship between innovation persistence and business performance growth in the former analyses. We assess the magnitude of the cumulative effect of the persistence of innovation on the four business performance outcomes by undertaking OLS regression on the derived 'matched sample'—the businesses in the treatment group plus the corresponding matched businesses in the control group. Kernel matching was the algorithm used to derive the balanced panel sample for the OLS regression.

8.4.1 Empirical model specification

The OLS model specified for the analysis is given by:

$$Log\ (\Delta Y_{i,[t,t+1]}) = p'_{it}\theta + x'_{it}\beta + \varepsilon_{it} \quad \text{, where } i = 1, 2, \ldots, 960\,;\ t = 1, 2, 3 \qquad (8.3)$$

where

$Y_{i,[t,t+1]}$ is a business performance growth from period t to $t+1$ for i-th business; We consider four growth measures – GO, VA, LP-GO and LP-VA growths;

p_{it} is a categorical innovation persistence variable with the following subcategories:

- Innovation-active in all four years (highly persistent innovator);
- Innovation-active in three years only (persistent innovator);
- Innovation-active in two years only (regular innovator);
- Innovation-active in one year only (intermittent innovator); and
- Noninnovation active in all years (persistent noninnovator).

x_{it} is a vector of observed covariates including a constant term;

θ, β are vectors of fixed, yet unknown, population parameters; and,

ε_{it} is the error term, such that $\varepsilon_{it} \sim N(0, \sigma^2)$.

Two different persistence model specifications are used. The first one uses dummy 0/1 for each of the innovation persistence category above (Model 1), whereas the second model treats the innovation persistence variable as categorical (Model 2). The estimated coefficients for the persistence variables show the added effect of innovation persistence on outcome growth (in percentages) between the beginning (2007/08) and the end (2010/11) of the study period compared with those businesses not undertaking innovations during the period.

8.4.2 Regression results: Any form of innovation

The model results in Table 8.20 show positive and significant coefficients for the persistence variables under both models, confirming the cumulative effects of innovation persistence. These significant effects are evident in the food industry as well as in the AgriFF and non-AgriFF samples. Where significant, the magnitude of the effects for Model 1 are higher for highly persistent small food business innovators than for less persistent innovators. For example, highly persistent innovators in the food industry had 60 per cent and 72 per cent higher VA and LP-VA growth, respectively, than small food businesses that did not innovate in any of those four years. In the AgriFF subsector, the results for the same performance growth measures are also positive but slightly higher at 63 per cent and 77 per cent, respectively. The same effects are more pronounced in the non-AgriFF subsector with 88 per cent and 107 per cent, respectively. For Model 1 in the non-AgriFF subsector, we also find positive and significant estimated coefficients for persistent and intermittent innovators.

The above regression findings, coupled with the PSM results, indicate that Australian small food businesses that engage in any particular form of innovation are more likely to be productive than those of non-innovation-active businesses (acceptance of *Hypothesis 9*). Evidently, highly persistent innovation-active small food businesses have higher performance growth (in terms of VA and LP, value-added based) than non-persistent innovation-active businesses (acceptance of Hypothesis 10) in the food industry as well as within the two subsectors.

Table 8.20

Impacts of Innovation Persistence on Small Food Businesses Performance Growth using Regression on the Derived Balanced Panel

	Persistence (Model 1)								Persistence (Model 2)	
Dependent variable	Highly persistent		Persistent		Regular		Intermittent		Categorical	
Food industry										
Gross output growth	0.011		-0.282		0.090		0.019		-0.017	
Value added growth	0.600	***	0.130		0.302		-0.167		0.127	***
LP-GO growth	0.246	*	-0.175		0.128		0.349	**	0.030	
LP-VA growth	0.722	***	0.375		0.364		0.221		0.166	***
AgriFF										
Gross output growth	0.092		-0.103		0.076		-0.049		0.007	
Value added growth	0.627	**	0.096		-0.164		-0.184		0.085	
LP-GO growth	0.679	**	0.232		0.301		0.101		0.139	**
LP-VA growth	0.777	**	0.293		0.420		-0.253		0.165	**
Non-AgriFF										
Gross output growth	0.110		-0.051		0.085		0.096		0.017	
Value added growth	0.878	***	0.414		0.637	*	0.111		0.209	***
LP-GO growth	0.146		-0.065		-0.178		0.492	***	0.009	
LP-VA growth	1.072	***	0.846	***	0.351		0.667	**	0.260	***

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

The regression results contained in the Appendix F further show that high performance growth was more likely to be found in small food businesses having collaboration, export capability, higher ICT intensity and certain market competition. The use of STEM skills was also found to have significant association with business performance growth.

8.4.3 Regression results: Innovation Dimension

In our panel regression analysis, we are now interested on the correlation between persistence of innovation in each type of innovations and business performance growth. Applying OLS for estimating equation (8.3) was carried out where the persistent categorical variable for the two persistence models is defined, say, for example, for goods and services innovation:

Innovation persistence is a categorical innovation variable with the following subcategories:

- Goods and services innovation-active in all four years (highly persistent innovator of goods and services);
- Goods and services innovation-active in three years only (persistent innovator of goods and services);
- Goods and services innovation-active in two years only (regular innovator of goods and services);
- Goods and services innovation-active in one year only (intermittent innovator of goods and services); and
- Goods and services non-innovation-active in all years (persistent noninnovator of goods and services).

We undertake this analysis for the other types of innovation using OLS regression.

8.4.3.1 Regression findings for innovation dimension

Table 8.21 shows positive and significant coefficients for the persistence variables under both models for organisational and managerial processes innovation in the food industry, confirming the cumulative effects of persistence in that type of innovation. These significant effects are not evident in the other types of innovation. Where significant, the magnitude of the effects for Model 1 are higher for highly persistent small food business innovators than for less persistent innovators. The same findings are revealed in the case of the AgriFF subsector (see Table 8.22), where higher performance growth in VA and LP-VA are significantly associated with high innovation persistence in organisational and managerial process innovation. However, we found significant innovation persistence effects for LP-GO growth in the operational process innovation. In the case of the non-AgriFF subsector (in Table 8.23), we found no significant association between being highly persistent innovators and performance growth in Model 1, but found one for LP-VA growth in the organisational and managerial performance type of innovation.

Table 8.21

Impacts of Innovation Persistence on Small Food Businesses Performance Growth using Regression on the Derived Balanced Panel: Food Industry by Type of Innovation

	Persistence (Model 1)								Persistence (Model 2)	
Dependent variable	Highly persistent		Persistent		Regular		Intermittent		Categorical	
Goods and services										
Gross output growth	-0.139		-0.005		-0.514	***	-0.217		-0.053	
Value added growth	0.232		0.184		0.346		-0.117		0.070	
LP-GO growth	0.038		0.094		-0.268		-0.070		-0.002	
LP-VA growth	0.332		0.253		0.639	*	0.052		0.108	
Organisational and managerial process										
Gross output growth	0.155		0.122		-0.138		0.004		0.020	
Value added growth	0.816	**	0.193		0.396		0.103		0.162	**
LP-GO growth	0.143		0.016		0.218		0.195		0.037	
LP-VA growth	0.874	**	0.544		0.928	**	0.329		0.247	***
Operational Process										
Gross output growth	0.074		-0.006		-0.463	***	-0.088		-0.024	
Value added growth	0.163		0.044		0.283		-0.114		0.050	
LP-GO growth	0.172		0.242		-0.242		0.032		0.030	
LP-VA growth	0.355		0.174		0.453	**	0.084		0.103	*
Marketing Methods										
Gross output growth	-0.052		0.075		-0.065		-0.229		-0.009	
Value added growth	0.384		0.465		0.064		0.066		0.100	
LP-GO growth	-0.212		0.235		0.147		-0.015		0.002	
LP-VA growth	0.189		0.688	*	0.104		-0.189		0.093	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table 8.22

Impacts of Innovation Persistence on Small Food Businesses Performance Growth using Regression on the Derived Balanced Panel: AgriFF Subsector by Type of Innovation

Dependent variable	Persistence (Model 1)								Persistence (Model 2)	
	Highly persistent		Persistent		Regular		Intermittent		Categorical	
Goods and services										
Gross output growth	-0.251		0.139		-0.640		-0.332		-0.111	
Value added growth	0.574		0.321		0.424		-0.011		0.138	
LP-GO growth	0.795		-0.023		0.059		0.089		0.119	
LP-VA growth	0.643		0.238		1.114		0.238		0.214	
Organisational and managerial process										
Gross output growth	0.015		0.146		-0.036		0.056		0.013	
Value added growth	1.567	***	0.619		0.308		0.484	*	0.276	***
LP-GO growth	0.228		-0.136		0.429		0.320		0.074	
LP-VA growth	1.790	**	0.608		0.633		0.503		0.330	**
Operational Process										
Gross output growth	0.045		0.051		-0.831	***	-0.103		-0.064	
Value added growth	0.768		-0.297		0.163		-0.278		0.035	
LP-GO growth	0.516		0.541	*	0.145		0.249		0.141	**
LP-VA growth	1.150	*	-0.164		0.983	**	-0.088		0.179	
Marketing Methods										
Gross output growth	-0.060		0.336		-0.451		-0.742	**	-0.031	
Value added growth	0.106		0.832		0.025		-0.047		0.039	
LP-GO growth	0.506		0.688		0.891	*	0.196		0.182	
LP-VA growth	-0.060		1.293		-0.278		-1.489	**	0.026	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Based of the above findings, we infer that Australian small food businesses that engage in organisational and managerial type of innovation are more likely to be productive than those of non-innovation-active businesses. For those small food business innovators of the organisational and managerial process who were persistently innovating, the likelihood of getting more productive was a reality, regardless of whether they belonged to the AgriFF or the Non-AgriFF subsector. These results are also supported by the ANOVA findings in Tables 8.10–8.12.

The regression results for investigating the association between innovation persistence and business growth for innovation dimension are contained in Appendix G.

8.5 Productivity dispersion analysis of the small food businesses

This section completes the picture of the overall framework in Figure 4.1–the investigation of the dynamics of innovation behaviour, business performance growth and productivity dispersion. We assess the association between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia (i.e., *Research Question 6*) and present them using graphs.

Table 8.23

Impacts of Innovation Persistence on Small Food Businesses Performance Growth using Regression on the Derived Balanced Panel: Non-AgriFF Subsector by Type of Innovation

	Persistence (Model 1)				Persistence (Model 2)
Dependent variable	Highly persistent	Persistent	Regular	Intermittent	Categorical
<u>Goods and services</u>					
Gross output growth	-0.055	-0.022	-0.361	-0.280	-0.021
Value added growth	0.170	-0.267	0.070	-0.545	0.000
LP-GO growth	-0.187	0.121	-0.460	-0.124	-0.029
LP-VA growth	0.009	0.092	0.009	-0.100	0.015
<u>Organisational and managerial process</u>					
Gross output growth	0.266	0.033	-0.045	0.042	0.037
Value added growth	0.835	-0.134	0.879 *	-0.277	0.144
LP-GO growth	0.147	0.385	0.344	0.405 **	0.099
LP-VA growth	0.845	0.453	1.199 **	0.114	0.242 **
<u>Operational Process</u>					
Gross output growth	0.093	-0.003	-0.109	-0.194	0.008
Value added growth	0.263	-0.114	0.151	-0.182	0.045
LP-GO growth	0.266	0.235	-0.070	0.224	0.053
LP-VA growth	0.494	0.190	0.428	0.312	0.118
<u>Marketing Methods</u>					
Gross output growth	0.307	0.157	-0.035	0.206	0.053
Value added growth	0.623	0.448	-0.054	0.132	0.127
LP-GO growth	-0.219	0.192	-0.123	-0.020	-0.014
LP-VA growth	0.191	0.719 *	0.031	-0.049	0.109

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

We use the interquartile range (IQR) to measure productivity dispersion. Recall that IQR shows how many times more productive the upper quartile is than the lower quartile, as shown in equation (4.24). LP-VA is selected for the IQR estimation. Its dispersion represents varying firm contributions to the economy per worker. We test for a significant difference in the mean productivity dispersion between two groups using the Wilcoxon Rank Sum test whereas for more than two groups we used the Kruskal-Wallis test.[41] These two nonparametric tests are appropriate to use because the numbers of observations in the groups are small and we cannot assume a normal distribution for the outcomes (i.e., the IQRs). Also, the subsequent tests confirm the rejection (or not) of *Hypothesis 11*.

When examining the results, it should be noted that the dispersion analysis has been limited to continuing businesses only during the four periods (i.e., not capturing any business entry or exit which are also relevant to analysing aggregate productivity growth).

8.5.1 Productivity dispersion for the food industry and its subsectors

Figure 8.6 shows the estimated LP-VA dispersion (IQR) over time for the food industry balanced sample. Overall, it exhibits a relatively stable trend from 2007/08 and slight increase in 2008/09, implying that the LP of small food businesses in the sample was somehow affected by the global financial crisis. The resulting magnitudes of dispersion here are within the dispersion values in Campbell et al. (2019) though the latter have downward trends (of varying degrees) in selected Australian industries. It is shown in a later subsection that the magnitude of the dispersion here is similar to the noninnovating small food businesses.

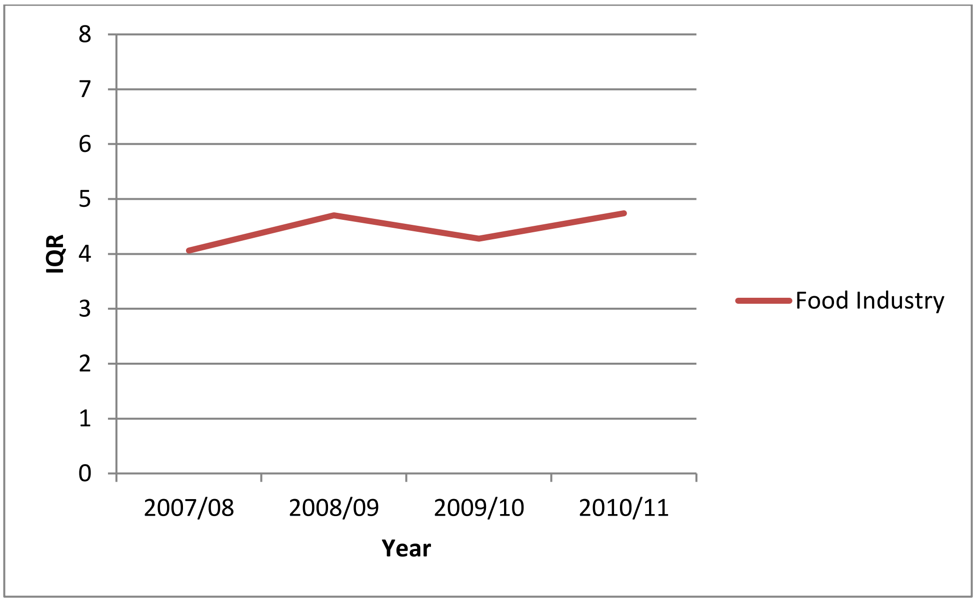


Figure 8.6. Labour productivity dispersion over time (food industry sample)

[41] Readers may refer to Statistics textbook for the description of Wilcoxon Rank Sum and Kruskal-Wallis tests.

Further examination of the dispersion results in the food subsectors, as shown in Figure 8.7, reveal that LP-VA dispersion is relatively stable for the AgriFF subsector but decreases nonetheless. The downward trends in dispersion are due to LP-VA levels for the bottom quartile growing faster than the top quartile. In the case of the non-AgriFF subsector, this dispersion was relatively flat during the first two years of the study period but increased during the later years, creating a huge difference between the two subsectors. The Wilcoxon Rank Sum test in Table 8.24 confirms a significant difference in the average LP-VA dispersion of small food businesses belonging to the AgriFF and the non-AgriFF subsectors. Although not shown in the results, we found that noninnovating small food businesses in the AgriFF subsector have lower LP-VA dispersion pulling the overall dispersion lower than the non-AgriFF subsector.

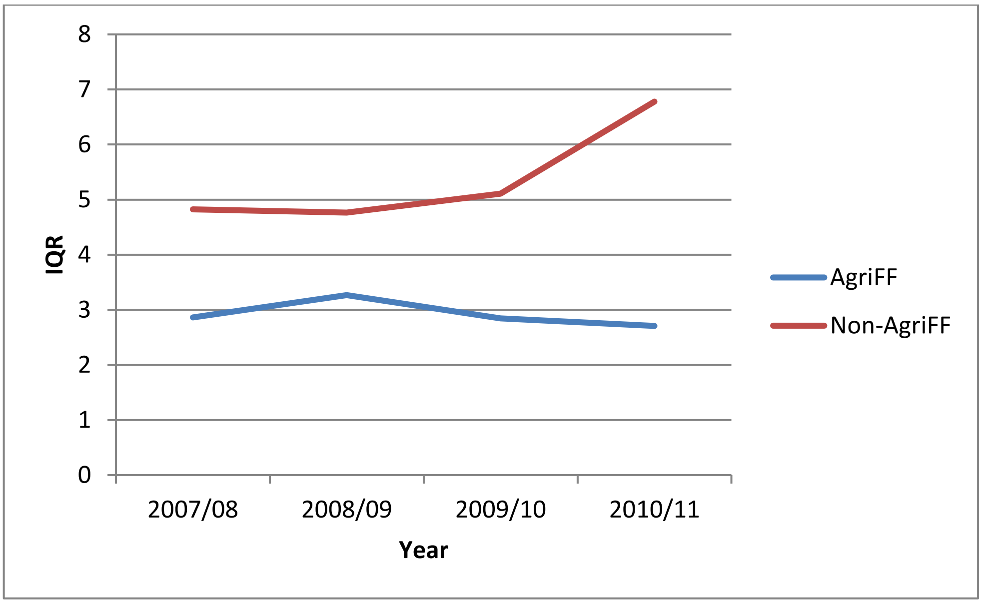


Figure 8.7. Labour productivity dispersion by subsector, 2007/08–2010/11

Table 8.24

Wilcoxon Rank Sum Test Result for Equality of Mean Productivity Dispersion (IQR) on Subsectors

	Z-statistic		*p-value*
AgriFF vs. Non-AgriFF	2.31	**	*0.021*

Note: The asterisks, **, denote significance at the 5% level.

8.5.2 Productivity dispersion by types of innovation

Considering the different types of innovating among small food businesses in the food industry, Figure 8.8 discloses trends for LP-VA dispersion by type of innovation. We see similar patterns for goods and services, and organisational and managerial process innovations. Dispersion in operational process innovation has an increasing trend whereas for marketing innovation it dipped down in 2008/09 then increased thereafter. An interesting finding here is that in all four types of innovation, the estimated dispersions are similar in magnitudes in 2009/10. Overall, small food businesses at the 75th percentile are about twice to four times as productive as those at the 25th percentile. Evidently, the Kruskal-Wallis test result in Table 8.25 depicts a statistically significant difference in the mean labour productivity dispersion within the four periods between the four types of innovation. Productivity dispersions of small food businesses vary between the different types of innovation.

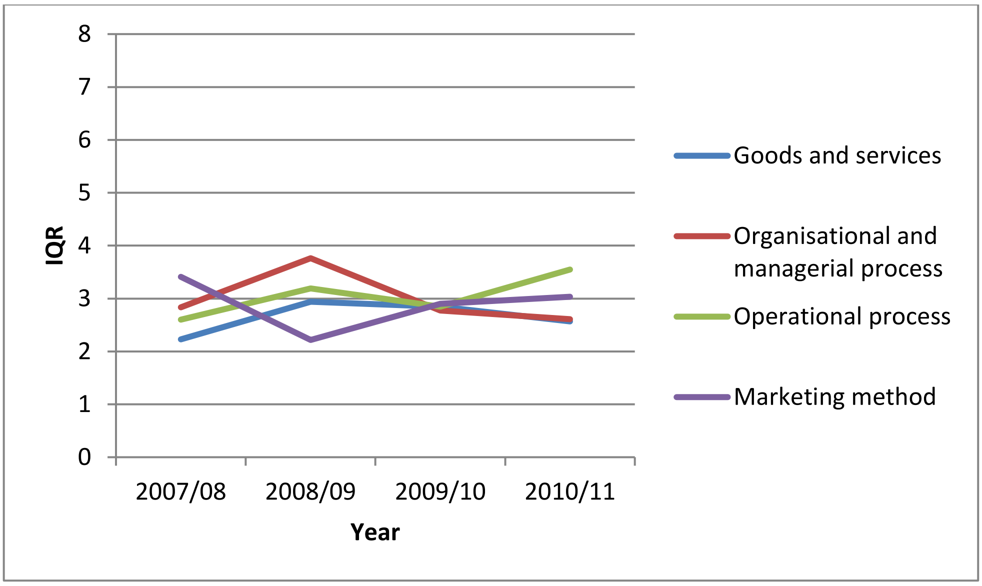


Figure 8.8. Labour productivity dispersion by type of innovation, 2007/08–2010/11

Table 8.25

Kruskal-Wallis Test Results for Equality of Mean Productivity Dispersion (IQR) on Food Industry

	Chi-squared		*p-value*
Between types of innovation	1.56	**	*0.668*
Between degrees of innovation	11.00	**	*0.443*

Note: The asterisks, **, denote significance at the 5% level.

8.5.3 Productivity dispersion for noninnovators, overall and persistent innovators

Figure 8.9 compares LP-VA dispersion by degree of innovation for any type of innovation. The levels of dispersion across the four periods differ between noninnovators, innovators and persistent innovators. Noninnovating small food businesses are more dispersed in terms of labour productivity than innovating businesses. Furthermore, the dispersion was even smaller for persistent innovators. The Wilcoxon Rank Sum test in Table 8.26 verifies that there were statistically significant differences in the mean LP-VA dispersions among the four periods for overall innovators, persistent innovators and noninnovators. The results also prove that when small food businesses engage in any form of innovation, the dispersion of growth in labour productivity levels of the top and bottom quartiles narrows. This finding is consistent with Foster et al. (2018) that innovation dynamics are important drivers of the dispersion in productivity across businesses within a narrowly defined sector such as the food industry.

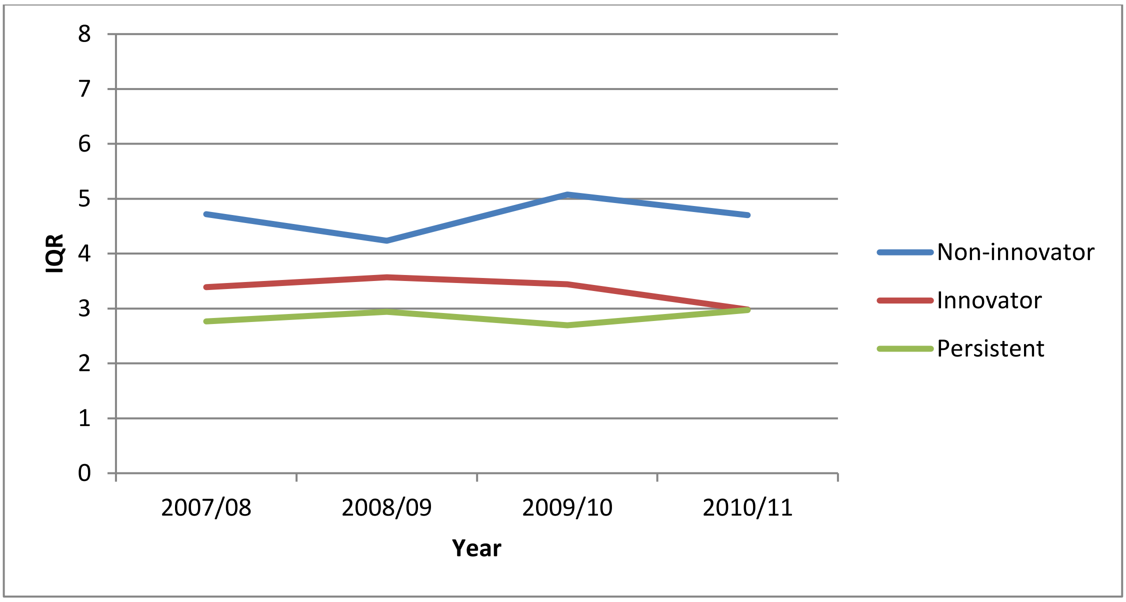


Figure 8.9. Comparison of labour productivity dispersion by degree of innovation, 2007/08–2010/11 (food industry sample)

Table 8.26

Wilcoxon Rank Sum Test Results for Equality of Mean Productivity Dispersion (IQR) for Overall Innovation in Food Industry

	Z-statistics		*p-value*
Innovator vs. noninnovator	2.31	**	*0.021*
Persistent vs. Innovator	2.31	**	*0.021*

Note: The asterisks, ** denote significance at the 5% level.

Considering each of the four different types of innovation, Figure 8.10 compares LP-VA dispersion by degree of innovation. We find similar patterns and results as obtained in Figure 8.9. Thus, whatever form of innovation the small food businesses engage in, persistent innovators have less LP-VA dispersion. Tests reveal that there were statistically significant differences in the mean LP-VA dispersion for the four periods among overall innovators, persistent innovators and noninnovators in each type of innovation (see Tables 8.27–8.28). An exception is marketing innovation where LP-VA dispersions among innovation-active and persistent innovators do not differ significantly.

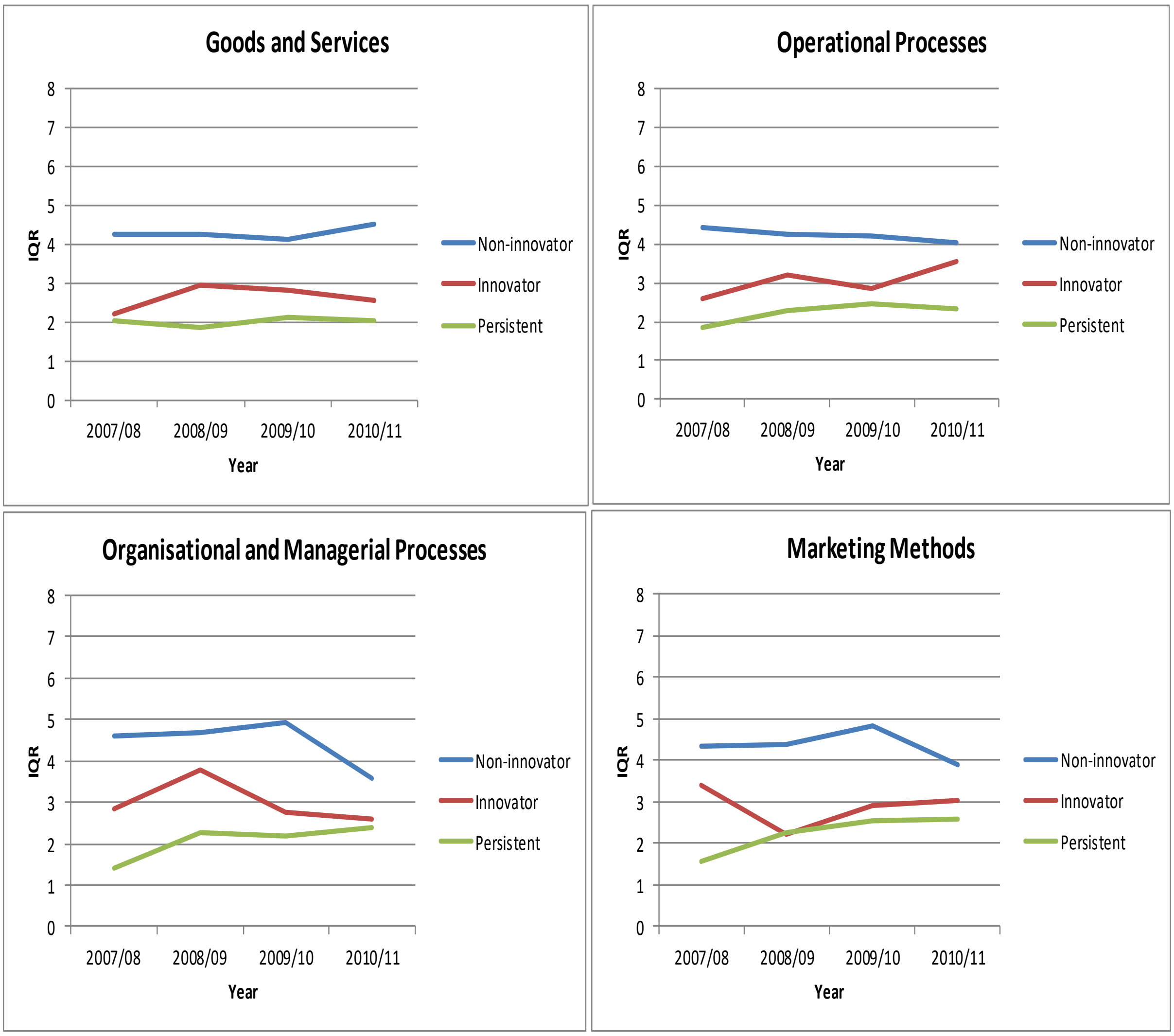


Figure 8.10. Comparison of labour productivity dispersion by type and degree of innovation, 2007/08–2010/11 (food industry sample)

Table 8.27

Kruskal-Wallis Test Results for Equality of Mean Productivity Dispersion (IQR) Between Degrees of Innovation on Food Industry, by Type of Innovation

	Chi-squared		*p-value*
Goods and services	9.85	***	*0.007*
Organisational and managerial process	9.27	***	*0.010*
Operational process	9.85	***	*0.007*
Marketing methods	8.35	**	*0.015*

Note: The asterisks, *** and **, denote significance at the 1% and 5% levels, respectively.

Table 8.28

Wilcoxon Rank Sum Test Results for Equality of Mean Productivity Dispersion (IQR) for Innovator and Noninnovator in Food Industry, by Type of Innovation

	Z-statistic		*p-value*
Innovator vs. noninnovator			
Goods and services	2.31	**	*0.021*
Organisational and managerial process	2.02	**	*0.043*
Operational process	2.31	**	*0.021*
Marketing methods	2.31	**	*0.021*
Persistent vs. innovator			
Goods and services	2.31	**	*0.021*
Organisational and managerial process	2.31	**	*0.021*
Operational process	2.31	**	*0.021*
Marketing methods	1.44		*0.149*

Note: The asterisks, **, denote significance at the 5% level.

8.5.4 Productivity dispersion and innovation persistence

In Figure 8.11, we assess the association between LP-VA dispersion and innovation persistence. For the food industry sample, we found that as the persistence of innovation intensified, LP-VA dispersion among small food businesses reduced. The differences in the mean dispersion between the four levels of innovation persistence were also found to be significant. In addition, the dispersion gaps between the intermittent innovators and highly persistent innovators across all time periods were wider and differ significantly, as supported by the test of equality of means in Table 8.29. These results imply that innovation persistence is an important factor in improving the business performance growth of small food businesses in Australia experiencing low productivity and could help lift aggregate productivity growth in the food sector.

Among the small food businesses in the AgriFF sample and, on average, across periods, we found no significant differences in LP-VA dispersion between the intensities of innovation persistence (see Table 8.29). Explicitly, the variability in dispersion was evident during the last two years of the study period in Figure 8.12. Differences in LP-VA dispersion among the sampled small food businesses in the non-AgriFF subsector are quite clear in Figure 8.13. Moreover, the mean dispersion differs significantly at the 1% level of significance and highly persistent innovators achieved lower productivity dispersion. Interestingly, regular innovators in both the AgriFF and the non-AgriFF subsectors showed an increasing trend of LP-VA dispersion. Based on these findings, the association between labour productivity dispersion and innovation persistence are more evident in the non-AgriFF subsector than in the AgriFF subsector.

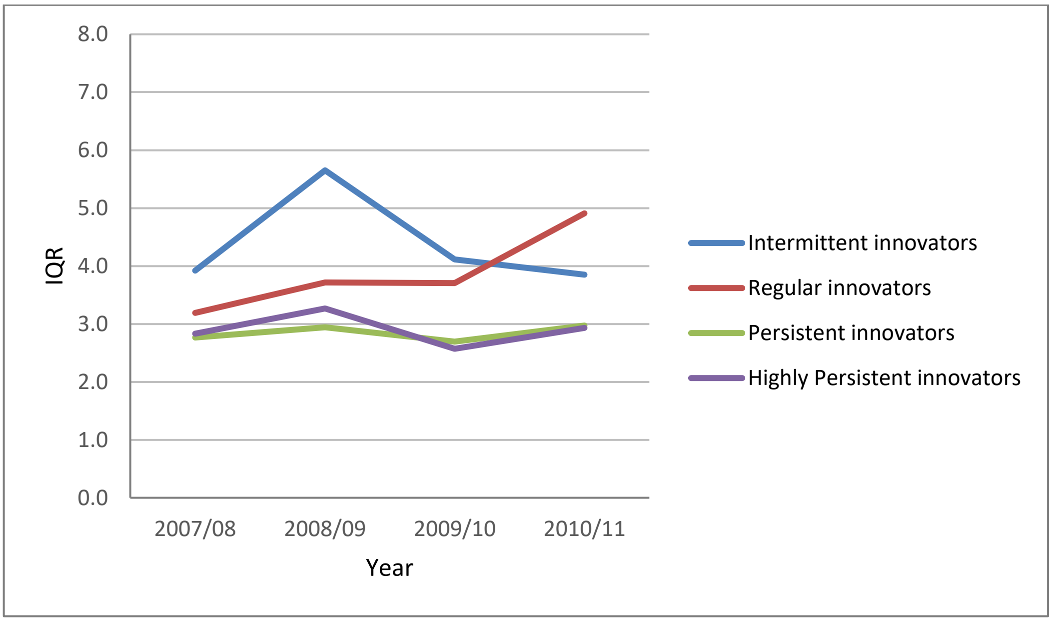


Figure 8.11. Labour productivity dispersion by degree of innovation persistence, 2007/08–2010/11 (food industry sample)

Table 8.29

Kruskal-Wallis and Wilcoxon Rank Sum Tests Results for Equality of Mean Productivity Dispersion (IQR) for Innovation Persistence for the Three Balanced Samples

	Between innovation persistence			Intermittent vs. highly persistent		
Sample	Chi-squared		p-value	Z-statistic		p-value
Food industry	11.27	**	*0.010*	2.31	**	*0.021*
AgriFF	2.58		*0.461*	1.16		*0.248*
Non-AgriFF	6.38	*	*0.095*	2.31	**	*0.021*

Note: The asterisks, ** and *, denote significance at the 5% and 10% levels, respectively.

8.5.5 Key drivers of innovation and productivity dispersion

In the previous subsection, we learned that there is a significant relationship between innovation dynamics and productivity dispersion, particularly in the food industry. In this section, we extend this relationship by looking at the selected key drivers of business innovation (identified in Chapter 6) and assessing their relevance with labour productivity dispersion. We calculated the IQR for LP-VA levels in terms of each key driver. For example, for collaboration, we got the IQRs among small food businesses that collaborate and compared them with the IQRs of businesses that did not engage in any form of collaboration. We repeated the same exercise for STEM skills, labour market flexibility, ICT intensity, export capability and market competition. To the best of the author’s knowledge, this is the first study that examines the relationship between key drivers of innovation and productivity dispersion in the Australian setting.

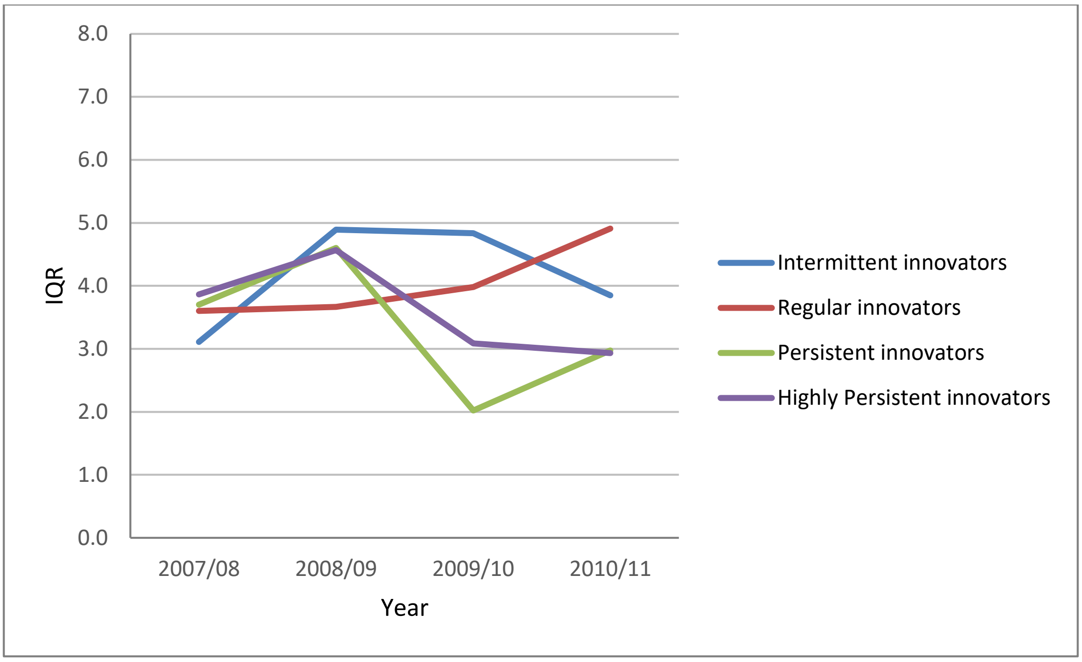


Figure 8.12. Labour productivity dispersion by degree of innovation persistence, 2007/08–2010/11 (AgriFF sample)

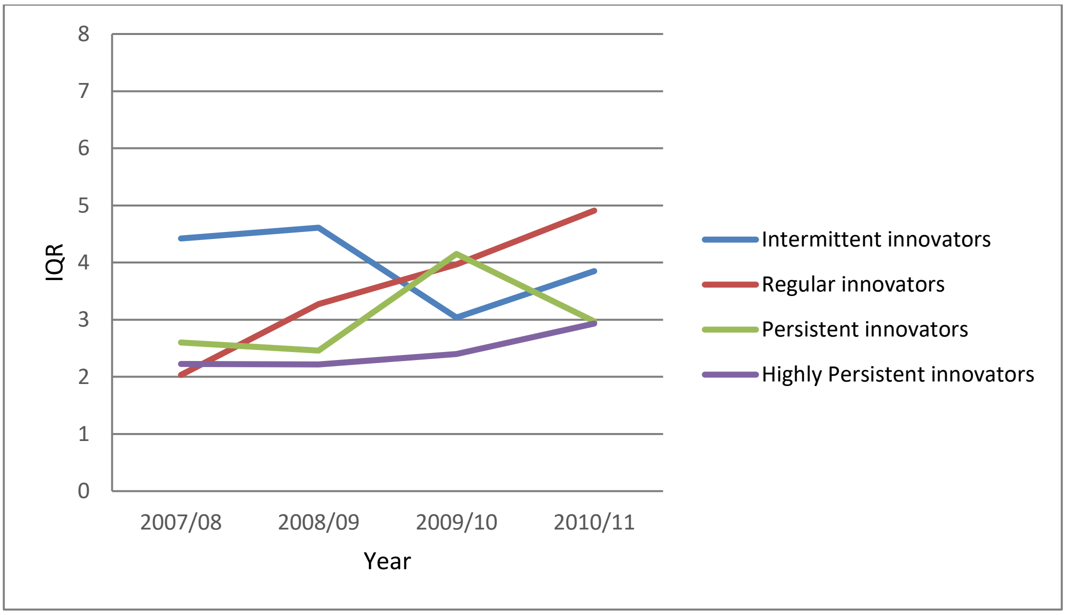


Figure 8.13. Labour productivity dispersion by degree of innovation persistence, 2007/08–2010/11 (Non-AgriFF sample)

Figure 8.14 shows the association between LP-VA dispersion and the six key drivers of innovation. It was found that small food businesses engaging in any form of collaboration have lower LP-VA dispersion than those not collaborating. This is also true for small food businesses where employees have labour market flexibility. In terms of ICT, having high to most ICT intensity decreased the LP-VA dispersion (see Table 8.30 for export capability, where Z=2.31 with p-value=0.021), which is consistent with the findings of Ito and Lechevalier (2009), who found evidence of a significant and positive impact of export intensity on productivity dispersion. On the other hand, we found no significant differences in the mean LP-VA dispersion among small food businesses reporting using employees with STEM skills and Non-STEM skills, despite the fact that we found in section 8.4.3 that those which used STEM skills had significant impact on business performance growth. In terms of market competition, we see the gap in LP-VA dispersion in Figure 8.14 between businesses having no market competition and those facing competition. However, the increasing pattern of dispersion for small food businesses having some degree of competition made the mean dispersion not significantly different from those not facing any market competitor. In contrast, Ito and Lechevalier (2009) used 10 years of business data to show that competition significantly affected productivity dispersion

Table 8.30

Wilcoxon Rank Sum Test Results for Equality of Mean Productivity Dispersion (IQR) for Selected Key Drivers of Innovation in the Food Industry

	Z-statistic		*p-value*
With collaboration	2.31	**	*0.021*
Market competition	1.44		*0.149*
ICT Intensity (High to Most intense)	2.31	**	*0.021*
Used STEM skills	0.29		*0.773*
Export capability	2.31	**	*0.021*
With flexible working arrangements	2.02	**	*0.043*

Note: The asterisks, **, denote significance at the 5% level.

.

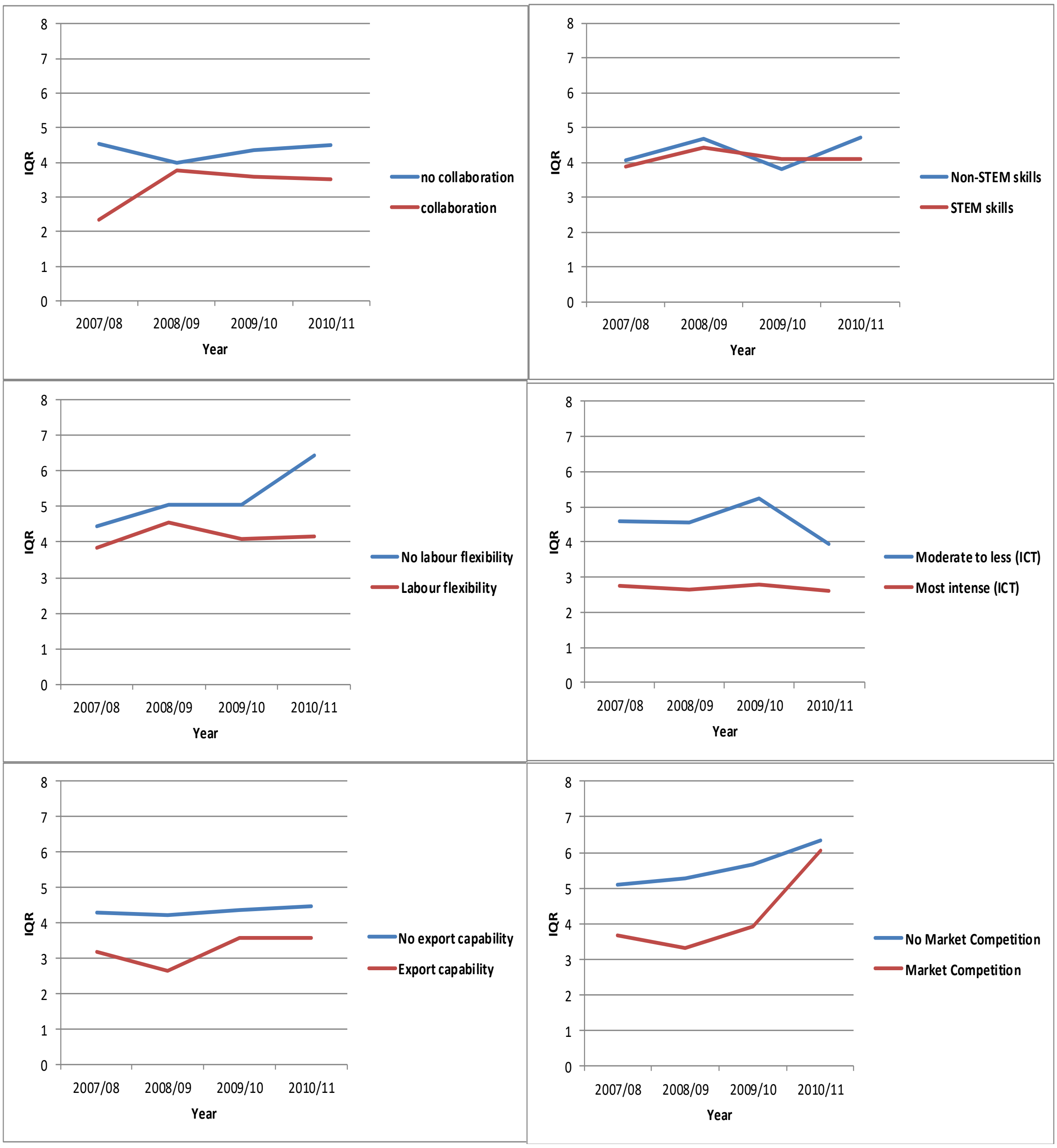


Figure 8.14. Labour productivity dispersion by selected drivers of innovation, 2007/08–2010/11 (food industry)

8.6 Summary of findings

In this chapter, we empirically examined the linkages between innovation persistence, business performance and productivity dispersion in small food businesses in Australia. We further distilled the analysis by looking at persistence behaviour of small food businesses in the goods and services, organisational and managerial processes, operational processes, and marketing methods innovations and determined its impact on performance growth. We also addressed the research question: *Do the Australian small food industry businesses sustain productivity growth if they engaged in any form of innovation?* We utilised four analytical approaches to quantify and test the above relationships.

We established significant association between the business performance measures and key drivers of innovation using the ANOVA and observed that GO, VA and LP-VA are correlated with the following factors: collaboration, market competition, ICT intensity, STEM skills, export capability, and within the sub-sectors to which the small food businesses belong. Gross output and LP-VA are significantly higher for innovators than for noninnovators and they vary among the four types of innovation. When it comes to innovation persistence, the association with the performance growth measures varies with more significant association reflected between the VA and LP-VA and the new processes and marketing methods innovation.

Using the PSM approach with kernel matching, we found evidence that innovation persistence of a particular type of innovation among small food businesses has significant impact on a range of growth outcomes in the food industry. Significant impacts commonly appear among highly persistent innovators. To supplement the PSM results, OLS regression analyses were undertaken to assess the magnitude of the cumulative effect of the persistence of innovation on the four business performance outcomes. The regression findings, coupled with the PSM results, reveal that Australian small food businesses that engage in any particular form of innovation are likely to be more productive than those of noninnovation active businesses (i.e., acceptance of *Hypothesis 9*). Specifically, highly persistent innovation-active small food businesses achieve higher performance growth in terms of VA and LP-VA than non-persistent innovation-active businesses (i.e., acceptance of *Hypothesis 10*) in the food industry and its subsectors. We also found that Australian small food businesses engaging in the organisational and managerial type of innovation are more likely to be productive especially for those who are persistently innovating whether they belong to the AgriFF subsector or the non-AgriFF subsector. This finding is fully supported by the ANOVA results.

The fourth empirical approach applied in this chapter is productivity dispersion analysis. Overall, for the food industry, we found that, on average, small food businesses at the 75th percentile of the LP-VA distribution were around 4.5 times more productive than small food businesses at the 25th percentile. The analysis also established that there is a significant difference in the mean LP-VA dispersion of small food businesses belonging to the AgriFF subsector and non-AgriFF subsector, and the significant association between labour productivity dispersion and innovation persistence was more evident in the non-AgriFF subsector. We also found that LP-VA dispersions among small food businesses varied between the different types of innovation, and whatever form of innovation they engaged in, such that persistent innovators had lower LP-VA dispersion. These findings are consistent with the recent international study on innovation and productivity dispersion by Foster et al. (2018).

In this chapter, we also addressed the research question: *What is the relationship between the key drivers of business innovation, business growth performance and productivity dispersion among small food businesses in Australia?* We found that there are significant associations between business growth performance, labour productivity dispersion and the four key drivers of innovation, namely: having collaboration, having high intense ICT, having flexible working arrangements and export capability. The regression results also show the use of STEM skills and having market competition have significant association with business performance growth.

8.7 Concluding remarks

We have established that innovation drives growth in the performances of the small food businesses in the Australian food industry and that persistent innovation is critical for small food businesses in both the AgriFF subsector and the non-AgriFF subsector. The empirical findings presented show that persistent small food business innovators have improved labour productivity performance compared with less persistent innovators and businesses that are not innovating. Finally, we have confirmed that there is a significant, positive and direct association between the key drivers of business innovation, innovation persistence, business growth performance and productivity dispersion among small food businesses in Australia. These results imply that innovation persistence is an important factor in improving the business performance growth of low productive small food businesses in Australia and could help lift aggregate productivity growth in the food sector.

The next chapter concludes the thesis by providing a synthesis of the results obtained from the various empirical analyses in the study and by integrating the key findings of the various chapters. It delivers an executive summary of important findings, policy implications, recommendations as well as areas for future research.

Chapter 9: Summary, Policy Implications and Conclusion

9.1 Introduction

This chapter provides a synthesis of the key findings of this study and draws some implications and conclusions.

Firstly, in this dissertation we have centred our interest on the small food businesses and how they play some innovative roles in the Australian economy. With the Australian and world population increasing, the demand for food within Australia and the global economy will continue to increase. This implies that there is need for Australian businesses, particularly the small food businesses, to be innovative, competitive and productive to increase the efficiency and effectiveness of food supply to enhance Australia's high level of food security and strong food exports. Improved efficiency and productivity will benefit the small food businesses in Australia through continued innovation, job creation, global competitiveness, and income growth. These benefits would be felt in the form of sustained economic opportunities for farmers, other food manufacturing and service providers, particularly in regional communities.

Secondly, we have verified whether the challenges to improve the small food businesses sector through innovation are currently happening within small food businesses in the Australian food industry. Empirical evidence has been assembled and evaluated on their innovation behaviours, on what drives these behaviours and the associated dynamics, particularly innovation persistence. The impact of innovation on the performance growth of these businesses is also assessed and our findings are linked to the government's innovation agenda and initiatives.

Thirdly, the ABS granted us access to the 2006/07–2010/11 BLD CURF which is the primary database and source of business-level data used in the empirical analyses in this dissertation. This was the last BLD panel to include the food industry component in the longitudinal dataframe capturing additional sampled food businesses in the three relevant industry divisions (i.e., agriculture, forestry and fishing, manufacturing, and wholesale trade), which permitted us to extend the empirical analyses to the AgriFF and non-AgriFF subsectors. The main contribution of this work is its originality and being the first to analyse these food industry sample data which were purposively built-in and funded to be included in the ABS BCS survey by the Australian Department of Agriculture but somehow left untouched. The breadth of the linked information from the ATO tax data and the ABS BCS results in the BLD provided information adequate to appropriately address the four aspects of innovation—the propensity of businesses to innovate; innovation dimensions (new products, new operational processes, new organisational/managerial processes, and new marketing methods); innovation intensity; and innovation persistence—as well as compile and analyse some business performance indicators—gross output, gross value added, labour productivity, and productivity dispersion. It was also a challenge, and worth noting, that all the empirical modellings and analyses for this dissertation were undertaken and completed using the ABS DataLab—a virtual but secured ABS environment where only authorised users, subject to legal compliance and policy, have access. This empirical work also adds to the literature showcasing the analytical use of the ABS confidentialised business survey and administrative microdata.

Fourthly, from a methodological perspective, we note that the richness of the ABS BLD CURF provided greater opportunities for employing the microeconometric techniques, from simple (used for sensitivity analyses) to more complex dynamic panel data and econometric modelling procedures—random effects probit model, pooled probit model, Poisson and negative binomial model, multivariate probit model, transition probability matrix, simple dynamic probit model, dynamic correlated random effects probit model, analysis of variance, propensity score matching, ordinary least squares, productivity measurement and productivity dispersion analysis—thereby, extracting meaningful and valid inferences despite the relatively short period covered in the investigation. Complexity was encountered when dealing with: (1) the lag effects and initial conditions on innovation; (2) the unobserved business-specific effects; and (3) correlation between unobserved heterogeneity and covariates. Nonlinear modelling drove the work to implement additional methods such as panel bootstrapping to arrive at robust standard errors for the estimators. This yielded to another remarkable contribution of this study in the simulation of robust standard errors for the impact measures (APEs) using modern bootstrapping procedures.

Lastly, to the best of my knowledge, this is the first study that has comprehensively and almost exhaustively covered the (technical, measurement and modelling) issues embedded in the CDM model. This was done by empirically testing a large number of hypotheses based on a consistent dataset. In some way, it sets a new benchmark on the research of business innovations and constitutes a contribution to the literature globally. In addition, a comprehensive investigation of the issues in relation to innovation and performance in the small and median businesses in the Australian food industry is also a distinct and valuable contribution to the literature. And finally, the discussion on implications to Australia's innovation policies in the next section are insightful, unique and valuable contribution.

For the rest of this chapter, section 9.2 provides reflection from the analytical findings and their relevant policy and practical implications. Recommendations on opportunities for future research directions follow in section 9.3. The chapter closes in section 9.4 with a brief summary of the significant contributions of this dissertation.

9.2 General discussion and policy implications

As part of the Australian government's Industry Innovation and Competitiveness Agenda, the food and agribusiness industry has been identified as a growth sector having competitive strength and potential to contribute to future economic growth in Australia. In this section, we discuss possible policy implications and possible course of action to strengthen and enhance the impact of innovation in the food and agribusiness industry. It should be noted that the scope of this study does not extend to examining the net social benefits of these individual initiatives. Therefore, there are no definitive policy prescriptions made, rather we identify areas where significant impacts are likely to exist so that policymaking bodies can assess the net social benefits of funding these initiatives.

As an industry that is dominated in terms of number of businesses, there is a need to encourage these small food businesses to innovate to become more competitive and productive. In Chapter 2, our findings revealed that the percentage of noninnovating small food businesses is evidently large (nearly 70 per cent) and, for the innovating businesses, it is 30 per cent. The rates of innovation in goods and services, organisational or managerial processes, and operational processes were also lower compared with the rate of innovation for all small businesses in Australia. In addition, barriers to innovation discourage small businesses from performing any types of innovation. The three most-frequently identified barriers to innovative activity among small food business innovators are a lack of access to additional funds, the cost of developing, introducing and implementing innovation, and government regulations and compliance.

Hence, to boost noninnovating small food businesses to engage in innovation, and for the current innovation-active businesses to sustain their successful innovation performances, the Australian government needs further evidence that would support their innovation initiatives and agenda for growing the Australian food industry. This study provides this evidence and our empirical findings identify the key factors that drive innovation, the dynamics of innovation dimensions and the performance of small food businesses in Australia.

9.2.1 Engaging in collaboration drives small food businesses to innovate

The empirical results presented in Chapters 6 and 7 indicate that collaboration strongly drives different forms of innovation within small food businesses in Australia. These further substantiate the value of collaboration as an important instrument in the Australian innovation system, conforming with the famous evolutionary theory, open innovation, and integration framework. The intensity of innovation significantly increased when small food businesses were involved in any form of collaborative arrangements such as joint R&D, joint buying, joint production of goods and services, integrated supply chains, joint marketing or distribution, and other collaborative arrangements specified by the businesses.

With the current DIIS' flagship programmes to support science, innovation, technology and the commercialisation of new ideas, such as the Industry Growth Centres Initiative and the Cooperative Research Centres Program (CRCP), our findings have several implications for the Australian small business owners as well as for policymakers. Firstly, through the CRCP initiatives, small food businesses have an opportunity to engage with scientists and researchers and other institutions (both domestic and international), say, through free or subsidised workshops, consultations and seminars for workforce skills improvements and capability building leading them to innovate. Another possibility is through the Growth Centre Services programme which provides access to skilled and experienced business advisers to help the small food businesses develop the skills, strategies and connections to accelerate growth in the Australian markets. The latter is more tailored toward organisational or managerial, and operational process innovations.

Secondly, collaboration is an important determinant of competitive advantage, hence, there is a need to support regional small food businesses to innovate and be nationally competitive. Small food businesses through the DIIS' Entrepreneurs' Programme can take advantage of the Business Advice and Facilitation Services to help them improve their growth capabilities and networks, engage with researchers, foster innovation and encourage commercialisation of new products, processes or services (innovations per se).

Thirdly, the results in our study support the government's FIAL initiative as the industry growth centre for the food and agribusiness sector. The insights from FIAL provides a good backdrop and learning framework for the small food business and take advantage of a range of workshops designed to give business owners the knowledge, skills and confidence to market their business. This sort of collaboration is expected to improve the marketing strategies of small businesses that would lead to enhanced marketing methods innovation.

Fourth, the results also support the DIIS-led initiative, the CRCP, which focuses on collaborative research partnerships between industry entities and research organisations. This will strengthen vertical and horizontal alliances between businesses. The CRCP is a potentially useful form of alliance to add value by improving the quality of R&D undertaken and the knowledge and skills of participants. It could also provide an organisational structure through which the DIIS could implement enabling policies. The CRCP through its Global Connection Fund encourages small-sized enterprises to collaborate with researchers on developing and/or testing technologies, products and services, including commercialisation that is good for innovation of products. Another government agenda supported by our findings is the NISA's programme on starting and supporting small businesses to help them establish and grow through increased collaboration. It would be good for the policy analysts to examine the net social benefits of the above mentioned programmes, particularly if they are accommodating the small food businesses.

9.2.2 Employing resources with STEM skills drives small food businesses to innovate

STEM is a driver of innovation. Without people who are educated in the latest science, technology, engineering and mathematics, innovation would be nearly impossible. Our empirical results confirm that having educated and skilled workforces, particularly with STEM capabilities, promotes innovation of any type among small food businesses in Australia. Small food businesses are expected to benefit from skilled and capable employees to properly communicate and exchange ideas with collaborators, partners and customers. The findings in the Australian small food businesses, particularly in their production processes are supported by the human capital theory and resources-based theory.

The Australian government currently supports strong STEM skills as one of the critical requirements for productivity and economic growth through the NISA initiative. The Australian Department of Education reformed their curricula putting priority on STEM subjects to secure the desirable (or necessary) skills needed by the workforce for businesses in the future to encourage more R&D and innovations. The IICA also promotes STEM skills in schools and reforms in the vocational education and training sector. Our results support these two agendas for business innovation. In addition, under the Office of the Chief Scientist initiative, industry businesses are now partnering with schools to improve STEM education to build the workforce of the future and assure the continued competitiveness and prosperity of Australia (Office of the Chief Scientist, 2019).

For small food and agribusiness businesses, not only are STEM skills needed by the employees but also non-STEM skills and capabilities. In Chapter 2, we report that the three most common types of skill shortages or deficiencies are transport, plant and machinery operational skills, trade skills, and financial skills for small businesses in the food and agribusiness sector. Evaluating the significant impacts of the above STEM initiatives are deemed necessary so that policy making bodies can assess the net social gains of funding these initiatives. Another possibility is for inclusion of Technical and Further Education, and Vocational Education and Training in the evaluation framework for improving and enhancing the skills of existing and future labour force in the food industry sector.

9.2.3 Higher ICT intensity drives small food businesses to innovate

The conceptual link between the use of information and communication technology and innovation is consistent with the empirical results presented in Chapters 6 and 7. The small food businesses that have high to most-intense ICT adoption are significantly more likely to innovate. This is evident among the small businesses in the non-Agriff sector compared with those in the AgriFF sector, particularly when it comes to products and marketing methods innovation. These results imply that innovation-active small food businesses in the manufacturing and wholesale trade industries may be utilising sophisticated forms of ICT in their food production, trading and marketing. To invigorate this, small food businesses are encouraged to continually review what ICT options are available and how they can benefit their innovation and business performance. We note that FIAL provides technical and innovation insights, and digital platforms and tools that would be useful for small food business innovation.

Low use of ICT is also reported among small businesses in the food and agribusiness sector in Chapter 2. There is a need for the small food businesses in the agricultural industry to upgrade and invest in ICT to foster innovation. The DIIS IICA through the FIAL initiative has programmes to build better economic infrastructure, such as recalibrating the National Broadband Network and providing good transport infrastructure to stimulate these small businesses to grow and innovate. Currently, the Australian Government provides reliable access on telecommunications infrastructure and Internet connectivity to the farmers and rural-based businesses to enable them to adopt ICT advances so that they can optimise their innovation systems and produce more improved food products and efficient services. Once acquired, it is expected that innovating small food businesses remain innovative and competitive, and noninnovating small food businesses become active innovators in both the domestic and international markets. Also, we note that access to high speed Internet is essential to realising e-business (or e-commerce) particularly for improved product marketing and increasing technology opportunities to the Australian farming community. The ICT initiatives are also areas in which governments in Australia (state and federal) can perform investigations on their net social benefits, particularly for the small regional food farming businesses.

ICT is a key to improving food security (FIAL, 2019a). The FIAL is introducing the digital transformation of agriculture as one of its initiatives, such as precision farming, Internet sensors and data-driven insights. FIAL has forecasted that the market for digital solutions in Australia's agricultural sector to be AU$665 million by 2022. These could be some answers to the demand of a new generation of small food business owners. According to FIAL (2019a), the potential benefits of digital agriculture in the Australian economy is an estimated increase of AU$20.3 billion in agricultural gross value of production as well as an AU$7.4 billion automation and labour savings (e.g., machinery, animal handling and product processing). Moreover, digitalisation in the farming community is expected to attract and retain the brightest of a younger generation in agriculture, living and working in regional and rural communities. The Food Agility Cooperative Research Centre is another government initiative focused on driving the application of digital technologies in the food industry (Food Agility, 2019).

9.2.4 Facing moderate-to-strong market competition pushes small food businesses to innovate

Our empirical findings support the Aghion et al. (2005) theory and the non-Schumpeterian results (i.e., increased market competition is associated with more innovation) in the small food businesses in Australia. Yet again, another area for the policy makers is evaluate current policies and potential initiatives that encourage the development of a domestic and internationally competitive environment leading towards productive small food businesses.

9.2.5 Flexibility in the working arrangements of employees makes small food businesses innovate

A novel contribution of this study is the investigation of the impact of work flexibility on innovation for small food businesses in Australia. Our findings reveal the importance of labour market flexibility to respond to the changing work environment and technological conditions of businesses in the food industry. The four types of flexible working arrangements—flexible working hours, flexible leave, job sharing, and working from home—are playing significant roles in influencing all four types of innovations and these are likely to encourage noninnovators of small food businesses to innovate. Currently, government agencies have started implementing flexible working arrangements but have no formal assessment of the impact of such policy on their work innovations and labour productivity. It would be imperative to have this assessment so that labour market flexibility can also be realised in the small food businesses.

9.2.6 Export capability and financial assistance also influence innovation

Our empirical results indicate significant association between export capability and small businesses undertaking overall innovation or marketing methods innovation in the food industry. Our findings reveal that access to export markets does not influence small food businesses to engage in the goods and services, organisational or managerial process and operational process innovations. It would be beneficial if the Australian government were to assist in the strengthening of export capability and participation (i.e., access to international markets) of small food businesses, particularly in rural and regional areas.

Access to finance is also crucial for undertaking innovations. As discussed in Chapter 3, lack of access to additional funds has been the most commonly-reported barrier to undertaking innovation in Australia (ABS, 2017b). The empirical results in Chapter 6 reveal that small food businesses that sought debt and/or equity forms of financial assistance are more likely to innovate, particularly in operational process innovation. This will evidently support the continued government assistance to enable small food businesses in Australia to sustain their innovation activities. It would be beneficial if the Australian Agricultural Innovation Systems cover small food businesses regarding the provision of financial support for R&D and access to research infrastructure, making the systems more collaborative and demand-driven to increase implementation of innovation activities for these businesses. NISA's initiative on culture and capital (i.e., backing Australian entrepreneurs by opening new sources of finance, embracing risk, taking on innovative ideas, and making more of our public research) may be a step in the right direction in obtaining R&D funding for the small food businesses

9.2.7 Innovation is persistent in small food businesses in Australia

Understanding the impact of persistent innovation is important for strategic management and public policy because, if innovation is persistent in businesses, then government assistance that kick-starts business innovation is expected to have a lasting effect on job creation and economic growth (Hendrickson et al., 2018).

Based on our findings in Chapter 7, there is reason to suggest that innovation persistence among small food businesses is brought about by significant learning and accumulation of knowledge due to their active engagement in collaboration. Until now, we cannot be sure if the argument on the sunk-cost-account hypothesis is supported by our empirical results, but what we can attest is that the small food businesses are utilising the STEM skills of their employees, high ICT intensity and labour force flexibility to continue their innovation activities. The success-breeds-success hypothesis is also supported by the significant effects in our simple dynamic modelling for all the innovation dimensions. Moreover, we find that the degree of persistence among the different types of innovation are dissimilar, which implies that small food businesses do not receive the same supporting theoretical arguments when it comes to their choice of innovative activity. Furthermore, our empirical results indicate that for food industry businesses, the degrees of persistence vary for the different types of innovation with marketing methods having the most significant and strongest persistence. This implies that, for noninnovating small food businesses, if businesses are to introduce new marketing methods, they must be prepared to make long-term commitments on the engagement, because the strong degree of persistence revealed in our results implies that more marketing methods innovation is expected to be realised for them in the future. As for the innovating businesses, it is less of a problem if they do not engage in goods and services innovation.

For policymakers, the fact that innovation behaviour of small food businesses is characterised by true state-dependence evident from the new marketing methods and new operational process implies that innovation-stimulating policy programmes for these two types of innovation open up additional potentially long-lasting effects. These results also highlight the role of innovation capabilities on the dynamics in the innovation behaviour of businesses for implementing new operational processes and new marketing methods in the food industry. If government assistance can be provided to AgriFF small food businesses engaging in products and marketing methods innovations and for non-AgriFF small food businesses engaging in organisational or managerial processes, operational processes and marketing methods innovations, then future innovations in these two subsectors may be sustained.

Our empirical results also confirm that unobserved heterogeneity is a key factor for innovation persistence, implying that there may be some other factors not covered in the modelling that would drive persistence of innovation in small food businesses. The results for the AgriFF and non-AgriFF subsector models also indicate that the allowance for correlation between unobserved heterogeneity and the regressors is important for the current small food businesses data. For the food industry, transitional probabilities indicate an overall presence of innovation persistence among innovating small food businesses despite their difficulties to engage in any particular type of innovation.

9.2.8 Innovation persistence improves business performance

In Chapter 8, we classify small food businesses according to the number of times they reported in the four-year panel that they introduced or implemented any new or significantly improved innovations, namely, were intermittent, regular, persistent, highly-persistent innovators and persistent noninnovators. The empirical results in Chapter 8 reveal that Australian small food businesses that engage in any type of innovation may increase performance growth more than those of noninnovation-active businesses. This is more evident for highly-persistent innovation-active small food businesses that have higher performance growth (in terms of value added and labour productivity–value-added based) compared with persistent noninnovation-active businesses in the food industry as well as within the AgriFF and non-AgriFF subsectors. For the food industry, the propensity score matching procedure found significant positive impacts on both the gross output and value-added growth for highly-persistent innovators but the labour productivity growth showed no statistically significant effects for any of the innovation persistence treatments. We have evidence that Australian innovation-active small food businesses are more productive. It is imperative to provide enabling environment to encourage these businesses to sustain their innovation activities.

It is worth looking at important government programmes that may be able to facilitate the small food businesses to innovate and be productive. The Australian Department of Agriculture currently has a programme that may help both innovators and noninnovators among small food businesses to boost their productivity and competitiveness. This is the Regional Food Producers' Innovation and Productivity Program (RFPIPP) that provides grants to regional food and seafood industries for innovation and technology improvements.[42] The DIIS' Entrepreneurs' Programme, which is the Australian Government's flagship initiative for business competitiveness and productivity, offers support to small businesses through four elements (DIIS, 2019):

- *Accelerating Commercialisation*—helps small- and medium-sized businesses, entrepreneurs and researchers to commercialise new products, services and processes;
- *Business Management*—provides access to a national network of experienced business advisers and facilitators to assist businesses to improve their business practices, become more competitive, and take advantage of growth and collaboration opportunities to increase their business capability to trade in Australian markets and/or markets in other countries;
- *Incubator Support*—assists new and existing incubators to improve the prospects of Australian start-ups achieving commercial success in international markets, through helping them to develop their business capabilities;
- *Innovation Connections*—with experienced innovation facilitators who work with businesses to identify knowledge gaps that inhibit their business growth.

9.2.9 Innovation impacts labour productivity dispersion

The empirical results in Chapter 8 indicate that the identified key drivers of business innovation and innovation persistence are important factors in potentially improving the business performance growth of less-productive small food businesses in Australia and could help lift aggregate productivity growth in the food industry. Understanding what influences the heterogeneity of the productivity performance of businesses can inform the potential productivity-enhancing policies needed to generate income growth and create jobs, particularly for small food businesses in Australia. Policies that promote innovation may increase productivity dispersion by lifting performance at the top end of the productivity distribution but, based on our empirical results, engaging in one or more of the four types of innovation lifts performance at the lower end of the labour productivity distribution, in this case, increasing aggregate productivity growth. Policies that would encourage noninnovating small food

[42] Innovation and technology improvements include: the design and implementation of new technologies, production or processing techniques; the adoption of food production or processing technologies developed overseas; the innovative redesign of existing production/processing lines to improve efficiencies and productivity.

businesses to become innovation-active are necessary to achieve positive productivity growth in the food industry, particularly for the businesses belonging to the AgriFF subsector.

The current work complements the pioneering work of Foster et al. (2018) in examining the relationship between innovation, productivity dispersion and productivity growth.

9.3 Implications for future research

Our empirical study has been limited by the food businesses data available for modelling, but offers opportunities for further research in terms of potential data sources and in refinements in methodologies, as outlined below.

In this study, we utilised the confidentialised BLD CURF from the ABS. The only business-level data that are currently accessible to approved external university researchers, hence the empirical applications are limited to the data items available in the ABS BLD. An alternative source of data is the Business Longitudinal Analysis Data Environment (BLADE). The Australian Government's Data Integration Partnership for Australia (DIPA)[43] project has just recently established BLADE—an integrated data resource which is a core component of the DIPA. The BLADE is a method for converting administratively reported data on an Australian Business Number (ABN) level into business units as defined by the ABS. It is also an environment for rationalising unit constructions in surveys and administrative datasets so they can be brought together for longitudinal analysis.[44] It was formerly known as the Expanded Analytical Business Longitudinal Database (see ABS, 2015e) which integrates all active Australian businesses' administrative data from the ATO with the collected survey data from the ABS using the ABS Business Register as the integrating spine. The ABN is used as the primary linking variable. The BLADE is developed to enable a better understanding of the

---

[43] DIPA is a whole-of-government initiative to make better use of existing public data. DIPA's goal is to inform the development of emerging social, economic, and environmental policy priorities and improve the delivery of government services. The ABS plays an important role in DIPA by: combining public data, as authorised by law; providing access to authorised users in specialised research units; providing a secure environment for analysis; managing the safe and secure storage of data; and expanding existing Commonwealth data integration projects to include new data sources (see ABS (2019d) for more information on BLADE and DIPA).

[44] The BLADE was initially created to enable Australia's participation in the OECD's Dynamics of Employment (DynEMP) and Micro Drivers of Productivity (MultiProd) projects as well as to provide a solid evidence base for productivity analysis, policy development and evaluation of its stakeholders. The BLADE has been developed by ABS in partnership with the Department of Industry, Innovation and Science (DIIS) which also provided financial support. Please refer to Hansell and Rafi (2018) for more information about the use of BLADE.

Australian economy, through statistical analysis to assist the research community undertake analysis and improve the evidence base for policy development and evaluation (DIIS, 2017b).

It is expected that the analysis using BLADE will complement the results in this study. With the creation of BLADE providing additional information for productivity type analysis, the business performance measures adopted in the current study can be revisited if improved volume measures of gross output and value-added including appropriate price deflators can be made available. With longer periods (i.e., 2000 onwards) covered by the BLADE data, linkages between innovation inputs, innovation outputs and productivity using the dynamic CDM is another candidate for future investigation. Moreover, the possibility of creating multifactor productivity that would account for both labour and capital inputs as well as the expansion of the additional factors (like managerial ability, R&D intensity, patents) and an improved ICT intensity measures using the integrated data in BLADE are various addition for future exploration and analysis by other researchers.

BLADE is currently being expanded to include new sources of data to meet the research priorities of the Department of Agriculture and Water Resources, and sources of data being explored for potential inclusion is the ABS Agricultural Census and the Rural Environment and Agricultural Commodities Survey datasets. Once these data are integrated with the BLADE, which also happen to contain the ATO's Pay as you go (PAYG) data, the combined data will enable possible research avenues utilising all registered businesses–small, medium and large–in the food and agribusiness industry. It would be good to compare the dynamics of innovation and performance in large or complex food businesses with the current study making use of BLADE. Another potential research study with these data would be to incorporate the food commodities, business entry/exit and some environmental variables (such as farm locations and water availability) in the dynamic modelling and analysis of innovation.

In the Diakosavvas & Frezal (2019) report, one of the structural challenges in the Australian food and agricultural sector is the increasing differences between small and large farms; hence, the use of the above newly integrated agricultural data with BLADE can be addressed with focus on innovation and performance growth. In the same report, the productivity challenge in Australia is to examine the availability of new technology and its impact on productivity growth which the current study has already addressed for small food businesses, but it is desirable to obtain evidence also from complex businesses. Analysing the dynamic linkages between innovation inputs (particularly R&D and investment on new technology), innovation outputs and business performance in the food industry using the Crépon, Duguet and Mairesse methodology may be viable using BLADE.

In terms of evaluating the effectiveness of the DIIS innovation initiatives for the small food businesses, it would be good if the DIIS could link their administrative data containing all those small food businesses participating in the program with BLADE under the DIPA project. In this way, authorised BLADE researchers could directly assess the impact of the government innovation initiatives on small food businesses. Another important government initiative in relation to innovation—the R&D tax incentive for businesses—can be analysed using the BLADE data. It would be necessary if policy analysts can assess the benefits of availing of R&D tax incentives to stimulate investment in R&D of small food businesses. There is evidence showing that R&D is often the first vital step in innovation, driving technological improvements that lead to productivity improvements and increased economic growth. If found beneficial, small food businesses can be encouraged to invest in R&D for goods and services, organisational or managerial processes, operational processes and marketing methods innovations. Currently, DIIS is looking at the impact of the Research & Development Tax Incentive on the composition and success of research using BLADE. Such a research project would assess whether the R&D Tax Incentive programme is leading to an increase in expenditure on R&D and whether it affects the composition of R&D conducted by Australian firms. The findings from this work could help to improve targeting and efficacy of government support for businesses.

For future work, looking at the dollars spent on pursuing the different government policies to support innovation is also important. The current study finds support for the general policies but does not include a demonstration of assessing the net social benefit as mentioned earlier. The government might have the general strategy right but might be pursuing it with the wrong priorities with the wrong amount of money relative to the benefit, hence, providing evidence on the effectiveness of the levels of support is the next step that will lead to this research agenda having real policy impact utilising BLADE and/or other administrative data.

As discussed in the overall conceptual framework, the current study covers the direct impact of innovation on business performance but the reverse relationship (i.e., how productivity influenced business innovation) is also a future extension for investigation, if possible using the BLADE data. Moreover, the analysis on the impact of innovation on productivity dispersion has been limited in the BLD CURF but can be expanded using BLADE following the work of

Campbell et al. (2019). The BLADE can possibly cover all the industries in the market sector of the economy where the interaction between the food industries (as dummy variable) with innovation outputs can be examined on modelling productivity dispersion.

For all the above-mentioned research extensions to be undertaken would require ABS support in the provision of ANZSIC food business identifiers in the BLADE integrated data.

To date, only ABS authorised researchers can access de-identified BLADE data for policy analysis, research, and statistical purposes. Access to BLADE microdata are currently being managed by the ABS to protect privacy and confidentiality; hence, authorised researchers are limited to ABS staff or persons from the government agencies who are seconded to the ABS. Under current arrangements, government employees, government contractors, and individuals sponsored by government (including academics), who are working on approved research projects, can apply to access BLADE microdata. However, section 15 of the Census and Statistics Determination 2018 (Information Release and Access) enables the Australian Statistician to provide access to other individuals for statistical or research purposes.

9.4 Conclusion

Small food businesses play a significant role in the Australian economy by creating jobs and businesses and offering service opportunities to the regional economies to ensure food security and meet the growing consumer demand. This dissertation establishes the dynamic relationships between the determinants of innovation, innovation persistence, business performance growth and changes in labour productivity dispersion to distinguish between four types of innovation (new goods and services, new organisational or managerial processes, new operational processes, and new marketing methods) within small businesses in the Australian food industry. This is the unique contribution of this research because no previous Australian study has examined this dynamism.

From a methodological perspective, this is the first study that has comprehensively and almost exhaustively covered the technical, measurement and modelling issues embedded in the CDM model. Analysing labour productivity dispersion using the ABS BLD CURF is relatively new, particularly when relating to the key drivers of innovation and innovation persistence by types of innovation. Providing empirical evidence that connects innovation behaviour and productivity dispersion in the small food business is also an added novelty to the recently growing body of literature on agriculture industry productivity dynamics.

From an empirical and practical perspective, our findings underscore the importance of understanding the key drivers of innovation; enabling environment; and for creating an appropriate platform for policy design, support and development, all of which are essential so that small food businesses are able to collaborate, innovate and contribute to a productive and progressive Australian economy. The current study is a significant addition to the empirical literature on food industry innovation, but a study on small food businesses in the AgriFF subsector using firm-level data is desirable to support the agricultural innovation systems. The empirical results from this study may support the government's policies and investments in growing the Australian food industry.

This study has provided empirical evidence that supports the Australian government's innovation agenda and initiatives that would motivate and trigger the small food businesses in Australia to start and/or continue to engage in innovation through development of new products or services, new operational processes, new marketing strategies and methods, and new organisational or managerial processes, for job creation, global competitiveness, and income growth. Finally, the results of this study may provide potential inputs to the 2019/20 DIIS' BLADE research project on assessing the impact of the Industry Growth Centre programme (particularly in the Food and Agribusiness Growth Sector) and the 2019/20 Productivity Commission's BLADE research project on firm-level insights into Australia's productivity performance, such as in evaluating the contribution of small businesses to the agricultural and manufacturing industry productivity growth (ABS, 2019e).

References

Aghion, P., Bergeaud, A., Lequin, M., & Melitz, M. (2018). *The impact of exports on innovation: theory and evidence.* NBER Working Paper No. 24600, National Bureau of Economic Research, Cambridge, MA.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: an inverted-U relationship. *Quarterly Journal of Economics*, 120, 701–728.

Aghion, P., & Howitt, P. (2009). *The Economics of Growth*. Cambridge, MA: MIT Press.

Alfranca, O., Rama, R., & von Tunzelmann, N. (2003). Competitive behaviour, design and technical innovation in food and beverage multinationals. *Int. J. Biotechnology*, *5*(3/4), 222–248.

Allison, P.D., & Waterman, R. (2002). Fixed-effects Negative Binomial regression models. Sociological Methodology, 32, 247–265.

Almus, S, & Czarnitzki, D. (2003). The effects of public R&D subsidies on firm's innovation activities: the case of Eastern Germany. Journal of Economic Statistics, 21(1), 226–236.

Altuzarra, A. (2017). Are there differences in persistence across different innovation measures? Innovation, 19(3), 353–371. DOI: 10.1080/14479338.2017.1331911

Andrews, D., Criscuolo, C., & Gal, P. (2016). The global productivity slowdown, technology divergence and public policy: a firm level perspective. OECD Productivity Working Papers, No 5., Paris.

Anthill. (2018). What is keeping business owners up at night? These are the top 10 challenges small business are facing in 2016. *Anthill Magazine*, 29 Jan 2016.

Antonelli, C., Crespi, F., & Scellato, G. (2012). Inside innovation persistence: New evidence from Italian micro-data. *Structural Change and Economic Dynamics*, *23*, 341– 353.

Antonelli C., Crespi, F., & Scellato, G. (2013). Internal and external factors in innovation persistence. *Economics of Innovation and New Technology*, *22*(3), 256–280.

Atkinson, J. (1984). *Manpower strategies for flexible organisations.* IMS Report No. 89. Institute of Manpower Studies, University of Sussex, Brighton.

Australian Bureau of Statistics. (2001). *Australian Standard Classification of Education (ASCED), 2001* (cat. no. 1292.0). Retrieve from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2002). *Small Business in Australia, 2001* (cat. no. 1321.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2006). *Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006* (cat. no. 1292.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2008). *Key Aspects of Innovation in Australian Businesses: Micro-Data Analysis of the 2003 and 2005 Innovation Surveys.* ABS Submission to the Review of the National Innovation System, Australian Bureau of Statistics, Canberra, ACT.

Australian Bureau of Statistics. (2013). *Microdata: Business Longitudinal Database, Australia 2006–07 to 2010–11* (cat. no. 8168.0.55.001). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015a). *Selected Characteristics of Australian Business, 2013–14* (cat. no. 8167.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015b). *Australian Industry, 2013–14* (cat. no. 8155.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015c). *Summary of IT Use and Innovation in Australian Business, 2013–14* (cat. no. 8166.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015d). *Summary of IT Use and Innovation in Selected Growth Sectors, Australia, 2013–14* (cat. no. 8166.0.80.001). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015f). *Characteristics of Businesses in Selected Growth Sectors Australia, 2013–2014* (cat. no. 8170.0). Retrieve from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2015e). *Information Paper: Construction of the Expanded Analytical Business Longitudinal Database, 2001–02 to 2012–13* (cat. no. 8171.0). Retrieve from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2017a). *Selected Characteristics of Australian Business 2015–2016* (cat. no. 8167.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2017b). *Summary of IT Use and Innovation in Australian Business, 2015–2016* (cat. no. 8166.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2017c). *Household Expenditure Survey, Australia: Summary of Results, 2015–2016* (cat. no. 6530.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2019a). *Counts of Australian Businesses, including Entries and Exits, June 2014 to June 2018* (cat. no. 8165.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2019b). *Australian Industry, 2017–2018* (cat. no. 8155.0). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2019c). *Characteristics of Australian Exporters, 2017–2018* (cat. no. 5368.0.55.006). Retrieved from http://www.abs.gov.au/ausstats

Australian Bureau of Statistics. (2019d). Data Integration Partnership for Australia. Retrieved from https://www.abs.gov.au/websitedbs/D3310114.nsf/home/Statistical+Data+Integration+-+Partnership+for+Australia+DIPA

Australian Bureau of Statistics. (2019e). Business Longitudinal Analysis Data Environment Research Projects. Retrieved from https://www.abs.gov.au/websitedbs/D3310114.nsf/home/Statistical+Data+Integration+-+BLADE+Research+Projects

Australian Securities and Investments Commission. (2013). *What is small business?* VIC: Author. Retrieved from https://asic.gov.au/for-business/your-business/small-business/small-business-overview

Australian Workforce and Productivity Agency (2013). *Human Capital and Productivity: Literature Review*. Canberra, ACT: Author.

Avermaete, T., Viaene, J., Morgan, E.J., & Crawford, N. (2003). Determinants of innovation in small food firms. *European Journal of Innovation Management, 6*, 8–17.

Avermaete, T., Viaene, J., Morgan, E.J., Pitts, E., Crawford, N., & Mahon, D. (2004). Determinants of product and process innovation in small food manufacturing firms. *Trends in Food Science and Technology*, *15*, 474–483.

Baregheh, A., Rowley, J., Sambrook, S., & Davies, D. (2012). Innovation in food sector SMEs. *Journal of Small Business and Enterprise Development, 19*, 300–321.

Bartelsman, E.J., & Doms, M. (2000). Understanding productivity: lessons from longitudinal microdata. *Journal of Economic Literature*, *28*, 569–594.

Bartelsman, E.J., & Wolf, Z. (2017). *Measuring productivity dispersion*. Tinbergen Institute Discussion Paper, 17-033/VI, Tinbergen Institute, Netherlands.

Bartoloni, E., & Baussola, M. (2017). Driving business performance: innovation complementarities and persistence patterns. *Industry and Innovation*. doi:10.1080/13662716.2017.1327843

Beatson, M. (1995). *Labour market flexibility*. Research Series No. 48, Employment Department, Moorfoot, Sheffield.

Becker, G.S. (1994). *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, 3rd edition.* National Bureau of Economic Research, Cambridge, MA: The University of Chicago Press.

Benavente, M. (2006). The Role of Research and Innovation in Promoting Productivity in Chile. Economics of Innovation and New Technology, 15(4-5), 301-315.

Berlingieri, G., Blanchenay, P., Calligaris, S., & Criscuolo, C. (2017). Firm-level productivity differences: insights from the OECD's multiProd project. *International Productivity Monitor*, (32), Spring 2017.

Bhattacharya, M., & Bloch, H. (2004). Determinants of innovation. *Small Business Economics*, *22*, 155–162.

Bhuiyan, A.B., Said, J., Ismail, M., Jani, M.F.M., & Fie, D.Y.G. (2016). The innovation drivers, strategies and performance of food processing SMEs in Malaysia. *Geografia-Malaysian Journal of Society and Space,* (12)2, 154 – 166.

Bianchini, S., & Pellegrino, G. (2017). Innovation persistence and employment dynamics. Institut d'Economia de Barcelona Working Paper N. 2017/03. Retrieved from https://ssrn.com/abstract=2919290 or http://dx.doi.org/10.2139/ssrn.2919290

Bigliardi, B., & Galati, F. (2013). Models of adoption of open innovation within the food industry. *Trends in Food Science & Technology, 30*, 16–26.

Bigliardi, B., & Galati, F. (2016). Which factors hinder the adoption of open innovation in SMEs?. *Technology Analysis & Strategic Management*, *28*, 869–885.

Bland, S., & Will, L. (2001). *Resource movements and labour productivity, an Australian illustration: 1994–95 to 1997–98*. Productivity Commission Staff Research Paper, AusInfo, Canberra.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*, 115–143.

Blundell, R., Griffith, R., & Van Reenen, J. (1995). Dynamic count data models of technological innovation. *The Economic Journal*, *105*(429), 333–344.

Blundell, R.W., & Smith, R.J. (1991). Initial conditions and efficient estimation in dynamic panel data models. *Annales d'Economie et de Statistique*, *20/21*, 109–123.

Brown, J.D., Dinlersoz, E., & Earle, S. (2016). *Does higher productivity dispersion imply greater misallocation? A theoretical and empirical analysis.* US Census Bureau Center for Economic Studies Paper No. CES-WP-16-42.

Brown, P., & Roper, S. (2017). Innovation and networks in New Zealand farming, *Australian Journal of Agricultural and Resource Economics,* 61, 422–442.

Brunker, D., & Orzechowska-Fischer, E. (2008). An analysis of developments in skills shortages that hampered innovation using the 2003 and 2005 Australian innovation surveys. Paper presented at the July 2008 ESAM – Wellington, ABS Canberra.

Cahill, S., Rich, T., & Cozzarin, B. (2015). Innovation in the Canadian food processing industry: Evidence from the workplace and employee survey. *International Food and Agribusiness Management Review*, *18*(2), 131–152.

Caiazza, R., & Stanton, J. (2016). The effect of strategic partnership on innovation: an empirical analysis. *Trends in Food Science & Technology, 54,* 208–212.

Caliendo, M., & Kopenig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31–72.

Campbell, S., Nguyen, T., Sibelle, A., & Soriano, F. (2019). *Measuring productivity dispersion in selected Australian industries*. Treasury-ABS Working Paper, 2019-02, The Treasury, Canberra.

Capitanio, F., Coppola, A., & Pascucci, S. (2009). Indications for drivers of innovation in the food sector. *British Food Journal*, *111*, 820–838.

Capitanio, F., Coppola, A., & Pascucci, S. (2010). Product and process innovation in the Italian food industry. *Agribusiness, 26*, 503–518.

Cappellari, L., & Jenkins, P. (2003). Multivariate probit regression using simulated maximum likelihood. *The Stata Journal, 3*, 278–294.

Cardamone, P., Pupo, V., & Ricotta, F. (2018). Exploring the relationship between university and innovation: evidence from the Italian food industry. *International Review of Applied Economics*, 32:5, 673–696. DOI: 10.1080/02692171.2017.1357681

Cefis, E. (2003a). Persistence in innovation and profitability, Rivista Internazionale di Scienze Sociali (111) *1*, 19–37. Retrieved from https://www.jstor.org/stable/41624117

Cefis, Elena. (2003b). Is There Persistence in Innovative Activities? *International Journal of Industrial Organization*, 21, 489–515. doi:10.1016/S0167-7187(02)00090-5.

Cefis, E., & Marsili, O. (2019). Good times, bad times: innovation and survival over the business cycle. *Industrial and Corporate Change*, *28*(3), 565–587. https://doi.org/10.1093/icc/dty072

Cefis, E., & Ciccarelli, M. (2005). Profit Differentials and Innovation. *Economics of Innovation and New Technology*, *14*(1–2), 43–61. doi:10.1080/1043859042000232160

Cefis, E., & Orsenigo, L. (2001). The Persistence of innovative activities: a cross-countries and cross-sectors comparative analysis. *Research Policy, 30*, 1139–58. doi:10.1016/S0048-7333(00)00139-6.

Chamberlain, G. (1984). Panel data. In Z. Griliches & M. Intriligator (Eds), *Handbook of Econometrics 2,* (pp. 1247–1318), Amsterdam: North-Holland.

Chaustowski, R., & Dolman, S. (2016). *Australia's food and agribusiness sector – data profile.* Economic and Analytical Services Division Paper. Department of Industry, Innovation and Science, Canberra, ACT.

Chesbrough, H. W. (2003). The era of open innovation. *MIT Sloan Management Review*, *44*, 35–41. Massachusetts Institute of Technology, Cambridge, MA.

Chung, H. (2009*). Flexibility for Whom? Working Time Flexibility Practices of European Companies.* Tilburg University, Tilburg.

Ciliberti, S., Carraresi, L., & Bröring, S. (2016a). Drivers of innovation in Italy: food versus pharmaceutical industry. *British Food Journal, 118*, 1292–1316.

Ciliberti, S., Carraresi, L., & Bröring, S. (2016b). External knowledge sources as drivers for cross-industry innovation in the Italian food sector: does company size matter?. *International Food and Agribusiness Management Review, 9*, 77–98.

Clausen, T., Pohjola, M, Sapprasert, K., & Verspagen, B. (2012). Innovation strategies as a source of persistent innovation. *Industrial and Corporate Change*, *21*(3), 553–585.

Cobbold, T. (2003). *A comparison of gross output and value-added methods of productivity estimation.* Productivity Commission Research Memorandum, Canberra.

Coca-Perraillon, M. (2006). *Matching with propensity scores to reduce bias in observational studies.* Paper presented at the 19th Annual NESUG Conference, Philadelphia, PA.

Cohen, W.M., & Klepper, S. (1996). Firm size and the nature of innovation within industries: the case of process and product R&D. The Review of Economics and Statistics, 232–243.

Cohen, W.M., & Levinthal, D.A. (1990). Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly*,128–152.

Colombelli, A., & von Tunzelmann, N. (2011). The persistence of innovation and path dependence. In C. Antonelli (Ed), Handbook on the Economic Complexity of Technological Change, Chapter 4, Edward Elgar Publishing.

Connolly, E., & Fox, K. (2014). *The impact of high-tech capital on productivity: evidence from Australia.* Paper presented at the 2003 Economic Measurement Group Workshop, UNSW CAER, Sydney.

Connolly, G., Trott, D., & Li, Y. (2012). *Workplace agreements and other determinants of labour productivity.* Paper presented to the 23rd Australian Labour Market Research Workshop, Swan Valley Oasis Resort, Henley Brook, Perth.

Correa, J. A. (2012). Innovation and competition: an unstable relationship. *Journal of Applied Econometrics, 27*, 160–166.

Crépon, B., & Duguet, E. (1997). Estimating the innovation function from the patent numbers: GMM on count panel data. Journal of Applied Econometrics, 12, 243–263.

Crepon, B., Duguet, E., & Mairesse, J. (1998). *Research, innovation, and productivity: an econometric analysis at the firm level*. Working Paper 6696, National Bureau of Economic Research, Cambridge, MA.

Crisculo, C., Haskel, J. & Martin, R. (2003). Building the evidence base for productivity policy using business data linking. *Economic Trends*, *600*, 39–49.

Cunningham, C., Foster, L., Grim, C., Haltiwanger, J., Pabilonia, S.W., Stewart, J. & Wolf, Z. (2019). *Dispersion in dispersion: measuring establishment-level differences in productivity*. US Census Bureau Center for Economic Studies Paper No. CES-WP-18-25R, Washington D.C.

Cunningham, S., Theilacker, M., Gahan, P., Callan, V., & Rainnie, A. (2016). *Skills and capabilities for Australian enterprise innovation*, Report for the Australian Council of Learned Academies, Melbourne, VIC.

De Martino, M., & Magnotti, F. (2017). The innovation capacity of small food firms in Italy. *European Journal of Innovation Management*, *3*, 362–383.

Department of Agriculture. (2014). *Australian food statistics, 2012-2013.* Canberra, ACT.

Department of Agriculture, and Water Resources. (2016). *Agriculture, farming and food.* Canberra, ACT. Retrieved from http://agriculture.gov.au/ag-farm-food/food

Department of Industry, Innovation and Science. (2008). *Collaborating to a purpose.* Review of the Cooperative Research Centres Program. Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2015a). *Australian Innovation System Report 2015*. Office of the Chief Economist. Retrieved from https://www.industry.gov.au/data-and-publications/australian-innovation-system-report/australian-innovation-system-report-2015

Department of Industry, Innovation and Science. (2015b). *National Innovation and Science Agenda*. Retrieved from https://www.industry.gov.au/data-and-publications/national-innovation-and-science-agenda-report

Department of Industry, Innovation and Science. (2017a). *Food and Agribusiness Industry*. Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2017b). *Australian Innovation System Report 2017.* Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2018a). *Australia 2030: Prosperity Through Innovation*. Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2018b). *Industry-research Collaboration.* Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2018c). *Growth Centres.* Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2018d). *Strategic Plan 2016–2020.* Canberra, ACT: Author.

Department of Industry, Innovation and Science. (2018e). *Cooperative Research Centres (CRC) Program.* Canberra, ACT: Author.

Department of Industry, Innovation, Science and Research. (2009). *Powering Ideas: An Innovation Agenda for the 21st Century*. Canberra, ACT: Author.

Department of Industry, Innovation, Science, Research and Tertiary Education. (2012b). *Australian Small Business, Key Statistics and Analysis*. Canberra, ACT: Author.

Department of Industry, Tourism and Resources. (2006). *Collaboration and Other Factors Influencing Innovation Novelty in Australian Businesses: An Econometric Analysis.* Canberra, ACT: Author.

Department of the Prime Minister and Cabinet. (2014). *Industry Innovation and Competitiveness Agenda: An Action Plan for a Stronger Australia*. Canberra: Author.

Dhamvithee, P., Shankar, B., Jangchud, A., & Wuttijumnong, P. (2005). New product development in Thai agro-industry: explaining the rates of innovation and success in innovation. International Food and Agribusiness Management Review, 8(3), 1–20.

Diakosavvas, D. & Frezal, C. (2019). Bio-economy and the sustainability of the agriculture and food system: Opportunities and policy challenges. OECD Food, Agriculture and Fisheries Papers, No. 136, Paris: OECD Publishing, Retrieved from https://doi.org/10.1787/d0ad045d-en

Domenech, J., Martinez-Gomez, V., & Mas-Verdu, F. (2014). Location and adoption of ICT innovations in the agri-food industry. *Applied Economics Letters, 21*, 421–424.

Dufty, N., & Jackson, T. (2018). *Information and communication technology use in Australian agriculture: A survey of broadacre, dairy and vegetable farms*. ABARES Research Report 18.15, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.

Duguet, E., & Monjon, S. (2004). *Is innovation persistent at the business level? An econometric examination comparing the propensity score and regression methods.* CMSE paper 04075, Paris.

Elnasri, A., & Fox, K. (2015). R&D, innovation and productivity: The role of public support. *KDI Journal of Economic Policy*, ISSN 2586-4130, Korea Development Institute (KDI), Sejong, 37(1), 73–96. http://dx.doi.org/10.23895/kdijep.2015.37.1.7

Elnasri, A., & Fox, K. (2017). The Contribution of research and innovation to productivity. *Journal of Productivity Analysis*, April 2017.

Essana-Nssah, B. (2006). *Propensity score matching and policy impact analysis.* World Bank Policy Research Working Paper 3877, The World Bank, Washington, D.C.

European Commission. (2016). *User guide to the SME Definition*. Publication Office of the European Union. Luxembourg.

Flaig, G., & Stadler, M. (1994). Success breeds success: the dynamics of the innovation process. Empirical Economics, 19, 55-68.

Food Agility. (2019b). Annual report, 2017–2018. Retrieved from https://www.food agility.com /posts/food-agility-crc-annual-report-2017-2018

Food Innovation Australia Limited. (2017). *Food and Agribusiness Sector Competitiveness Plan*. Food Innovation Australia Ltd, Melbourne, VIC.

Food Innovation Australia Limited. (2018). *FIAL Annual Reports*. Food Innovation Australia Ltd, Melbourne, VIC. Retrieved from https://fial.com.au/fial-reports - 15 Oct 2018

Food Innovation Australia Limited. (2019a). Digital Transformation. Retrieved from https://fial.com.au/insights

Food Innovation Australia Limited. (2019b). Technical and Innovation Insights. Retrieved from https://fial.com.au/insights

Foreman-Peck, J. (2010). *Effectiveness and efficiency of SME Innovation Policy*. Retrieved from http://www.isbe.org.uk/content/assets/C. Business_Support_Policy_and_Practice-_James_Foreman-Peck.pdf

Fortuin, F., & Omta, O. (2009). Innovation drivers and barriers in food processing. *British Food Journal*, *111*(8), 839–851.

Foster, L., Grim, C., Haltiwanger, J., & Wolf, Z. (2016). Firm-level dispersion in productivity: Is the devil in the details? *American Economic Review Papers and Proceedings*, 106(5), 95–98.

Foster, L., Grim, C., Haltiwanger, J., & Wolf, Z. (2018). *Innovation, productivity dispersion, and productivity growth.* US Census Bureau Center for Economic Studies Paper No. CES-WP-18-08, Washington, D.C.

Galati, F., Bigliardi, B., & Petroni, A. (2016). Open innovation in food firms: Implementation strategies, drivers and enabling factors. *International Journal of Innovation Management 20*(3), 1650042.

Gago, D., & Rubalcaba, L. (2007). Innovation and ICT in service firms: towards a multidimensional approach for impact assessment. *Journal of Evolutionary Economics 17*, 25–44.

Gellynck, X., & Kühne, B. (2010). Horizontal and vertical networks for innovation in the traditional food sector. *International Journal of Food System Dynamics, 2*, 123–132.

Giannetti, C., & Madia, M. (2013). Work arrangements and firm innovation: is there any relationship? *Cambridge Journal of Economics*, 37*(2)*, 273–297. https://doi.org/10.1093/cje/bes067

Gort, M., & Klepper, S. (1982). Time paths in the diffusion of product innovations. The Economic Journal, 92(367), 630–653.

Grant, R.M. (1991). A resource based theory of competitive advantage. *California Management Review, 3,* 114–135.

Green, L., Jones, B., & Miles, I. (2007). *Mini Study 02 – Skills for Innovation, Global Review of Innovation Intelligence and Policy Studies*, University of Manchester, UK: Pro Inno Europe.

Greene, W.H. (2012). *Econometric Analysis*, *7th edn*. Upper Saddle River, NJ: Prentice Hall.

Gretton, P., Gali, J., & Parham, D. (2003). *The Effects of ICTs and Complementary Innovations on Australian Productivity Growth*. Productivity Commission, Canberra, ACT.

Griffith, R., Haskel, J., & Neely, A. (2006).Why is Productivity so dispersed? *Oxford Review of Economic Policy*, *22*(4), 513–525.

Griffiths, W., & Webster, E. (2009). *What governs firm-level R&D: internal or external factors?* Melbourne Institute Working Paper Series 13, University of Melbourne, Melbourne, VIC.

Grossman, G.M., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies, 58*, 43.

Grunert, K., Harmsen, H., Meulenberg, M., Kuiper, E., Ottowitz, T., Declerck, F., Traill, B., & Göransson, G. (1997). A framework for analysing innovation in the food sector. In B. Traill & K. Grunert (Eds), *Product and Process Innovation in the Food Industry* (pp. 1–37), London, England: Blackie Academic and Professional.

Guarascio, D. (2017). *Persistence of innovation and patterns of firm growth.* Paper presented at the DRUID17, NYU Stern School of Business, New York.

Guarascio, D., & Tamagni, F. (2016). Persistence of innovation and patterns of firm growth. LEM Working Paper Series, No. 2016/31, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM), Pisa.

Guo, S., & Fraser, M.W. (2015). Propensity Score Analysis: Statistical Methods and Applications. California: SAGE.

Hall, B.H., Lotti, F., & J. Mairesse. (2012). Evidence on the impact of R&D and investments on innovation and productivity in Italian firms. *Economics of Innovation and New Technology*. iFirst. 1–12.

Hansell, D., & Rafi, B. (2018). Firm-level analysis using the ABS' business longitudinal analysis data environment (BLADE). *The Australian Economic Review*, *51*(1), 132–138.

Heckman, J. J. (1981). Statistical Models for Discrete Panel Data. In: C. Manski, & D. McFadden (Eds.), *Structural analysis of discrete data with econometric applications* (pp. 114–178), Cambridge, MA.

Heijs, J., & Herrera, L. (2004).*The Distribution of R&D subsidies and its effect on the fiscal outcome of innovation policy.* Working Paper No. 46, Institute for Industrial and Financial Analysis, University Completense of Madrid, Madrid.

Heinrich, C., Maffioli, A., & Vázquez, G. (2010). *A primer for applying propensity-score matching*, Impact evaluation guidelines, Strategy Development Division, Technical Notes No. IDB-TN-161, Inter-American Development Bank, Washington, D.C.

Hendrickson, L., Taylor, D., Ang, L., Cao, K., Nguyen, T., & Soriano, F. (2018). *The impact of persistent innovation on business growth.* Office of the Chief Economist Research Paper 2/2018. Department of Industry, Innovation and Science, Canberra, ACT.

Hendrickson, L., Bucifal, S., Balaguer, A., & Hansell, D. (2015). *The employment dynamics of Australian entrepreneurship*, Office of the Chief Economist Research Paper 4/2015. Department of Industry, Innovation and Science, Canberra, ACT.

Hensher, D.A., Rose, J.M., & Greene, W.H. (2015). *Applied Choice Analysis, 2nd edn*. New York: Cambridge University Press.

Henttonen, K., & Lehtimäki, H. (2017). Open innovation in SMEs: collaboration modes and strategies for commercialization in technology-intensive companies in forestry industry. *European Journal of Innovation Management*, *20*, 329–347.

Herrera, L., & Nieto, M. (2006). *The regional dimension of the distribution and effects of public incentives directed towards innovation of firms.* Working Paper 03-06, Departamento de Direccion y Economica de la Empresa, Universidad de Leon, Leon.

Hirsch, S., & Gschwandtner, A. (2013). Profit persistence in the food industry: evidence from five European countries. *European Review of Agricultural Economics*, *40*(5), 741–759.

Hogan, L. (2017). *Food demand in Australia: trends and food security issues, 2017.* Department of Agriculture and Water Resources, Canberra, ACT. Retrieved from http://www.agriculture.gov.au/abares/research-topics/food-demand/trends-and-food-security-australia-2017 - 15 Oct 2018

Huiban, J.-P., & Bouhsina, Z. (1998). Innovation and the quality of labour factor: an empirical investigation in the French food industry. *Small Business Economics*, *10*, 389–400.

Intellectual Property Australia. (2014). *The Australian Food Industry: A Patent Analytics Report.* Canberra, ACT: Author.

Ito, K., & Lechevalier, S. (2009). The evolution of the productivity dispersion of firms: a reevaluation of its determinants in the case of Japan. *Review of World Economics*, *145*, 405-429.

Jasper, G., & Stanley, D. (2019). Patented innovation and firm value in the U.S. food and drink industry: The economic importance of high-quality product innovation. Journal of Agricultural & Food Industrial Organization, De Gruyter, 17(2), 1–14.

Karantininis, K., Sauer, J., & Furtan, W.H. (2010). Innovation and integration in the agri-food industry. *Food Policy*, *35*,112–120.

Kauhanen, A., & Roponen, S. (2010). Productivity dispersion: A case study. *Research in Economics*, *64*, 97–100.

Khan, F., Salim, R., Bloch, H., & Islam, N. (2017). The public R&D and productivity growth in Australia's broadacre agriculture: is there a link? *Australian Journal of Agricultural and Resource Economics*, *61*, 285–303.

Kleinknecht, A., Flore N. van Schaik, F.N., & Zhou, H. (2014). Is flexible labour good for innovation? Evidence from firm-level data. *Cambridge Journal of Economics*, *38*, 1207–1219.

Kleinknecht , A., Oostendorp , R.M., Pradhan, M.P., & Naastepad, C.W.M. (2006). Flexible labour, firm performance and the Dutch job creation miracle. *International Review of Applied Economics*, *20*, 171–187.

Köllinger, P. (2005). *Why IT matters: an empirical study of e-business usage, innovation, and firm performance*. Discussion Papers of DIW Berlin 495. German Institute for Economic Research, Berlin.

Kuhne, B., Gellynck, X., & Weaver, R.D. (2015). Enhancing innovation capacity through vertical, horizontal, and third-party networks for traditional foods. *Agribusiness*, *31*(3), 294–313.

Lamb, D. (2013). *Game changer: the role of broadband connectivity in Australian farms and why we need to get this right?* Grains Research and Development Corporation Update Paper. Grains Research and Development Corporation, Canberra, ACT.

Latham, W., & Le Bas, C. (2006). The Economics of Persistent Innovation: An Evolutionary View. Berlin: Springer.

Le Bas, C., & Scellato, G., (2014). Firm innovation persistence: a fresh look at the frameworks of analysis. *Econnomics of Innovation and New Technology*, *23*(5–6), 423–446.

Leeuwen, van G., & Klomp, L. (2006). On the contribution of innovation to multifactor productivity growth. Economics of Innovation and New Technology, 15(4-5), 367–390.

Lieponen, A. (2005). Skills and innovation. International Journal of Industrial Organisation, 2(3). 303–323.

Lindfield Partners. (2018). *Top 10 business challenges facing small business owners in 2018?* The Lindfield Partners PTY Ltd, Lindfield, NSW. Retrieved from https://www.lindfieldpartners.com.au/news/what-are-the-top-10-business-challenges-facing-small-business-owners-in-2018 - 15 Oct 2018

Lööf, H. & Heshmati, A. (2002). Knowledge capital and performance heterogeneity. International Journal of Production Economics, 76(1), 61–85.

Lundvall, B-A. (2010). *National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning.* New York, NY: Anthem Press.

Machin, S., & Van Reenan, J. (1998). Technology and changes in skill structure: evidence from seven OECD countries. *Quarterly Journal of Economics*, *113*(4), 1215–1244.

Maietta, O.W. (2015). Determinants of university-firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Research Policy, 44*, 1341–1359.

MacCormack, A., Forbath, T., Brooks, P., & Kalaher, P. (2007). Innovation through global collaboration: A new source of competitive advantage. Harvard Business School Working Paper 07-079, Boston, MA.

Malerba, F., & Orsenigo, L. (1993). Technological regimes and firm behaviour, *Industrial Corporate Change, 2*(1), 45–71.

Mallawaarachchi, T., Walcott, J., Hughes, N., Gooday, P., Georgeson, L., & Foster, A. (2009). *Promoting productivity in the agriculture and food sector value chain: issues for R&D investment*. ABARE and BRS report to the Rural R&D Council, Canberra.

Máñez, J. A., Rochina, M. E., Sanchis, A., & Sanchis, J. A. (2009). The role of sunk costs in the decision to invest in R&D. *The Journal of Industrial Economics*, *57*, 712–735.

Marangos, S., & Warren, L. (2017). A mapping for managers: open innovation for R&D intensive SMEs in the life science sector, *European Journal of Innovation Management 20*, 210–229.

Marginson, S., Tytler, R., Freeman, B., & Roberts, K. (2013). *STEM: Country Comparisons. International comparisons of science, technology, engineering and mathematics (STEM) education.* Australian Academy of Learned Academies (ACOLA). Melbourne, Australia.

Martin, R. (2008). *Productivity dispersion, competition and productivity measurement.* Centre for Economic Performance Discussion Paper No. 692.

Martínez-Ros, E., & Labeaga, J. M. (2009). Product and process innovation: persistence and complementarities. *European Management Review*, *6*(1), 64–75.

Martinez-Sanchez, A., Vela-Jimenez, M. J., Perez-Perez, M., & de-Luis-Carnicer, P. (2008). Workplace flexibility and innovation: the moderator effect of international cooperation. *Personnel Review, 37*, 647–665.

Matopoulos, A., Vlachopoulou, A., Manthou, V., & Manos, B. (2007). A conceptual framework for supply chain collaboration: empirical evidence from the agri-food industry. *Supply Chain Management: An International Journal,* 12(3), 177– 186.

McAdam, M., McAdam R., Dunn, A., & McCall C. (2014). Development of small and medium-sized enterprise horizontal innovation networks: UK agri-food sector study. *International Small Business Journal*, *32*, 830–853.

Michie, J., & Sheehan, M. (2003). Labour market deregulation, 'flexibility' and innovation. *Cambridge Journal of Economics*, *27*, 123–143.

Michie, J., & Sheehan-Quinn, M. (2001). Labour market flexibility, human resource management and corporate performance. *British Journal of Management*, *12*, 287–306.

Mullen, J., Sheng, Y., & Gray, E. M. (2010). Public investment in R&D and agriculture productivity in Australia. In 16th Conference: Productivity at the Crossroads: Creating a Socially, Economically and Environmentally Responsible World. (pp. 19). Australia: Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES).

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica, 46*, 69–85.

Nelson, R.R. (1993). *National Innovation Systems: A Comparative Analysis.* Oxford, New York: Oxford University Press.

Nelson R.R., & Winter, S.G. (1982). *An Evolutionary Theory of Economic Change*. Harvard Cambridge, MA: University Press.

Nossal, K. (2011). *From R&D to productivity growth: investigating the role of innovation adoption in Australian Agriculture.* Rural Industries Research and Development Corporation Publication No. 10/160, ABARES.

Nossal, K. & Lim, K. (2011). Innovation and productivity in the Australian grains industry. ABARES research report 11.06, Canberra. Retrieved from https://grdc.com.au/

data/assets/pdf_file/0023/170285/innovation-and-productivity-in-the-australian-grains-industry.pdf.pdf

OECD. (2001). OECD Productivity Manual. Paris: Author.

OECD. (2003). *A proposed classification of ICT goods*. Paper prepared by the Working Party on Indicators for the Information Society. Organisation for Economic Co-operation and Development, Paris.

OECD. (2005a). *The measurement of scientific and technological activities: Guidelines for collecting and interpreting innovation data, Oslo manual*. Paper prepared by the Working Party of the National Experts on Scientific and Technology Indicators. Organisation for Economic Co-operation and Development, Paris.

OECD. (2005b). *OECD SME and Entrepreneurship Outlook 2005*. Organisation for Economic Co-operation and Development, Paris.

OECD. (2017). OECD Economic surveys: France 2017. Paris: Author. Retrieved from https://doi.org/10.1787/eco_surveys-fra-2017-en

Office of the Chief Scientist. (2019). STEM Partnerships Forum: First meeting. Retrieved from https://www.chiefscientist.gov.au/2017/05/stem-partnerships-forum-first-meeting

Oliveira, C., Ruffoni, E., Maçada, A., & Padula, A.D. (2019). Innovation capabilities in the food processing industry in Brazil. British Food Journal, 121(11), 2901–2918. Retrieved from https://doi.org/10.1108/BFJ-10-2018-0647

Oulton, N. (1998). Competition and the dispersion of labour productivity amongst UK companies. *Oxford Economic Papers*, *50* (1998), 23–38.

Palangkaraya, A. (2012). *The link between innovation and export: Evidence from Australia's small and medium enterprises.* ERIA Discussion Paper Series 2012-08, Melbourne Institute of Applied Economic and Social Research and the Intellectual Property Research Institute of Melbourne, VIC.

Palangkaraya, A., Spurling, T., & Webster, E. (2015). Does innovation make (SME) firms more productive? In A. Moore, & J. Simon (Eds), *Small Business Conditions and Finance* (pp. 181–199), Reserve Bank of Australia, Sydney, NSW.

Palangkaraya, A., Spurling, T. & Webster, E. (2016). *What Drives Firm Innovation? A Review of the Economics Literature*. Centre for Transformative Innovation, Swinburne University of Technology, Melbourne, VIC.

Parisi, M.L., Schiantarelli, F., & Sembenelli, A. (2006). Productivity, innovation and R&D: Micro evidence for Italy. *European Economic Review*, *50* (8), 2037–2061.

Parker, T. (2017). The DataLab of the Australian Bureau of Statistics. *The Australian Economic Review*, *50*, 478–483.

Parsons, L.S. (2001). *Reducing Bias in a Propensity Score Matched-Pair Sample Using Greedy Matching Techniques.* Proceedings of the Twenty-Sixth Annual SAS Users Group International Conference, Cary, NC.

Parsons, L.S. (2004). *Performing a 1:N Case Control Match on Propensity Score*. Proceedings of the Twenty-Ninth SAS Users Group International Conference, Montreal, Canada.

Peters, B. (2005). *Persistence of innovation: Stylised facts and panel data evidence*, ZEW Discussion Paper No. 05–81.

Peters, B. (2008). Innovation and firm performance: An empirical investigation for German firms. *ZEW Economic Studies, 38,* Heidelberg.

Peters, B. (2009). Persistence of innovation: stylised facts and panel data evidence. *Journal of Technology Transfer*, *34*(2), 226–243.

Phillips, R. (1997). *Innovation and firm performance in Australian manufacturing.* Staff Research Paper, Industry Commission, Commonwealth of Australia, ISBN 0646335235.

Polder, M., Van Leeuwen, G., Mohnen, P., & Raymond, W. (2009). *Productivity effects of innovation modes*. Statistics Netherlands Discussion Paper No. 09033, The Hague, Netherlands.

Rafi, B. (2017). Participation in South Australian innovation and investment funds: Impact on firm performance. Office of the Chief Economist Research Paper 1/2017. Department of Industry, Innovation and Science, Canberra, ACT.

Rao, S., Ahmad, A., Horsman, W., & Kaptein-Russell, P. (2001). The importance of innovation for productivity. *International Productivity Monitor*, Centre for the Study of Living Standards, *2*, 1–18.

Raymond, W., Mairesse, J., Mohnen, P., & Palm, F. (2015). Dynamic models of R&D, innovation and productivity: Panel data evidence for Dutch and French manufacturing. *European Economic Review, 78,* 285–306.

Raymond, W., Mohnen, P., Palm, F., & van der Loeff, S.S. (2010). Persistence of Innovation in Dutch manufacturing: Is it spurious? *The Review of Economics and Statistics*, *92*(3), 495–504.

Reilly, P. A. (2001). *Flexibility at Work: Balancing the Interest of Employer and Employee*. Hampshire: Gower Publishing Limited.

Rogers, M. (2004). Networks, firm size and innovation. *Small Business Economics*, *22*, 141–153.

Roper, S., & Hewitt-Dundas, N. (2008). Innovation persistence: Survey and case-study evidence. *Research Policy*, *37*(1), 149–162.

Rotaru, C.I. (2013). Discrete choice panel data modelling using the ABS business longitudinal database. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Rotaru, C., Dzhumasheva, S., & Soriano, F. (2013). Propensity score matching: An application using the ABS business characteristics survey. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Rotaru, C., & Soriano, F. (2013). *Flexible working arrangements, collaboration, ICT and innovation: A panel data analysis.* Paper presented at the 2013 Economic Measurement Group (EMG) Workshop, UNSW, Sydney, NSW.

Salim, R., Mamun, S.A. K., & Hassan, K. (2016). Role of communication technologies in broadacre agriculture in Australia: an empirical analysis using panel data. *Australian Journal of Agricultural and Resource Economics, 60*, 243–264.

Sauer, J. (2017). *Estimating the link between farm productivity and innovation in the Netherlands*. OECD Food, Agriculture and Fisheries Papers 102, Paris: OECD Publishing.

Schmidt, T. (2007). *Motives for innovation co-operation: Evidence from the Canadian survey of innovation*. Discussion paper no. 07-018, Centre for European Economic Research, Mannheim, Germany.

Schmookler, J. (1966). *Invention and Economic Growth.* Cambridge, MA: Harvard University Press.

Schreyer, P., & Pilat, D. (2001). *Measuring productivity*. OECD Economic Studies No. 33, 2001/11.

Schubert, T., & Tavassoli, S., (2019). *Product innovation and educational diversity in top and middle management teams*. Papers in Innovation Studies, Paper no. 2019/03, Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University, Sweden.

Schumpeter, J. (1942). *Capitalism, Socialism, and Democracy*. New York: Harper and Brothers Publishers.

Shanks, S., & Zheng, S. (2006). *Econometric modelling of R&D and Australia's productivity*. Productivity Commission Staff Working Paper, Canberra.

Sheng, Y., Jackson, T., & Gooday, P. (2016). Resource reallocation and its contribution to productivity growth in Australian broadacre agriculture. *Australian Journal of Agricultural and Resource Economics*, *61*(1), 56–75.

Sheng, Y., Mullen, J., & Zhao, S. (2011). *A turning point in agricultural productivity: consideration of the causes.* ABARES Research Report 11.4 for the Grains Research and Research and Development Corporation, Canberra.

Sheng, Y., Zhao, S., Nossal, K., & Zhang, D. (2014). Productivity and farm size in Australian agriculture: reinvestigating the returns to scale. *Australian Journal of Agricultural and Resource Economics, 59*, 16–38.

Small-business. (2018). In *YourDictionary online*. Retrieved from https://www.your dictionary .com/SMALL-BUSINESS

Smit, M.J., Abreu, M.A., & de Groot, H.L.F. (2015). Micro-evidence on the determinants of innovation in the Netherlands: The relative importance of absorptive capacity and agglomeration externalities. *Papers in Regional Science*, *94*, 249–272.

Smith, R., & Hendrickson, L. (2016). *The effect of age on Australian small-to-medium enterprises*. Office of the Chief Economist Research Paper 1/2016. Department of Industry, Innovation and Science, Canberra, ACT.

Soames, L., Brunker, D., & Talgaswatta, T. (2011). Competition, innovation and productivity in Australian businesses. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Soriano, F.A. (2018, November). Impact of innovation on business performance and productivity dispersion: The case of small food industry businesses in Australia. Paper presented at the 2018 Economic Measurement Group (EMG) Workshop, UNSW Sydney, NSW.

Soriano, F., & Abello, R. (2015). Modelling the relationships between the use of STEM skills, collaboration, R&D, and innovation among Australian businesses, *Australian Journal of Labour Economics*, *18*, 345–374.

Soriano, F.A., Villano, R. A., Fleming, E.M., & Battese, G.B. (2017, July). Dynamics of innovation persistence in small food industry businesses in Australia. Contributed paper presented at the 2017 Australian Conference of Economists, Sydney, NSW.

Soriano, F.A., Villano, R. A., Fleming, E.M., & Battese, G.B. (2019, February). Dynamics of innovation, business performance and productivity dispersion in the small food businesses in Australia. Paper presented at the 63rd Annual Conference of the Australasian Agricultural and Resource Economics Society, Melbourne, VIC.

Soriano, F.A., Villano, R.A., Fleming, E.M., and Battese, G.E. (2018). What's driving innovation in small businesses in Australia? The case of the food industry, Australian Journal of Agricultural and Resource Economics, 63(1), 39–71.

Srholec, M. (2016). Persistence of cooperation on innovation: econometric evidence from panel micro data. *Prague Economic Papers*, *25*, 53–70.

Stanwick, J. (2011). Innovation: Its links with productivity and skill development – at a glance. National Centre for Vocational Education Research, Department of Education, Employment and Workplace Relation, Adelaide.

Statistics New Zealand. (2015). *Rolling Mean Employment.* Wellington: Author.

Stoneman, P. (1983). The Economic Analysis of Technological Change. New York: Oxford University Press.

Storey, D.J. (1994). *Understanding the Small Business Sector*, London: Routledge.

Storey, J., Quitas, P., Taylor, P., & Fowle, W. (2002). Flexible employment contracts and their implications for product and process innovation. *International Journal of Human Resource Management*, *13*, 1–18.

Stuart, E.A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science, 25*(1), 1–21.

Sutton, J. (1991). *Sunk costs and market structure.* Cambridge, MA: MIT Press.

Syverson, C. (2003). Product Substitutability and Productivity Dispersion. University of Chicago and NBER, July 2003.

Syverson, C. (2004). Market structure and productivity: A concrete example. *Journal of Political Economy*, *112*(6), 1181-1222.

Tavassoli, S., & Karlsson, C. (2015). Persistence of various types of innovation analysed and explained. *Research Policy*, *44*, 1887–1901.

Tavassoli, S., & Karlsson, C. (2017). The role of regional context on innovation persistency of firms. *Papers in Innovation Studies,* Paper no. 2017/11, Centre for Innovation, Research and Competence in the Learning Economy (CIRCLE), Lund University, Sweden.

Tether, B., Mina, A., Consoli, D., & Gagliardi, D. (2005). *A Literature Review on Skills and Innovation. How Does Successful Innovation Impact on the Demand for Skills and How Do Skills Drive Innovation*? ESRC Centre on Innovation and Competition, University of Manchester.

Tirole, J. (1988). *The Theory of Industrial Organisation*. Cambridge, MA: MIT Press

Tiy, L., Berry, O., & Taylor, D. (2013). Business innovation and the use of information and communications technology – an update. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Todhunter, J., & Abello, R. (2011). Business innovation and the use of information and communications technology. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Toner, P. (2011). *Workforce skills and innovation: an overview of major themes in the literature*. STI Working Paper Series. Directorate for Science, Technology and Industry, OECD, Paris.

Traill, W.B., & Meulenberg, M. (2002). Innovation in the food industry. *Agribusiness*, *18*(1), 1–21.

Triguero A., (2019). Does the sector matter? The role of open innovation in the adoption of eco-innovations in food versus non-food industries (in Chapter 6) of *Research on Open-*

Innovation Strategies and eco-innovation in Agro-Food industries (Triguero A. & Gonzales-Moreno A., (Eds), Oxford, UK: Chartridge.

Triguero, A., Corcoles, D., & Cuerva, M.C. (2013). Differences in innovation between food and manufacturing firms: an analysis of persistence, *Agribusiness*, *29*, 273–292.

Triguero, A., Córcoles, D., & Cuerva, M. (2014). Persistence of innovation and firm's growth: evidence from a panel of SME and large Spanish manufacturing firms. *Small Business Economics*, *43*, 787–804.

Triguero, A., Fernadez, S., & Saez-Martinez, F.J. (2018). Inbound open innovative strategies and eco-innovation in the Spanish food and beverage industry. *Sustainable Production and Consumption*, (15), 49-64.

Triguero-Cano, A., & D. Corcoles-Gonzales. (2013). Understanding the innovation: An analysis of persistence for Spanish manufacturing firms. *Research Policy*. *42*(2), 340–352.

Tuhin, R. (2016). *Modelling the relationship between innovation and exporting: evidence from Australian SMEs.* Office of the Chief Economist Research Paper 3/2016. Department of Industry, Innovation and Science, Canberra, ACT.

Tuhin, R., & Swanepoel, J. (2017). *Export behaviour and business performance: evidence from Australian microdata*. Office of the Chief Economist Research Paper 7/2016. Department of Industry, Innovation and Science, Canberra, ACT.

Vancauteren, M. (2018). The effects of human capital, R&D and firm's innovation on patents: a panel study on Dutch food firms. *The Journal of Technology Transfer*, *43*(4), 901-922.

Van Zon, A. (2001). A simple endogenous growth model with asymmetric employment opportunities by skills. Maastricht Economic Research Institute on Innovation and Technology (MERIT) Infonomics Research Memorandum series 2001-09, Netherlands.

Wixe, S., Nilsson, P., Naldi, L., & Westlund, H. (2017). *Disentangling innovation in small food firms: The role of external knowledge, support, and collaboration*. The Royal Institute of Technology, Centre of Excellence for Science and Innovation Studies (CESIS) Electronic Working Paper Series 44. Sweden.

Wong, M., Page, D., Abello, R., & Pang, K.P. (2007). Explorations of innovation and business performances using linked firm-level data. *ABS Methodology Research Papers.* Australian Bureau of Statistics, Canberra, ACT.

Wooldridge, J.M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics, 20*, 39–54.

Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Wooldridge, J. (2012). Panel Data Models with Heterogeneity and Endogeneity. Programme Evaluation for Policy Analysis, Institute for Fiscal Studies. Retrieved from https://www.ifs.org.uk/docs/wooldridge%20session%204.pdf

Wooldridge, J.M. (2013). *Correlated random effects panel data models*. IZA European Summer School in Labor Economics Course Material. Buch/Ammersee, Germany.

World Bank. (2011). *ICT in agriculture: connecting smallholders to knowledge, networks, and institutions*. The World Bank Report No. 64605. Washington, DC.

Xayavong, V., Kingwell, R., & Islam, N. (2015). How training and innovation link to farm performance: a structural equation analysis. *Australian Journal of Agricultural and Resource Economics, 60*, 227–242.

Xia, C., Zhao, S., & Valle, H. (2017). Productivity in Australia's broadacre and dairy industries, in *Agricultural Commodities*: March quarter 2017, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra.

Zawislak, P.A., Alves, A.C., Tello-Gamarra, J., Barbieux, D., & Reichert, F.M., (2012). Innovation capability: From technology development to transaction capability. *Journal of Technology Management and Innovation*, *7* (2), 14–27.

Zhao, S., Sheng, Y., & Gray, E. (2012). Measuring productivity of the Australian broadacre and dairy industries: concepts, methodology and data, In K.O. Fuglie, S.L. Wang, & V.E. Ball (Eds), *Productivity growth in agriculture: an international perspective*, CABI, Wallingford.

Zhou, H., Dekker, R., & Kleinknecht, A. (2011). Flexible labour and innovation performance: evidence from longitudinal firm-level data. *Industrial and Corporate Change, 20*, 941–968.

Zouaghi, F., & Sanchez, M. (2016). Has the global financial crisis had different effects on innovation performance in the agri-food sector by comparison to the rest of the economy? *Trends in Food Science & Technology, 50*, 230–242.

Appendices

Appendix A

List of Four-Digit ANZSIC06 Codes and Activities Used in Defining Australia's Food and Agribusiness Growth Sector, by Industry Subdivision

ANZSIC06 code and activity classification	Industry subdivision
0121 Mushroom Growing 0122 Vegetable Growing (Under Cover) 0123 Vegetable Growing (Outdoors) 0131 Grape Growing 0132 Kiwifruit Growing 0133 Berry Fruit Growing 0134 Apple and Pear Growing 0135 Stone Fruit Growing 0136 Citrus Fruit Growing 0137 Olive Growing 0139 Other Fruit and Tree Nut Growing 0141 Sheep Farming (Specialised) 0142 Beef Cattle Farming (Specialised) 0143 Beef Cattle Feedlots (Specialised) 0144 Sheep-Beef Cattle Farming 0145 Grain-Sheep or Grain-Beef Cattle Farming 0146 Rice Growing 0149 Other Grain Growing 0151 Sugar Cane Growing 0159 Other Crop Growing—not elsewhere classify (n.e.c) 0160 Dairy Cattle Farming 0171 Poultry Farming (Meat) 0172 Poultry Farming (Eggs) 0180 Deer Farming 0192 Pig Farming 0193 Beekeeping 0199 Other Livestock Farming n.e.c.	Agriculture
0201 Offshore Longline and Rack Aquaculture 0202 Offshore Caged Aquaculture 0203 Onshore Aquaculture	Aquaculture
0411 Rock Lobster and Crab Potting 0412 Prawn Fishing 0413 Line Fishing 0414 Fish Trawling, Seining and Netting 0419 Other Fishing	Fishing, Hunting and Trapping

List of Four-Digit ANZSIC06 Codes and Activities…continued

ANZSIC06 code and activity classification	**Industry subdivision**
0529 Other Agriculture and Fishing Support Services	Agriculture, Forestry and Fishing Support Services
1111 Meat Processing 1112 Poultry Processing 1113 Cured Meat and Smallgoods Manufacturing 1120 Seafood Processing 1131 Milk and Cream Processing 1132 Ice Cream Manufacturing 1133 Cheese and Other Dairy Product Manufacturing 1140 Fruit and Vegetable Processing 1150 Oil and Fat Manufacturing 1161 Grain Mill Product Manufacturing 1162 Cereal, Pasta and Baking Mix Manufacturing 1171 Bread Manufacturing (Factory based) 1172 Cake and Pastry Manufacturing (Factory based) 1173 Biscuit Manufacturing (Factory based) 1174 Bakery Product Manufacturing (Nonfactory based) 1181 Sugar Manufacturing 1182 Confectionery Manufacturing 1191 Potato, Corn and Other Crisp Manufacturing 1192 Prepared Animal and Bird Feed Manufacturing 1199 Other Food Product Manufacturing n.e.c.	Food Product Manufacturing
1211 Soft Drink, Cordial and Syrup Manufacturing 1212 Beer Manufacturing 1213 Spirit Manufacturing 1214 Wine and Other Alcoholic Beverage Manufacturing	Beverage and Tobacco Product Manufacturing
2461 Agricultural Machinery and Equipment Manufacturing	Specialised Machinery and Equipment Manufacturing
6620 Farm Animal and Bloodstock Leasing	Rental and Hiring Services

Source: ABS (2015d)

Appendix B

Patterns of Innovation over the Four-year Period for the Food Industry and Subsectors Samples

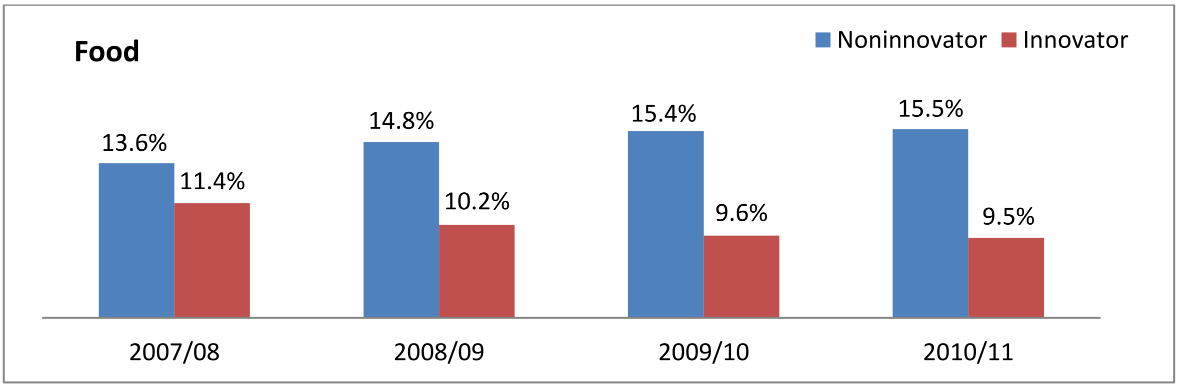


Figure B.1. Innovation-active and non-innovation-active businesses in the food industry sample, by year, 2007/08–2010/11.

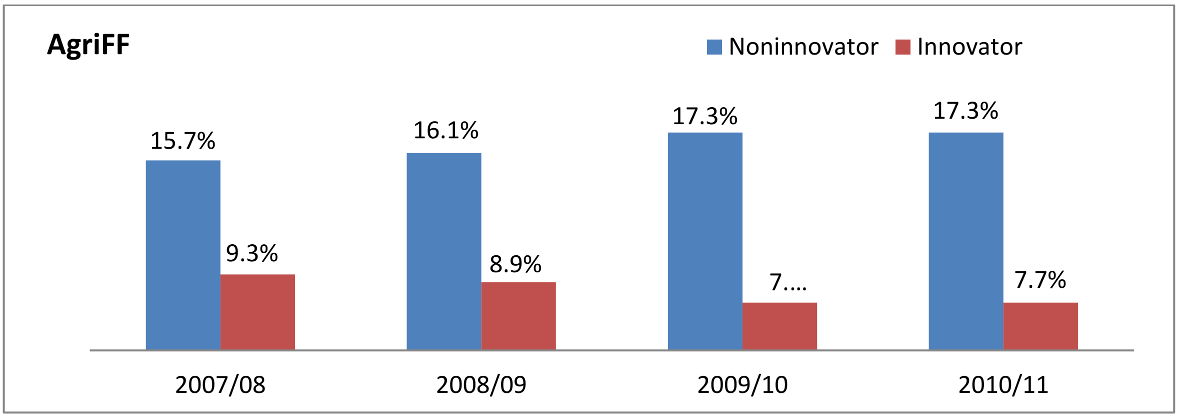


Figure B.2. Innovation-active and non-innovation-active businesses in the AgriFF sample, by year, 2007/08–2010/11.

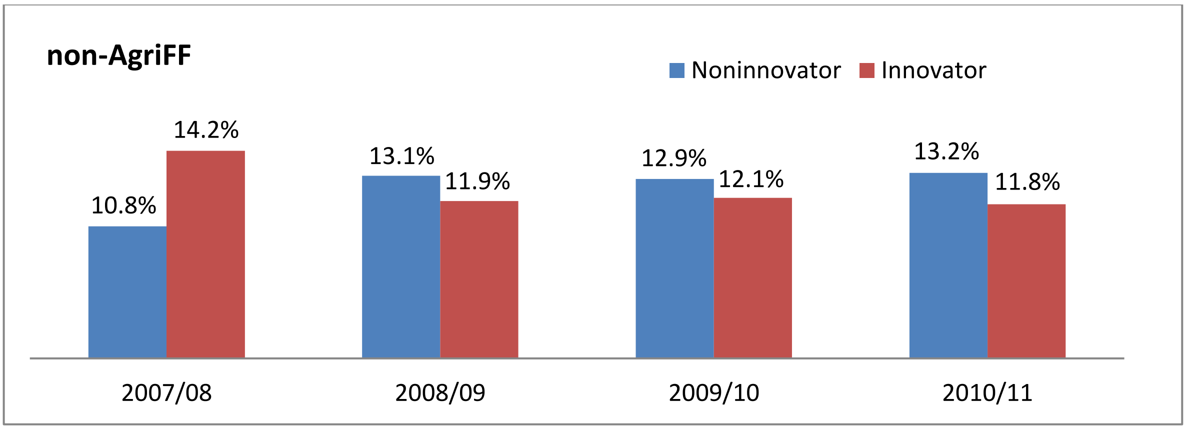


Figure B.3. Innovation-active and non-innovation-active businesses in the non-AgriFF sample, by year, 2007/08–2010/11.

Appendix C

Subsector Probability Density Distributions for the Four Types of Innovation

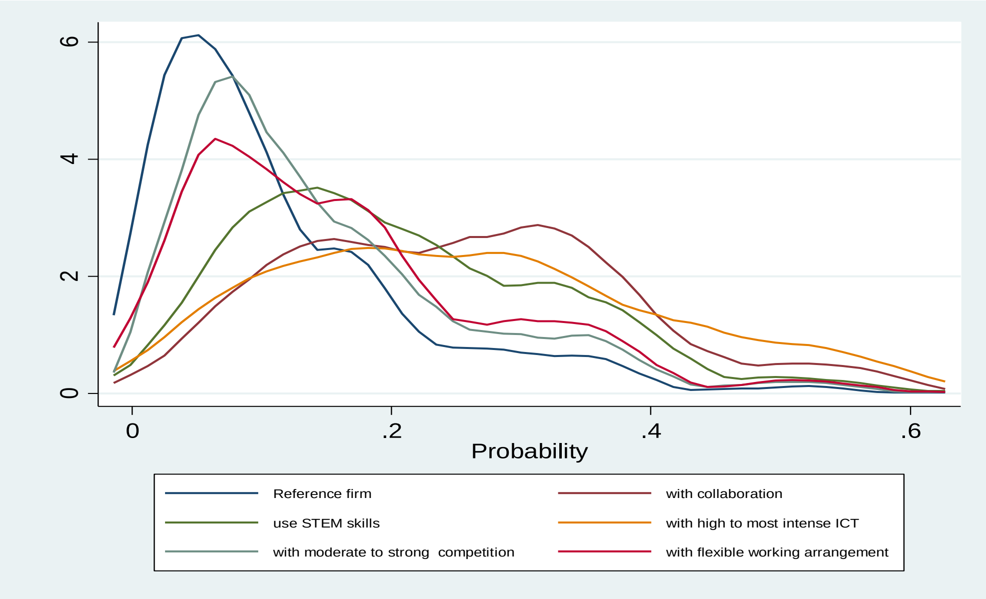


Figure C.1. Impact of drivers on the probability density function —goods and services innovation in the AgriFF subsector (Multivariate probit).

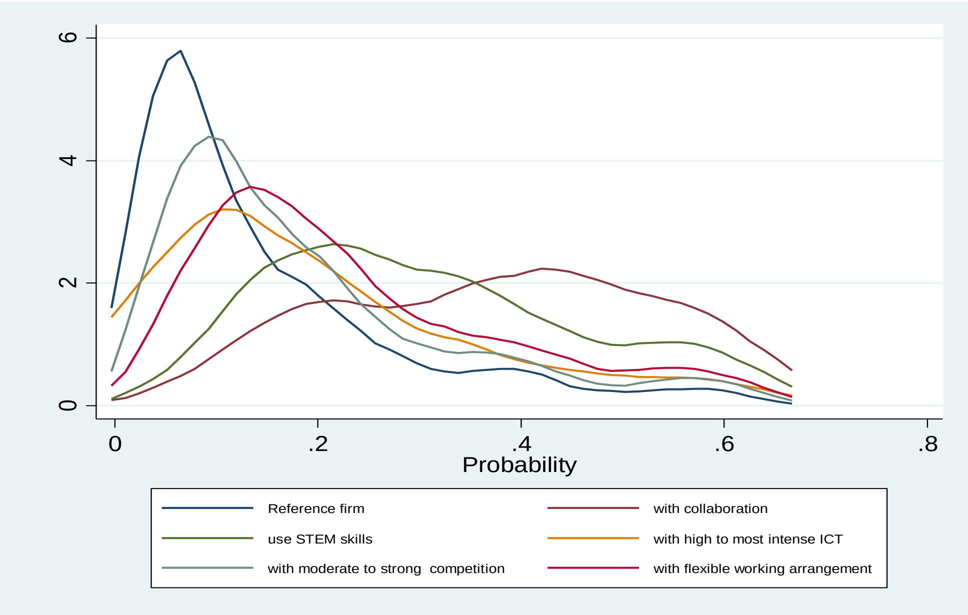


Figure C.2. Impact of drivers on the probability density function—organisational and managerial innovation in the AgriFF subsector (Multivariate probit).

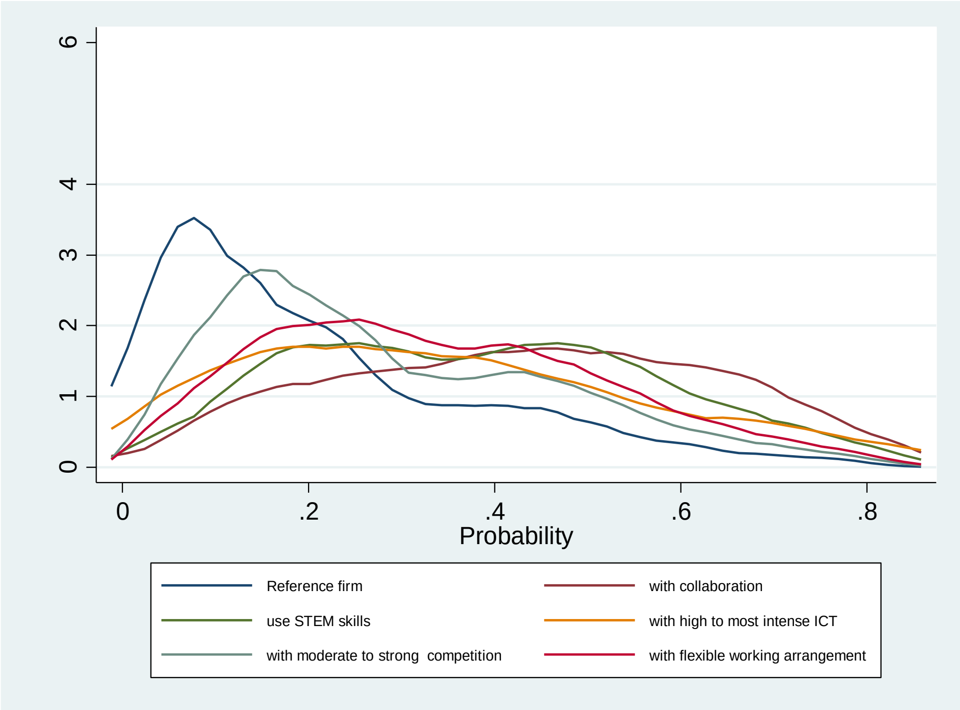


Figure C.3. Impact of drivers on the probability density function—operational process innovation in the AgriFF subsector (Multivariate probit).

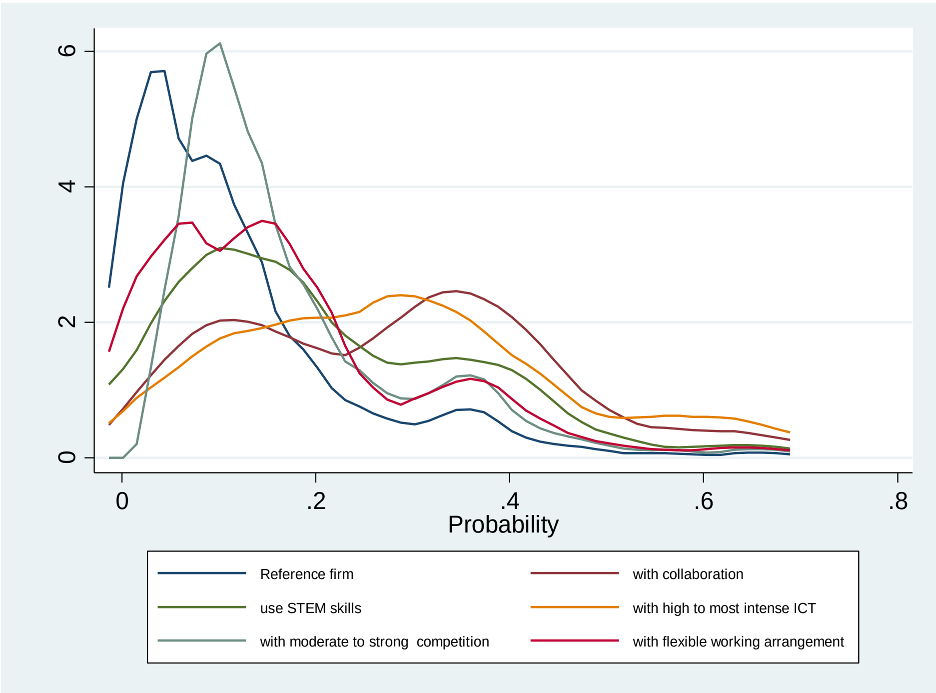


Figure C.4. Impact of drivers on the probability density function—marketing methods innovation in the AgriFF subsector (Multivariate probit).

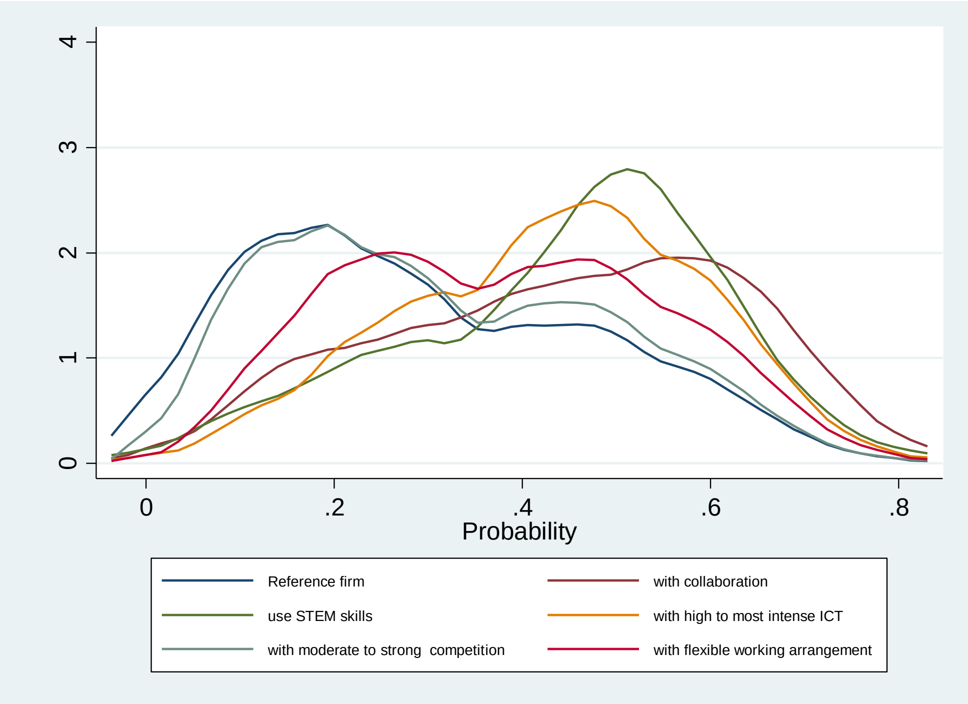


Figure C.5. Impact of drivers on the probability density function—goods and services innovation in the non-AgriFF subsector (Multivariate probit).

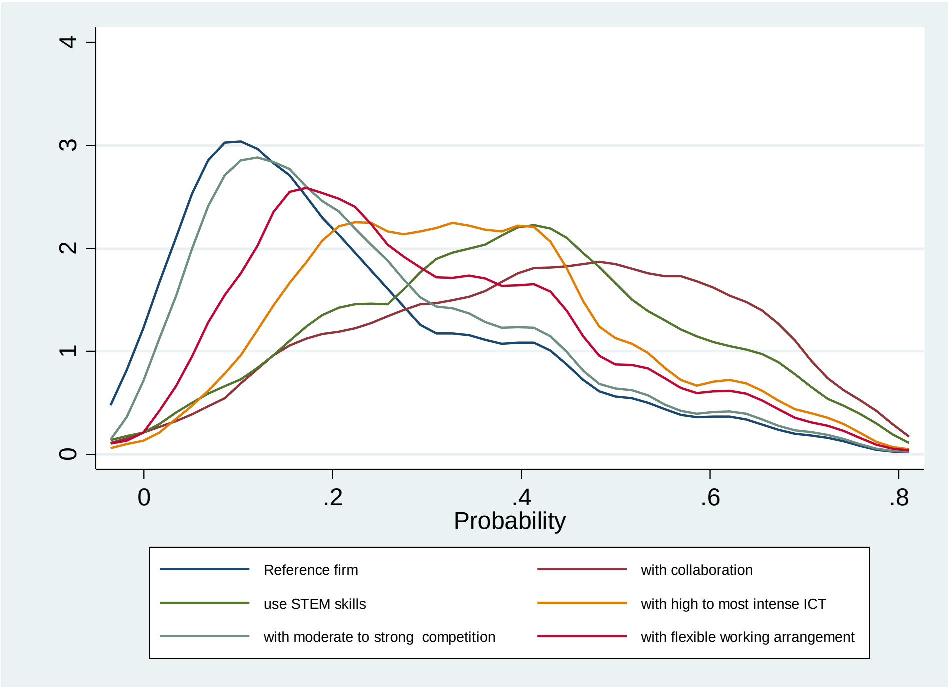


Figure C.6. Impact of drivers on the probability density function—organisational and managerial innovation in the non-AgriFF subsector (Multivariate probit).

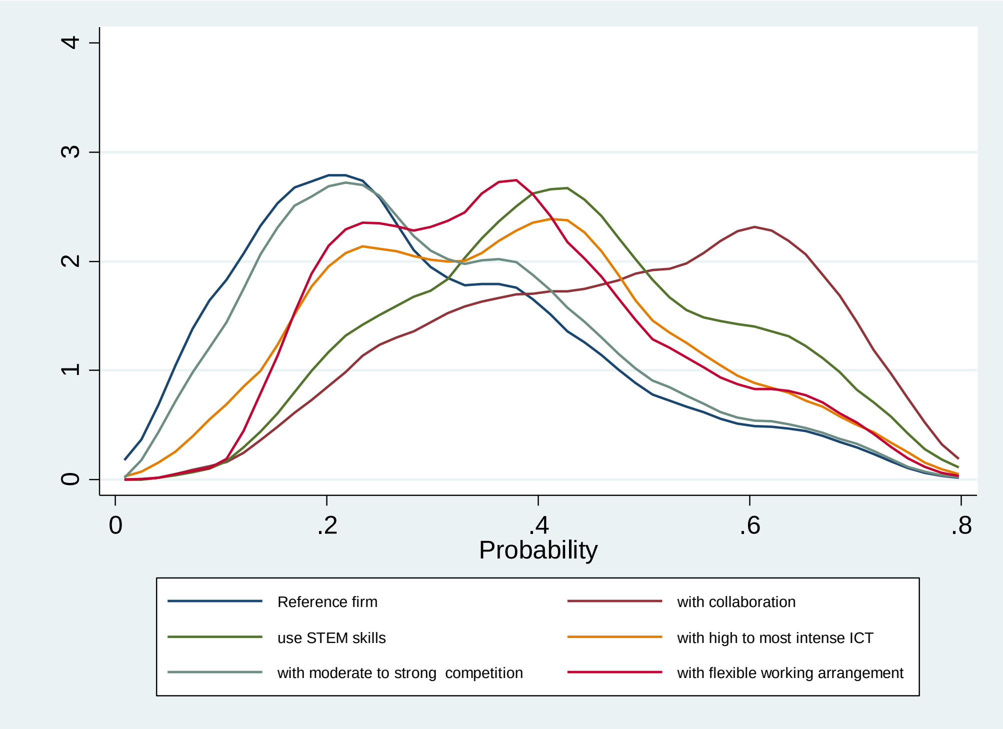


Figure C.7. Impact of drivers on the probability density function—operational process innovation in the non-AgriFF subsector (Multivariate probit).

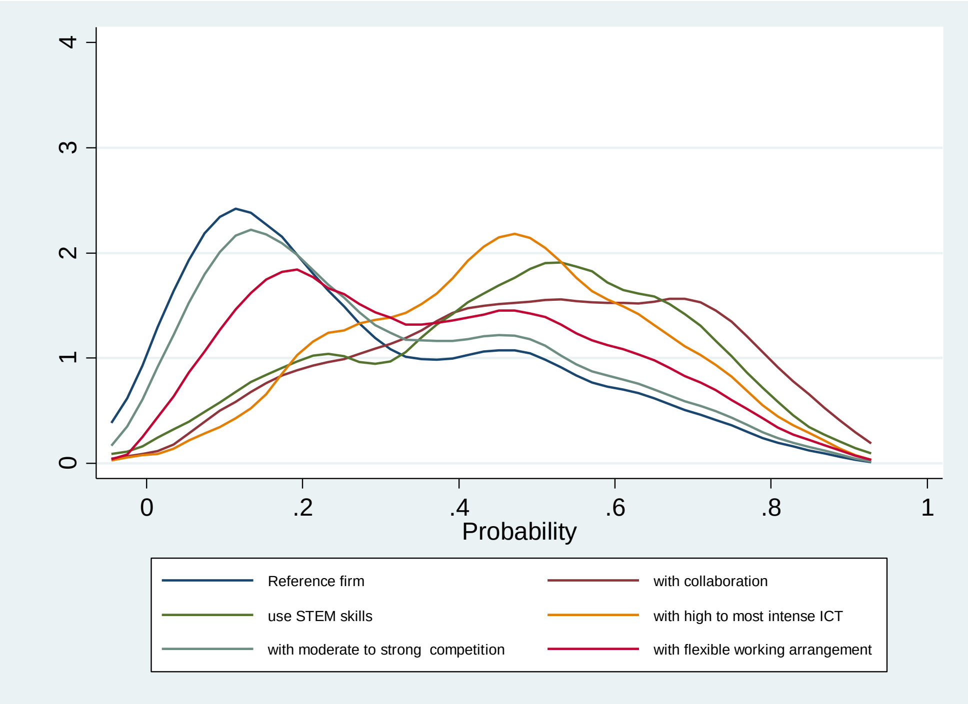


Figure C.8. Impact of drivers on the probability density function—marketing methods innovation in the non-AgriFF subsector (Multivariate probit).

Appendix D

Summary Statistics for the APE Distributions in the Dynamic Correlated Random Effects Probit Modelling

Table D.1

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Overall Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0084	0.0287	0.0403	0.0487	0.0518	0.0001	-0.6146	2.2848
Innovation (initial condition, t=0)	0.0714	0.1819	0.2263	0.2510	0.2609	0.0022	-1.0073	3.1787
With collaboration	0.0517	0.1328	0.1740	0.2029	0.2129	0.0019	-0.6874	2.3959
Market competition								
Minimal	0.0827	0.1544	0.2188	0.2686	0.2866	0.0039	-0.3728	1.8097
Moderate	0.0524	0.1058	0.1594	0.2024	0.2164	0.0007	0.5540	2.1989
Strong	0.0679	-0.1089	-0.0888	-0.0639	0.2547	0.0007	0.5536	2.1982
ICT Intensity								
Moderate	0.0052	0.0186	0.0270	0.0325	0.0348	0.0001	-0.6125	2.2614
High	0.0484	0.1593	0.2090	0.2454	0.2577	0.0029	-0.7327	2.5034
Most intense	0.0213	0.0670	0.0919	0.1095	0.1165	0.0007	-0.6488	2.3473
Used STEM skills	0.0452	0.2037	0.2563	0.2922	0.3047	0.0034	-0.8333	2.7285
Market location (Local only)	-0.0378	-0.0355	-0.0289	-0.0205	-0.0059	0.0001	0.5686	2.2254
With flexible working arrangements	0.0461	0.1238	0.1585	0.1866	0.1982	0.0016	-0.7064	2.5251
Sought debt and/or equity finance	0.0050	0.0171	0.0247	0.0300	0.0322	0.0001	-0.5588	2.2059
Financial year								
2008/09	-0.1038	-0.0975	-0.0792	-0.0578	-0.0155	0.0006	0.5597	2.2091
2009/10	-0.1155	-0.1082	-0.0881	-0.0636	-0.0178	0.0007	0.5540	2.1989
2010/11	-0.1162	-0.1089	-0.0888	-0.0639	-0.0179	0.0007	0.5536	2.1982

Table D.2

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Goods and Services Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0029	0.0209	0.0383	0.0585	0.0713	0.0004	0.0587	1.6938
Innovation (initial condition, t=0)	0.0297	0.1428	0.2166	0.2829	0.3114	0.0063	-0.3276	1.8925
With collaboration	0.0021	0.0156	0.0285	0.0449	0.0550	0.0003	0.1049	1.6913
Market competition								
Minimal	0.0336	0.1005	0.1700	0.2715	0.3402	0.0088	0.2431	1.7668
Moderate	0.0094	0.0339	0.0640	0.1185	0.1759	0.0027	0.5877	2.0380
Strong	0.0112	0.0395	0.0738	0.1346	0.1953	0.0032	0.5489	1.9929
ICT Intensity								
Moderate	-0.0684	-0.0509	-0.0321	-0.0173	-0.0027	0.0004	-0.2676	1.8357
High	0.0211	0.0941	0.1476	0.1901	0.2150	0.0030	-0.3375	1.9051
Most intense	0.0069	0.0362	0.0612	0.0859	0.1023	0.0008	-0.0970	1.7613
Used STEM skills	0.0175	0.0864	0.1408	0.2016	0.2388	0.0042	-0.0440	1.6989
Market location (Local only)	-0.0025	-0.0020	-0.0012	-0.0006	-0.0001	0.0000	-0.1577	1.6963
With flexible working arrangements	0.0074	0.0402	0.0711	0.1121	0.1430	0.0017	0.1621	1.7591
Sought debt and/or equity finance	0.0015	0.0110	0.0208	0.0329	0.0409	0.0001	0.1201	1.6987
Financial year								
2008/09	-0.1558	-0.1310	-0.0884	-0.0499	-0.0115	0.0019	-0.0156	1.6650
2009/10	-0.2073	-0.1704	-0.1104	-0.0608	-0.0135	0.0036	-0.0950	1.6609
2010/11	-0.1792	-0.1491	-0.0990	-0.0552	-0.0125	0.0026	-0.0514	1.6609

Table D.3

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Organisational or Managerial Process Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0006	0.0209	0.0383	0.0585	0.0140	0.0000	0.1901	1.7392
Innovation (initial condition, t=0)	0.0099	0.0571	0.0904	0.1317	0.1553	0.0017	-0.0172	1.7713
With collaboration	0.0181	0.0920	0.1404	0.1939	0.2235	0.0033	-0.1291	1.8220
Market competition								
Minimal	0.0071	0.0225	0.0394	0.0686	0.0954	0.0007	0.4838	1.9039
Moderate	0.0098	0.0303	0.0524	0.0896	0.1212	0.0011	0.4368	1.8533
Strong	0.0082	0.0257	0.0448	0.0774	0.1063	0.0009	0.4640	1.8818
ICT Intensity								
Moderate	0.0039	0.0253	0.0430	0.0710	0.0993	0.0008	0.3920	1.9238
High	0.0414	0.1732	0.2501	0.3307	0.3755	0.0082	-0.2032	1.8879
Most intense	0.0035	0.0226	0.0387	0.0642	0.0906	0.0006	0.4093	1.9390
Used STEM skills	0.0408	0.1600	0.2255	0.2916	0.3372	0.0061	-0.2006	1.9364
Market location (Local only)	-0.0272	-0.0220	-0.0138	-0.0079	-0.0011	0.0001	-0.1760	1.7398
With flexible working arrangements	0.0091	0.0471	0.0764	0.1168	0.1517	0.0017	0.2376	1.8251
Sought debt and/or equity finance	0.0020	0.0136	0.0233	0.0375	0.0462	0.0002	0.1626	1.7274
Financial year								
2008/09	-0.0763	-0.0596	-0.0355	-0.0199	-0.0031	0.0005	-0.2643	1.7660
2009/10	0.0007	0.0043	0.0074	0.0115	0.0139	0.0000	0.1006	1.7194
2010/11	-0.0338	-0.0274	-0.0168	-0.0096	-0.0016	0.0001	-0.1879	1.7351

Table D.4

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Operational Process Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0082	0.0385	0.0627	0.0834	0.0926	0.0006	-0.2938	1.7805
Innovation (initial condition, t=0)	0.0389	0.1390	0.2019	0.2469	0.2615	0.0039	-0.5333	2.0816
With collaboration	0.0150	0.0645	0.1027	0.1320	0.1446	0.0014	-0.3775	1.8848
Market competition								
Minimal	0.0072	0.0195	0.0368	0.0638	0.0813	0.0006	0.2780	1.6854
Moderate	0.0215	0.0539	0.0956	0.1504	0.1804	0.0026	0.1086	1.6113
Strong	0.0296	0.0718	0.1240	0.1885	0.2201	0.0036	0.0416	1.6049
ICT Intensity								
Moderate	0.0104	0.0377	0.0668	0.0989	0.1143	0.0011	-0.0759	1.6546
High	0.0095	0.0347	0.0618	0.0919	0.1068	0.0009	-0.0638	1.6499
Most intense	0.0076	0.0285	0.0513	0.0774	0.0905	0.0007	-0.0374	1.6412
Used STEM skills	0.0465	0.1602	0.2220	0.2685	0.2926	0.0045	-0.5498	2.2081
Market location (Local only)	0.0008	0.0043	0.0076	0.0108	0.0123	0.0000	-0.1651	1.6782
With flexible working arrangements	0.0243	0.0826	0.1273	0.1743	0.1980	0.0026	-0.1527	1.7734
Sought debt and/or equity finance	0.0020	0.0097	0.0164	0.0227	0.0257	0.0001	-0.1996	1.7171
Financial year								
2008/09	-0.0794	-0.0716	-0.0530	-0.0328	-0.0080	0.0005	0.2606	1.7599
2009/10	-0.1178	-0.1047	-0.0764	-0.0458	-0.0108	0.0011	0.2122	1.7146
2010/11	-0.1195	-0.1063	-0.0774	-0.0463	-0.0109	0.0011	0.2100	1.7127

Table D.5

Selected Summary Statistics for the Distribution of the APE Estimates for Food Industry (Marketing Methods Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0035	0.0423	0.0814	0.1255	0.1471	0.0020	-0.0424	1.7114
Innovation (initial condition, t=0)	0.0023	0.0295	0.0581	0.0917	0.1102	0.0012	0.0185	1.7058
With collaboration	0.0075	0.0758	0.1353	0.1951	0.2258	0.0045	-0.1863	1.7943
Market competition								
Minimal	0.0309	0.0776	0.1251	0.2587	0.4416	0.0155	0.8696	2.4098
Moderate	0.0242	0.0630	0.1037	0.2235	0.4064	0.0131	0.9426	2.5600
Strong	0.0322	0.0803	0.1289	0.2648	0.4474	0.0159	0.8575	2.3862
ICT Intensity								
Moderate	-0.0089	-0.0064	-0.0038	-0.0019	-0.0001	0.0000	-0.3194	1.8796
High	0.0051	0.0555	0.0998	0.1482	0.1769	0.0028	-0.0877	1.7710
Most intense	0.0067	0.0692	0.1219	0.1766	0.2068	0.0037	-0.1588	1.7912
Used STEM skills	0.0052	0.0558	0.1008	0.1552	0.1857	0.0032	-0.0548	1.7491
Market location (Local only)	-0.0978	-0.0817	-0.0513	-0.0260	-0.0019	0.0009	-0.0197	1.6853
With flexible working arrangements	0.0017	0.0216	0.0420	0.0714	0.0890	0.0008	0.1595	1.7287
Sought debt and/or equity finance	0.0002	0.0036	0.0076	0.0133	0.0164	0.0000	0.1688	1.6839
Financial year								
2008/09	-0.1328	-0.1096	-0.0636	-0.0342	-0.0026	0.0017	-0.1084	1.7057
2009/10	-0.0934	-0.0780	-0.0473	-0.0259	-0.0021	0.0008	-0.0393	1.7144
2010/11	-0.1378	-0.1137	-0.0655	-0.0351	-0.0027	0.0019	-0.1171	1.7053

Table D.6

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Overall Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0099	0.0372	0.0534	0.0668	0.0721	0.0003	-0.4438	1.9975
Innovation (initial condition, t=0)	0.0565	0.1602	0.2074	0.2396	0.2532	0.0026	-0.7238	2.4231
With collaboration	0.0601	0.1746	0.2244	0.2615	0.2741	0.0030	-0.6845	2.3677
Market competition								
Minimal	-0.0043	-0.0037	-0.0024	-0.0013	-0.0005	0.0000	-0.0892	1.5401
Moderate	0.0575	0.1254	0.1864	0.2378	0.2593	0.0034	-0.2030	1.6548
Strong	0.0590	0.1283	0.1894	0.2416	0.2634	0.0035	-0.2066	1.6580
ICT Intensity (High-to-most-intense)	0.0280	0.0948	0.1307	0.1586	0.1705	0.0015	-0.5461	2.1419
Used STEM skills	0.0581	0.1595	0.2077	0.2436	0.2573	0.0029	-0.6866	2.3711
Market location (Local only)	0.0106	0.0455	0.0701	0.0953	0.1061	0.0008	-0.2631	1.8036
With flexible working arrangements	0.0477	0.1282	0.1731	0.2110	0.2281	0.0025	-0.4838	2.0668
Sought debt and/or equity finance	-0.0586	-0.0533	-0.0396	-0.0265	-0.0057	0.0002	0.2987	1.8458
Financial year								
2008/09	-0.0749	-0.0688	-0.0534	-0.0380	-0.0070	0.0003	0.4154	1.9896
2009/10	-0.1116	-0.1025	-0.0785	-0.0554	-0.0095	0.0008	0.3771	1.9389
2010/11	-0.0893	-0.0820	-0.0636	-0.0449	-0.0081	0.0005	0.4003	1.9693

Table D.7

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Goods and Services Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0079	0.0490	0.0813	0.1273	0.1924	0.0025	0.4727	2.1601
Innovation (initial condition, t=0)	0.0168	0.0843	0.1362	0.2120	0.5327	0.0107	1.1623	4.0800
With collaboration	0.0053	0.0346	0.0581	0.0908	0.1504	0.0015	0.6308	2.4496
Market competition								
Minimal	0.0013	0.0061	0.0116	0.0192	0.0532	0.0002	1.4169	4.2424
Moderate	0.0066	0.0281	0.0504	0.0787	0.1749	0.0019	1.1109	3.3685
Strong	0.0082	0.0344	0.0607	0.0938	0.1995	0.0025	1.0468	3.2123
ICT Intensity (High-to-most-intense)	0.0044	0.0297	0.0513	0.0820	0.1342	0.0013	0.6000	2.3203
Used STEM skills	0.0044	0.0440	0.0742	0.1153	0.1913	0.0023	0.6181	2.4417
Market location (Local only)	-0.0897	-0.0522	-0.0319	-0.0180	-0.0025	0.0006	-0.6870	2.4417
With flexible working arrangements	0.0005	0.0039	0.0072	0.0124	0.0233	0.0000	0.8639	2.7334
Sought debt and/or equity finance	-0.1552	-0.0731	-0.0402	-0.0202	-0.0030	0.0017	-1.0632	3.1196
Financial year								
2008/09	-0.1661	-0.1057	-0.0594	-0.0387	-0.0059	0.0020	-0.7296	2.2908
2009/10	-0.2632	-0.1497	-0.0801	-0.0510	-0.0073	0.0050	-0.8857	2.5638
2010/11	-0.1592	-0.1021	-0.0576	-0.0376	-0.0058	0.0018	-0.7184	2.2741

Table D.8

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Organisational or Managerial Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	-0.0713	-0.0474	-0.0263	-0.0154	-0.0019	0.0004	-0.5762	2.0728
Innovation (initial condition, t=0)	0.0082	0.0511	0.0805	0.1322	0.3562	0.0076	1.4357	4.1261
With collaboration	0.0125	0.0679	0.1029	0.1524	0.1923	0.0025	0.1570	1.8515
Market competition								
Minimal	-0.1892	-0.0904	-0.0468	-0.0261	-0.0071	0.0023	-1.0954	3.1655
Moderate	0.0165	0.0477	0.0746	0.1182	0.1603	0.0017	0.4675	1.8971
Strong	0.0063	0.0195	0.0316	0.0528	0.0783	0.0004	0.6178	2.1072
ICT Intensity (High-to-most-intense)	-0.0033	-0.0023	-0.0014	-0.0008	-0.0001	0.0000	-0.4703	1.9870
Used STEM skills	0.0529	0.1903	0.2505	0.3169	0.3933	0.0067	-0.0340	2.1514
Market location (Local only)	0.0013	0.0094	0.0158	0.0283	0.0414	0.0001	0.5361	2.0447
With flexible working arrangements	0.0099	0.0485	0.0761	0.1136	0.1669	0.0018	0.4524	2.1239
Sought debt and/or equity finance	0.0004	0.0028	0.0046	0.0079	0.0112	0.0000	0.4555	1.9763
Financial year								
2008/09	-0.0513	-0.0332	-0.0197	-0.0111	-0.0016	0.0002	-0.5699	2.1002
2009/10	0.0025	0.0154	0.0260	0.0412	0.0565	0.0002	0.3626	1.8868
2010/11	-0.0038	-0.0026	-0.0016	-0.0009	-0.0001	0.0000	-0.4793	1.9918

Table D.9

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Operational Process Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0036	0.0266	0.0455	0.0721	0.0868	0.0007	0.0364	1.7093
Innovation (initial condition, t=0)	0.0370	0.1705	0.2544	0.3413	0.6309	0.0216	0.6970	2.7776
With collaboration	0.0166	0.0932	0.1464	0.2029	0.2348	0.0042	-0.2055	1.8378
Market competition								
Minimal	-0.1876	-0.0984	-0.0433	-0.0176	-0.0031	0.0031	-0.9214	2.5369
Moderate	0.0148	0.0583	0.1117	0.1796	0.2263	0.0042	0.2781	1.6449
Strong	0.0213	0.0793	0.1461	0.2255	0.2740	0.0059	0.2091	1.6169
ICT Intensity (High-to-most-intense)	0.0023	0.0171	0.0301	0.0486	0.0591	0.0003	0.0836	1.7156
Used STEM skills	0.0088	0.0537	0.0905	0.1354	0.1622	0.0022	-0.0417	1.7395
Market location (Local only)	0.0001	0.0007	0.0013	0.0022	0.0028	0.0000	0.1525	1.7058
With flexible working arrangements	0.0218	0.0961	0.1688	0.2409	0.2978	0.0065	0.0102	1.7481
Sought debt and/or equity finance	-0.0694	-0.0544	-0.0309	-0.0163	-0.0020	0.0005	-0.2114	1.7113
Financial year								
2008/09	-0.0726	-0.0608	-0.0388	-0.0234	-0.0038	0.0005	-0.0511	1.7280
2009/10	-0.1190	-0.0980	-0.0597	-0.0353	-0.0054	0.0013	-0.1156	1.7225
2010/11	-0.1263	-0.1035	-0.0627	-0.0370	-0.0056	0.0014	-0.1255	1.7223

Table D.10

Selected Summary Statistics for the Distribution of the APE Estimates for AgriFF Subsector (Marketing Methods Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0044	0.0352	0.0793	0.1223	0.1861	0.0029	0.3356	1.9677
Innovation (initial condition, t=0)	-0.1658	0.0013	0.0047	0.0095	0.0416	0.0019	-2.3651	7.3471
With collaboration	0.0073	0.0493	0.1122	0.1692	0.2426	0.0049	0.2289	1.8590
Market competition								
Minimal	0.0019	0.0109	0.0175	0.0354	0.1769	0.0010	2.0500	7.0193
Moderate	0.0211	0.0810	0.1154	0.1917	0.4650	0.0101	1.3448	3.9544
Strong	0.0226	0.0854	0.1212	0.1999	0.4740	0.0106	1.3210	3.8766
ICT Intensity (High-to-most-intense)	0.0064	0.0472	0.1035	0.1606	0.2276	0.0045	0.2609	1.8467
Used STEM skills	0.0031	0.0268	0.0637	0.1051	0.1660	0.0023	0.4538	2.0522
Market location (Local only)	0.0002	0.0018	0.0048	0.0089	0.0159	0.0000	0.7021	2.3542
With flexible working arrangements	0.0015	0.0120	0.0311	0.0549	0.0951	0.0008	0.6189	2.2531
Sought debt and/or equity finance	-0.1055	-0.0549	-0.0294	-0.0108	-0.0013	0.0010	-0.8243	2.5380
Financial year								
2008/09	-0.0611	-0.0366	-0.0214	-0.0084	-0.0005	0.0003	-0.5888	2.1942
2009/10	-0.0597	-0.0358	-0.0209	-0.0083	-0.0005	0.0003	-0.5858	2.1899
2010/11	-0.1044	-0.0594	-0.0339	-0.0130	-0.0008	0.0009	-0.6791	2.3336

Table D.11

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Overall Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0024	0.0178	0.0245	0.0291	0.0307	0.0001	-0.8090	2.6584
Innovation (initial condition, t=0)	0.0432	0.2370	0.2873	0.3099	0.3181	0.0034	-1.4119	4.4797
With collaboration	0.0164	0.0861	0.1211	0.1409	0.1479	0.0012	-0.7720	2.4881
Market competition								
Minimal	0.1039	0.4744	0.5692	0.6543	0.6847	0.0165	-1.0303	3.5975
Moderate	0.0302	0.0884	0.1574	0.2086	0.2229	0.0039	-0.3172	1.6536
Strong	0.0678	0.1671	0.2585	0.3227	0.3446	0.0074	-0.3837	1.7520
ICT Intensity (High-to-most-intense)	0.0114	0.0709	0.0968	0.1105	0.1164	0.0007	-0.8808	2.7523
Used STEM skills	0.0658	0.2540	0.3446	0.3908	0.4017	0.0079	-0.9102	2.6981
Market location (Local only)	-0.0933	-0.0888	-0.0753	-0.0542	-0.0052	0.0005	0.7913	2.6187
With flexible working arrangements	0.0123	0.0735	0.0987	0.1140	0.1205	0.0007	-0.8678	2.8355
Sought debt and/or equity finance	0.0181	0.1000	0.1411	0.1643	0.1715	0.0017	-0.7880	2.5150
Financial year								
2008/09	-0.1382	-0.1313	-0.1081	-0.0793	-0.0068	0.0011	0.7743	2.6265
2009/10	-0.1285	-0.1222	-0.1010	-0.0736	-0.0061	0.0010	0.7723	2.6124
2010/11	-0.1453	-0.1378	-0.1133	-0.0842	-0.0073	0.0012	0.7759	2.6367

Table D.12

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Goods and Services Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	-0.0216	-0.0195	-0.0152	-0.0084	-0.0003	0.0000	0.4400	1.8926
Innovation (initial condition, t=0)	0.0248	0.2628	0.3584	0.5025	0.6866	0.0277	0.4159	2.3202
With collaboration	-0.0857	-0.0767	-0.0596	-0.0305	-0.0009	0.0007	0.3839	1.7994
Market competition								
Minimal	0.1548	0.3942	0.5242	0.6254	0.6635	0.0191	-0.5934	2.2947
Moderate	0.0054	0.0333	0.0788	0.1551	0.1895	0.0039	0.3001	1.5976
Strong	0.0124	0.0661	0.1431	0.2460	0.2877	0.0084	0.1297	1.5309
ICT Intensity (High-to-most-intense)	0.0075	0.1079	0.1674	0.2056	0.2208	0.0010	-0.2131	2.0027
Used STEM skills	0.0144	0.1704	0.2417	0.2847	0.3019	0.0055	-0.7917	2.5631
Market location (Local only)	0.0007	0.0223	0.0424	0.0553	0.0615	0.0003	-0.4070	1.8329
With flexible working arrangements	0.0093	0.1084	0.1734	0.2202	0.2460	0.0041	-0.4357	2.0296
Sought debt and/or equity finance	0.0094	0.1343	0.1926	0.2316	0.2476	0.0039	-0.7031	2.4121
Financial year								
2008/09	-0.1514	-0.1391	-0.1098	-0.0713	-0.0049	0.0016	0.5391	2.0775
2009/10	-0.1520	-0.1396	-0.1103	-0.0715	-0.0050	0.0017	0.5386	2.0764
2010/11	-0.1875	-0.1725	-0.1350	-0.0844	-0.0055	0.0026	0.5081	2.0159

Table D.13

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Organisational or Managerial Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0019	0.0340	0.0542	0.0763	0.0861	0.0006	-0.2448	1.9334
Innovation (initial condition, t=0)	0.0045	0.0617	0.0984	0.1472	0.3048	0.0046	0.9291	3.4523
With collaboration	0.0107	0.1274	0.1827	0.2286	0.2514	0.0041	-0.5945	2.4250
Market competition								
Minimal	0.0950	0.1958	0.3158	0.4831	0.5750	0.0230	0.1923	1.6289
Moderate	0.0157	0.0433	0.0883	0.1830	0.3069	0.0077	0.7592	2.2763
Strong	0.0241	0.0627	0.1220	0.2382	0.3659	0.0111	0.6399	2.0681
ICT Intensity (High-to-most-intense)	0.0029	0.0470	0.0708	0.0978	0.1178	0.0010	-0.2131	2.0027
Used STEM skills	0.0196	0.1811	0.2495	0.3019	0.3310	0.0063	-0.7682	2.8309
Market location (Local only)	-0.0135	-0.0117	-0.0079	-0.0048	-0.0002	0.0000	0.1305	1.8349
With flexible working arrangements	0.0020	0.0308	0.0515	0.0759	0.0891	0.0006	-0.0755	1.8529
Sought debt and/or equity finance	0.0023	0.0388	0.0627	0.0890	0.0996	0.0008	-0.2496	1.9351
Financial year								
2008/09	-0.0948	-0.0823	-0.0536	-0.0323	-0.0021	0.0008	0.0975	1.7981
2009/10	-0.0356	-0.0313	-0.0215	-0.0134	-0.0009	0.0001	0.2135	1.8799
2010/11	-0.0591	-0.0520	-0.0349	-0.0214	-0.0015	0.0003	0.1668	1.8422

Table D.14

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Operational Process Innovation)

Variables	APE Percentiles					Other Measures		
	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0227	0.0600	0.0834	0.1010	0.1084	0.0006	-0.4887	2.0964
Innovation (initial condition, t=0)	0.0631	0.1330	0.2003	0.3004	0.4482	0.0096	0.6423	2.4270
With collaboration	0.0174	0.0471	0.0673	0.0818	0.0875	0.0004	-0.4993	2.0408
Market competition								
Minimal	0.0605	0.1142	0.1701	0.2132	0.2314	0.0028	-0.2823	1.7170
Moderate	0.0079	0.0171	0.0293	0.0411	0.0477	0.0002	-0.0301	1.6190
Strong	0.0267	0.0545	0.0877	0.1169	0.1308	0.0011	-0.1484	1.6467
ICT Intensity (High-to-most-intense)	0.0013	0.0040	0.0059	0.0075	0.0081	0.0000	-0.3792	1.9058
Used STEM skills	0.1514	0.2811	0.3297	0.3616	0.3803	0.0031	-0.8309	2.8584
Market location (Local only)	0.0030	0.0092	0.0141	0.0179	0.0195	0.0000	-0.3524	1.8704
With flexible working arrangements	0.0237	0.0552	0.0780	0.0978	0.1075	0.0006	-0.2824	1.8508
Sought debt and/or equity finance	0.0423	0.1092	0.1450	0.1708	0.1810	0.0014	-0.5755	2.2109
Financial year								
2008/09	-0.0700	-0.0659	-0.0534	-0.0379	-0.0150	0.0002	0.4264	1.9100
2009/10	-0.1145	-0.1068	-0.0847	-0.0592	-0.0224	0.0007	0.3692	1.8534
2010/11	-0.0964	-0.0902	-0.0720	-0.0506	-0.0196	0.0005	0.3926	1.8756

Table D.15

Selected Summary Statistics for the Distribution of the APE Estimates for Non-AgriFF Subsector (Marketing Methods Innovation)

	APE Percentiles					Other Measures		
Variables	Smallest	25	50	*75*	Largest	Variance	Skewness	Kurtosis
Innovation (t-1)	0.0009	0.0492	0.0763	0.1013	0.1098	0.0010	-0.4930	2.1239
Innovation (initial condition, t=0)	0.0025	0.0921	0.1497	0.2063	0.3990	0.0089	0.6202	2.7353
With collaboration	0.0032	0.1226	0.1721	0.2161	0.2313	0.0036	-0.6880	2.5538
Market competition								
Minimal	0.1121	0.3101	0.4914	0.6903	0.7396	0.0379	-0.1550	1.5894
Moderate	0.0089	0.0481	0.1154	0.3005	0.4194	0.0192	0.5597	1.7897
Strong	0.0157	0.0751	0.1661	0.3846	0.4909	0.0262	0.4261	1.6388
ICT Intensity (High-to-most-intense)	0.0032	0.1128	0.1662	0.2139	0.2328	0.0038	-0.5700	2.3025
Used STEM skills	0.0043	0.1372	0.1960	0.2471	0.2648	0.0047	-0.7024	2.5739
Market location (Local only)	-0.1350	-0.1237	-0.0946	-0.0631	-0.0012	0.0014	0.5396	2.2482
With flexible working arrangements	0.0004	0.0124	0.0208	0.0291	0.0323	0.0001	-0.3185	1.8803
Sought debt and/or equity finance	0.0010	0.0558	0.0860	0.1114	0.1238	0.0012	-0.4760	2.1600
Financial year								
2008/09	-0.1940	-0.1748	-0.1286	-0.0801	-0.0019	0.0029	0.3735	2.0565
2009/10	-0.1270	-0.1148	-0.0874	-0.0576	-0.0016	0.0012	0.4660	2.2641
2010/11	-0.1765	-0.1589	-0.1176	-0.0748	-0.0019	0.0024	0.3978	2.1083

Appendix E

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth: Nearest Neighbour and Radius Matching Results

Table E.1

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Nearest Neighbour Matching: Food Industry by Type of Innovation

Outcomes	Highly persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Goods and services					
Gross output growth ($)	-285,957	728,402	-487,656	-285,957	-870,803
Value added growth ($)	-234,007	492,468*	-163,773	-234,007	334,534
LP-GO growth (ratio)	-0.06	0.16	2.09	-0.06	0.64
LP-VA growth (ratio)	0.34	-0.41	5.44	0.34	1.48
Organisational and managerial process					
Gross output growth ($)	710,161	-406,909	172,506	710,161	26,490
Value added growth ($)	-11,844	152,118	-22,503	-11,844	219,334
LP-GO growth (ratio)	3.23	-0.19	2.08	3.23	2.07
LP-VA growth (ratio)	1.54*	1.36***	3.39	1.54*	2.88**
Operational Process					
Gross output growth ($)	827,070	529,446	-193,926	827,070	693,276
Value added growth ($)	-174,113	75,994	-19,473	-174,113	85,882
LP-GO growth (ratio)	-3.04	0.94**	-1.88	-3.04	-4.48
LP-VA growth (ratio)	0.81	0.80	5.87*	0.81	1.89*
Marketing Methods					
Gross output growth ($)	857,809	2,874	742,720	857,809	-605,569
Value added growth ($)	-195,389	1,339,301	100,440	-195,389	7,678
LP-GO growth (ratio)	2.99	0.57	2.83	2.99	1.37
LP-VA growth (ratio)	0.10	2.42	7.61	0.10	2.06

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table E.2

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Nearest Neighbour Matching: AgriFF Subsector by Type of Innovation

Outcomes	Highly Persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	13,331	148,218	36,444	13,331	14,404
Value added growth ($)	44,278	94,243	61,165	44,278	40,654
LP-GO growth (ratio)	-0.71	0.12	5.00	-0.71	1.75
LP-VA growth (ratio)	-0.09	-0.87	12.73	-0.09	1.42
Organisational and managerial process					
Gross output growth ($)	-24,199	-223,301	53,936	-24,199	7,245
Value added growth ($)	-150,358	-323,043	-56,894	-150,358	-29,352
LP-GO growth (ratio)	0.58	-0.17	3.37	0.58	1.39
LP-VA growth (ratio)	-0.18	0.42	5.98	-0.18	5.33
Operational Process					
Gross output growth ($)	13,552	-359,027	-2,377	13,552	-46,506
Value added growth ($)	-104,789*	-404,501	-7,698	-104,789*	-89,753
LP-GO growth (ratio)	0.73*	0.28	4.53	0.73*	1.39
LP-VA growth (ratio)	1.40	-0.97	13.29	1.40	4.82*
Marketing Methods					
Gross output growth ($)	-145,013	-388,458	77,434	-145,013	-4,186
Value added growth ($)	-188,307	149,325	9,511	-188,307	-50,895
LP-GO growth (ratio)	-0.36	1.61	11.43	-0.36	1.70
LP-VA growth (ratio)	0.55	0.23	32.43*	0.55	3.72

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively.

Table E.3

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Nearest Neighbour Matching: Non-AgriFF Subsector by Type of Innovation

Outcomes	Highly Persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	-156,678	1,263,913*	-2,028,076	-156,678	209,773
Value added growth ($)	-375,069	532,226	911,491	-375,069	543,969
LP-GO growth (ratio)	-0.04	-0.04	-0.10	-0.04	-0.15
LP-VA growth (ratio)	-0.55	-0.27	0.43	-0.55	-0.27
Organisational and managerial process					
Gross output growth ($)	1,632,505	135,042	1,822,489	1,632,505	1,798,701
Value added growth ($)	-102,297	669,456	679,128	-102,297	503,713
LP-GO growth (ratio)	5.67	-0.19	0.24	5.67	3.02
LP-VA growth (ratio)	0.89	0.95	0.85*	0.89	0.58
Operational Process					
Gross output growth ($)	1,773,182	491,110	300,017	1,773,182	1,537,390
Value added growth ($)	-190,567	-40,308	170,690	-190,567	285,879
LP-GO growth (ratio)	-8.83	0.66**	-6.74	-8.83	-4.40
LP-VA growth (ratio)	0.32	-0.19	1.33	0.32	0.46
Marketing Methods					
Gross output growth ($)	3,071,898	-1,388,292	2,057,167	3,071,898	1,060,451
Value added growth ($)	110,078	1,149,383	343,121	110,078	251,495
LP-GO growth (ratio)	8.66	0.61*	-0.19	8.66	2.17
LP-VA growth (ratio)	-0.45	3.23	-0.59	-0.45	0.59

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively

Table E.4

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Radius Matching: Food Industry by Type of Innovation

Outcomes	Highly Persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovators
Goods and services					
Gross output growth ($)	1,772,120	-345,177	-746,115	-29,037	-184,822
Value added growth ($)	1,133,188	429,688**	-159,838	-110,132	235,018
LP-GO growth (ratio)	-2.30	-0.62	1.40	-2.54*	-1.19
LP-VA growth (ratio)	-0.28	-0.26	4.65	-0.35	1.24
Organisational and managerial process					
Gross output growth ($)	3,418,104	39,180	203,097	586,971	193,458
Value added growth ($)	1,977,708	164,883	166	-95,421	190,351
LP-GO growth (ratio)	-0.10	-0.29	1.73	3.41	2.01
LP-VA growth (ratio)	7.88	0.77	3.28	1.27	2.74**
Operational Process					
Gross output growth ($)	2,584,549*	328,637	90,643	740,094	721,395*
Value added growth ($)	1,228,077	54,904	-6,754	-290,855	68,984
LP-GO growth (ratio)	-0.12	-0.26	-2.17	-0.92	-1.51
LP-VA growth (ratio)	0.91	0.67	5.73*	0.41	1.89*
Marketing Methods					
Gross output growth ($)	-511,277	469,319	1,051,281	752,739	292,943
Value added growth ($)	333,521	1,663,232	247,733	-103,259	100,625
LP-GO growth (ratio)	0.15	0.63	2.59	3.09	1.82
LP-VA growth (ratio)	-0.34	2.62	7.37	0.43	2.00

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively

Table E.5

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Radius Matching: AgriFF Subsector by Type of Innovation

Outcomes	Highly Persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	-243,391*	57,409	-90,228	6,929	-8,085
Value added growth ($)	17,224	35,590	50,707	62,726	55,362
LP-GO growth (ratio)	1.41	0.39	5.20	-0.36	1.51
LP-VA growth (ratio)	2.48***	-0.45	13.06	-2.22	3.11
Organisational and managerial process					
Gross output growth ($)	-142,828	-22,252	17,297	-26,349	36,470
Value added growth ($)	12,399	-43,484	-16,393	-102,992	25,718
LP-GO growth (ratio)	0.04	-0.48	3.37	0.85	1.41
LP-VA growth (ratio)	19.96	0.42	5.76	0.09	5.13
Operational Process					
Gross output growth ($)	581,668***	53,765	-18,588	57,671	-14,490
Value added growth ($)	458,832	-44,624	-19,860	-96,756	-65,225
LP-GO growth (ratio)	0.92***	0.88	4.20	0.38	1.32
LP-VA growth (ratio)	0.16	-0.81	12.81	0.97	4.42
Marketing Methods					
Gross output growth ($)	-511,277	-487,261	-1,656	60,397	53,938
Value added growth ($)	333,521	243,245	-111,736	-6,979	4,583
LP-GO growth (ratio)	0.15	0.41	10.80	0.21	1.85
LP-VA growth (ratio)	-0.34	1.43	32.60*	0.57	3.83

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively

Table E.6

Impacts of Innovation Persistence (ATT) on Small Food Businesses Performance Growth using Radius Matching: Non-AgriFF Subsector by Type of Innovation

Outcomes	Highly Persistent innovators	Persistent innovators	Regular innovators	Intermittent innovators	Overall innovator
Goods and services					
Gross output growth ($)	2,192,563	428,523	-3,292,283**	-2,951,330**	-180,454
Value added growth ($)	1,478,296	304,250	542,889	199,330	360,340
LP-GO growth (ratio)	-2.31	-0.89	-1.34	-1.64	-1.73
LP-VA growth (ratio)	-0.06	-0.34	-0.20	-0.74**	-0.07
Organisational and managerial process					
Gross output growth ($)	5,036,394**	1,640,434*	1,984,258	936,537	1,592,862
Value added growth ($)	5,394,996	776,543**	827,631	-183,227	435,572
LP-GO growth (ratio)	-0.12	0.34	0.18	5.74	2.21
LP-VA growth (ratio)	1.37	0.83	0.63	0.89	0.60
Operational Process					
Gross output growth ($)	3,818,786	465,127	400,616	1,831,693	1,463,496*
Value added growth ($)	1,713,780	225,020	123,238	-497,470	251,769
LP-GO growth (ratio)	0.28	-0.90	-3.42	-3.35	-2.71
LP-VA growth (ratio)	0.58	-0.10	1.41	0.15	0.66
Marketing Methods					
Gross output growth ($)	1,862,084	-1,387,221	1,884,056	2,525,913	875,189
Value added growth ($)	444,688	943,245	407,779	-304,864	160,167
LP-GO growth (ratio)	-0.43	0.51	-0.01	8.73	2.27
LP-VA growth (ratio)	0.43	3.40	-0.47	-0.67**	0.65

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively

Appendix F

OLS Regression Results for Business Performance and Innovation Persistence (Overall Innovation)

Table F.1

Regression Results for Business Performance and Innovation Persistence: Food Industry

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.01	*0.12*			0.60 ***	*0.19*			0.25 *	*0.13*			0.72 ***	*0.22*		
Persistent innovators	-0.28	*0.19*			0.13	*0.21*			-0.17	*0.15*			0.37	*0.23*		
Regular innovators	0.09	*0.12*			0.30	*0.20*			0.13	*0.14*			0.36	*0.23*		
Intermittent innovators	0.02	*0.13*			-0.17	*0.20*			0.35 **	*0.14*			0.22	*0.23*		
Persistence (Categorical)			-0.017	*0.026*			0.127 ***	*0.042*			0.030	*0.030*			0.166 ***	*0.047*
Sub-industry (Non-AgriFF)	-0.10	*0.10*	-0.083	*0.097*	-0.44 ***	*0.16*	-0.44 ***	*0.16*	-0.17	*0.11*	-0.14	*0.11*	-0.36 **	*0.18*	-0.36 **	*0.18*
With collaboration	0.25 **	*0.10*	0.238 **	*0.097*	0.79 ***	*0.16*	0.81 ***	*0.16*	0.14	*0.11*	0.12	*0.11*	0.70 ***	*0.18*	0.70 ***	*0.18*
Market competition																
Minimal	0.07	*0.17*	0.03	*0.17*	0.56 **	*0.26*	0.56 **	*0.26*	-0.04	*0.19*	-0.08	*0.19*	0.52 *	*0.31*	0.50	*0.31*
Moderate	-0.04	*0.15*	-0.07	*0.15*	0.21	*0.24*	0.23	*0.24*	-0.08	*0.17*	-0.15	*0.17*	0.24	*0.29*	0.22	*0.29*
Strong	0.10	*0.12*	0.05	*0.12*	0.24	*0.20*	0.23	*0.20*	0.12	*0.14*	0.06	*0.14*	0.25	*0.24*	0.23	*0.24*
ICT Intensity																
Moderate	-0.07	*0.17*	-0.06	*0.17*	0.39	*0.27*	0.42	*0.27*	0.02	*0.19*	0.02	*0.19*	0.28	*0.29*	0.28	*0.28*
High	-0.15	*0.26*	-0.20	*0.26*	-0.58	*0.44*	-0.56	*0.44*	-0.36	*0.29*	-0.44	*0.30*	-1.09 **	*0.47*	-1.11 **	*0.47*
Most intense	-0.03	*0.19*	-0.01	*0.19*	-0.08	*0.30*	-0.02	*0.30*	-0.13	*0.22*	-0.14	*0.22*	-0.31	*0.33*	-0.30	*0.33*
Used STEM skills	-0.235 **	*0.091*	-0.225 **	*0.091*	-0.50 ***	*0.15*	-0.48 ***	*0.15*	-0.22 **	*0.10*	-0.22 **	*0.10*	-0.34 **	*0.17*	-0.34 **	*0.17*
Market location (Local only)	0.26 **	*0.11*	0.26 **	*0.11*	0.94 ***	*0.19*	0.91 ***	*0.19*	0.09	*0.13*	0.11	*0.13*	0.74 ***	*0.22*	0.74 ***	*0.22*
With flexible working arrangements	-0.044	*0.091*	-0.044	*0.091*	0.00	*0.15*	0.02	*0.15*	-0.18 *	*0.10*	-0.20 *	*0.10*	-0.26	*0.18*	-0.27	*0.17*
Sought debt and/or equity finance	-0.01	*0.10*	-0.039	*0.097*	-0.01	*0.16*	-0.02	*0.16*	-0.06	*0.11*	-0.10	*0.11*	-0.13	*0.18*	-0.14	*0.18*
Intercept	0.03	*0.22*	0.06	*0.22*	-0.99 ***	*0.37*	-1.06 ***	*0.36*	0.10	*0.26*	0.20	*0.25*	-0.80 *	*0.43*	-0.78 *	*0.42*
Log Likelihood	-304.36		-307.47		-342.57		-344.783		-345.61		-351.44		-357.59		-357.87	
Adjusted R-squared	0.049		0.039		0.377		0.374		0.073		0.047		0.291		0.298	
Number of observations (n)	310		310		255		255		310		310		244		244	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table F.2

Regression Results for Business Performance and Innovation Persistence: AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.09	*0.22*			0.63 **	*0.26*			0.68 **	*0.27*			0.78 **	*0.37*		
Persistent innovators	-0.10	*0.21*			0.10	*0.24*			0.23	*0.25*			0.29	*0.36*		
Regular innovators	0.08	*0.21*			-0.16	*0.24*			0.30	*0.25*			0.42	*0.34*		
Intermittent innovators	-0.05	*0.19*			-0.18	*0.21*			0.10	*0.23*			-0.25	*0.31*		
Persistence (Categorical)			0.007	*0.045*			0.085	*0.055*			0.139 **	*0.055*			0.165 **	*0.076*
With collaboration	0.45 **	*0.18*	0.43 **	*0.18*	1.06 ***	*0.20*	1.07 ***	*0.20*	-0.13	*0.22*	-0.15	*0.21*	0.85 ***	*0.29*	0.87 ***	*0.29*
Market competition																
Minimal	0.26	*0.29*	0.25	*0.28*	-0.22	*0.31*	-0.29	*0.31*	0.21	*0.35*	0.20	*0.34*	0.37	*0.46*	0.32	*0.45*
Moderate	-0.01	*0.23*	-0.02	*0.22*	0.37	*0.25*	0.41	*0.25*	-0.54 *	*0.28*	-0.56 **	*0.27*	-0.30	*0.36*	-0.21	*0.35*
Strong	0.01	*0.16*	-0.01	*0.15*	0.24	*0.18*	0.28	*0.18*	-0.26	*0.20*	-0.29	*0.18*	0.12	*0.27*	0.15	*0.26*
ICT Intensity (High to Most intense)	-0.80 ***	*0.30*	-0.79 ***	*0.29*	0.57	*0.40*	0.72 *	*0.38*	-0.72 *	*0.36*	-0.71 **	*0.34*	-0.19	*0.54*	-0.06	*0.50*
Used STEM skills	-0.37 **	*0.15*	-0.36 **	*0.15*	-0.43 **	*0.17*	-0.40 **	*0.17*	-0.07	*0.18*	-0.06	*0.18*	-0.17	*0.26*	-0.14	*0.25*
Market location (Local only)	-0.20	*0.28*	-0.22	*0.28*	-0.17	*0.37*	-0.11	*0.37*	-0.11	*0.34*	-0.15	*0.33*	-0.39	*0.56*	-0.40	*0.55*
With flexible working arrangements	-0.13	*0.15*	-0.11	*0.14*	-0.13	*0.18*	-0.11	*0.18*	-0.45 **	*0.18*	-0.43 **	*0.17*	-0.70 ***	*0.26*	-0.62 **	*0.25*
Sought debt and/or equity finance	-0.010	*0.163*	-0.04	*0.16*	-0.26	*0.19*	-0.27	*0.20*	-0.01	*0.20*	-0.04	*0.19*	-0.32	*0.28*	-0.37	*0.28*
Intercept	0.48	*0.34*	0.50	*0.32*	0.43	*0.42*	0.25	*0.41*	0.59	*0.40*	0.62	*0.38*	0.93	*0.66*	0.79	*0.63*
Log Likelihood	-120.90		-121.31		-84.27		-87.48		-143.72		-144.27		-125.66		-127.17	
Adjusted R-squared	0.058		0.077		0.298		0.275		0.058		0.075		0.146		0.150	
Number of observations (n)	123		123		91		91		123		123		94		94	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table F.3

Regression Results for Business Performance and Innovation Persistence: Non-AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.11	*0.12*			0.88 ***	*0.26*			0.15	*0.15*			1.07 ***	*0.25*		
Persistent innovators	-0.05	*0.14*			0.41	*0.31*			-0.07	*0.17*			0.85 ***	*0.29*		
Regular innovators	0.08	*0.16*			0.64 *	*0.33*			-0.18	*0.19*			0.35	*0.31*		
Intermittent innovators	0.10	*0.15*			0.11	*0.33*			0.49 ***	*0.18*			0.67 **	*0.31*		
Persistence (Categorical)			0.017	*0.027*			0.209 ***	*0.058*			0.009	*0.034*			0.260 ***	*0.058*
With collaboration	0.07	*0.12*	0.06	*0.12*	0.31	*0.25*	0.34	*0.25*	0.03	*0.14*	-0.03	*0.15*	0.37	*0.23*	0.33	*0.23*
Market competition																
Minimal	0.61 *	*0.34*	0.58 *	*0.33*	0.44	*0.83*	0.32	*0.81*	-0.01	*0.42*	0.19	*0.41*	0.35	*1.13*	0.60	*1.09*
Moderate	0.45	*0.33*	0.43	*0.32*	0.00	*0.80*	-0.10	*0.78*	0.56	*0.40*	0.75 *	*0.40*	0.70	*1.10*	0.93	*1.07*
Strong	0.65 **	*0.33*	0.65 **	*0.31*	0.22	*0.80*	0.13	*0.78*	0.49	*0.40*	0.75 *	*0.40*	0.62	*1.09*	0.87	*1.05*
ICT Intensity (High to Most intense)	0.13	*0.12*	0.13	*0.12*	-0.63 **	*0.26*	-0.59 **	*0.25*	-0.16	*0.14*	-0.20	*0.15*	-0.58 **	*0.24*	-0.61 **	*0.24*
Used STEM skills	-0.21 *	*0.11*	-0.22 **	*0.11*	-0.38	*0.25*	-0.44 *	*0.24*	-0.27 **	*0.14*	-0.27 *	*0.13*	-0.56 **	*0.23*	-0.53 **	*0.22*
Market location (Local only)	0.38 ***	*0.11*	0.39 ***	*0.11*	1.27 ***	*0.24*	1.24 ***	*0.23*	0.26 *	*0.13*	0.33 **	*0.13*	1.17 ***	*0.23*	1.23 ***	*0.22*
With flexible working arrangements	-0.05	*0.12*	-0.05	*0.11*	0.14	*0.26*	0.13	*0.26*	0.10	*0.14*	0.06	*0.14*	0.15	*0.27*	0.11	*0.26*
Sought debt and/or equity finance	0.01	*0.12*	0.00	*0.12*	0.74 ***	*0.25*	0.73 ***	*0.25*	-0.09	*0.15*	-0.10	*0.15*	0.62 **	*0.25*	0.62 **	*0.25*
Intercept	-0.82 **	*0.34*	-0.80 **	*0.32*	-1.44 *	*0.80*	-1.31 *	*0.78*	-0.66	*0.42*	-0.83 **	*0.41*	-2.01 *	*1.12*	-2.21 **	*1.08*
Log Likelihood	-107.74		-108.42		-193.67		-194.36		-137.98		-143.57		-189.65		-190.95	
Adjusted R-squared	0.207		0.143		0.427		0.435		0.133		0.087		0.468		0.471	
Number of observations (n)	152		152		138		138		152		152		137		137	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Appendix G

Regression Results for Business Performance and Innovation Persistence (Innovation Dimension)

Table G.1

Regression Results for Business Performance and Innovation Persistence: Goods and Services Innovation in the Food Industry

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	-0.14	*0.22*			0.23	*0.30*			0.04	*0.24*			0.33	*0.36*		
Persistent innovators	0.00	*0.22*			0.18	*0.28*			0.09	*0.23*			0.25	*0.34*		
Regular innovators	-0.51 ***	*0.20*			0.35	*0.29*			-0.27	*0.21*			0.64 *	*0.34*		
Intermittent innovators	-0.22	*0.16*			-0.12	*0.23*			-0.07	*0.17*			0.05	*0.27*		
Persistence (Categorical)			-0.053	*0.046*			0.070	*0.060*			-0.002	*0.048*			0.108	*0.072*
Sub-industry (Non-AgriFF)	0.05	*0.14*	0.09	*0.14*	-0.13	*0.21*	-0.13	*0.20*	-0.14	*0.15*	-0.11	*0.15*	-0.03	*0.25*	-0.08	*0.24*
With collaboration	0.06	*0.14*	0.06	*0.14*	0.18	*0.19*	0.15	*0.18*	0.13	*0.15*	0.14	*0.14*	0.08	*0.22*	0.05	*0.22*
Market competition																
Minimal	-0.27	*0.31*	-0.15	*0.30*	-0.37	*0.47*	-0.34	*0.46*	-0.07	*0.33*	0.00	*0.32*	-0.55	*0.66*	-0.51	*0.64*
Moderate	-0.26	*0.28*	-0.18	*0.28*	-0.64	*0.44*	-0.58	*0.44*	-0.10	*0.30*	-0.05	*0.29*	-0.81	*0.63*	-0.72	*0.62*
Strong	-0.15	*0.26*	-0.08	*0.25*	-0.53	*0.41*	-0.47	*0.41*	0.03	*0.27*	0.06	*0.27*	-0.72	*0.61*	-0.63	*0.59*
ICT Intensity																
Moderate	-0.03	*0.23*	0.01	*0.24*	0.28	*0.29*	0.26	*0.29*	-0.09	*0.25*	-0.06	*0.25*	0.14	*0.34*	0.10	*0.33*
High	-0.21	*0.32*	-0.11	*0.32*	0.07	*0.43*	0.04	*0.42*	-0.46	*0.34*	-0.40	*0.33*	-0.09	*0.64*	-0.16	*0.63*
Most intense	0.03	*0.25*	0.08	*0.25*	0.32	*0.32*	0.30	*0.31*	-0.26	*0.27*	-0.23	*0.27*	-0.03	*0.36*	-0.08	*0.36*
Used STEM skills	-0.04	*0.14*	0.00	*0.13*	-0.08	*0.19*	-0.06	*0.18*	-0.27 *	*0.14*	-0.25 *	*0.14*	-0.35	*0.23*	-0.36	*0.22*
Market location (Local only)	0.31 **	*0.16*	0.33 **	*0.16*	-0.09	*0.23*	-0.11	*0.23*	0.08	*0.17*	0.10	*0.17*	-0.07	*0.26*	-0.08	*0.26*
With flexible working arrangements	-0.07	*0.15*	-0.01	*0.15*	0.00	*0.21*	0.00	*0.21*	-0.19	*0.16*	-0.16	*0.16*	-0.43	*0.28*	-0.46 *	*0.28*
Sought debt and/or equity finance	-0.10	*0.14*	-0.10	*0.14*	-0.08	*0.19*	-0.09	*0.19*	-0.12	*0.15*	-0.12	*0.15*	-0.11	*0.23*	-0.13	*0.23*
Intercept	0.20	*0.38*	-0.09	*0.36*	0.54	*0.55*	0.52	*0.52*	0.51	*0.40*	0.34	*0.38*	1.14	*0.75*	1.22 *	*0.70*
Log Likelihood	-187.26		-190.65		-171.32		-172.2		-198.02		-199.21		-177.38		-178.54	
Adjusted R-squared	0.089		0.052		0.073		0.061		0.079		0.066		0.124		0.108	
Number of observations (n)	170		170		135		135		170		170		125		125	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.2

Regression Results for Business Performance and Innovation Persistence: Organisational and Managerial Innovation in the Food Industry

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.15	*0.25*			0.82 **	*0.34*			0.14	*0.29*			0.87 **	*0.38*		
Persistent innovators	0.12	*0.22*			0.19	*0.33*			0.02	*0.25*			0.54	*0.35*		
Regular innovators	-0.14	*0.18*			0.40	*0.26*			0.22	*0.21*			0.93 ***	*0.29*		
Intermittent innovators	0.00	*0.15*			0.10	*0.22*			0.20	*0.17*			0.33	*0.24*		
Persistence (Categorical)			0.020	*0.047*			0.162 **	*0.067*			0.037	*0.054*			0.247 ***	*0.073*
Sub-industry (Non-AgriFF)	0.02	*0.14*	0.05	*0.14*	-0.47 **	*0.22*	-0.48 **	*0.21*	-0.09	*0.16*	-0.09	*0.16*	-0.25	*0.23*	-0.31	*0.23*
With collaboration	0.20	*0.13*	0.21 *	*0.13*	0.42 **	*0.18*	0.44 **	*0.18*	0.00	*0.15*	-0.04	*0.15*	0.21	*0.21*	0.21	*0.21*
Market competition																
Minimal	-0.14	*0.30*	-0.12	*0.30*	0.11	*0.40*	0.07	*0.40*	0.18	*0.34*	0.16	*0.34*	0.58	*0.42*	0.48	*0.42*
Moderate	-0.20	*0.23*	-0.18	*0.22*	0.03	*0.32*	0.01	*0.31*	-0.04	*0.26*	-0.06	*0.26*	0.17	*0.37*	0.04	*0.36*
Strong	-0.12	*0.20*	-0.10	*0.20*	0.29	*0.29*	0.27	*0.28*	0.12	*0.23*	0.11	*0.23*	0.44	*0.33*	0.36	*0.33*
ICT Intensity																
Moderate	0.08	*0.27*	0.10	*0.27*	0.20	*0.36*	0.20	*0.35*	0.07	*0.31*	0.02	*0.30*	0.15	*0.37*	0.09	*0.36*
High	-0.94 **	*0.38*	-0.94 **	*0.37*	-0.55	*0.60*	-0.59	*0.59*	-0.78 *	*0.43*	-0.86 **	*0.42*	-2.20 **	*0.75*	-2.38 ***	*0.72*
Most intense	0.02	*0.28*	0.03	*0.27*	0.25	*0.38*	0.24	*0.36*	-0.23	*0.32*	-0.30	*0.31*	-0.15	*0.40*	-0.22	*0.39*
Used STEM skills	-0.12	*0.12*	-0.10	*0.12*	-0.34 *	*0.18*	-0.33 *	*0.18*	-0.18	*0.14*	-0.21	*0.14*	-0.31	*0.20*	-0.32	*0.20*
Market location (Local only)	-0.10	*0.17*	-0.07	*0.16*	0.11	*0.26*	0.11	*0.25*	0.18	*0.19*	0.18	*0.19*	0.24	*0.28*	0.15	*0.27*
With flexible working arrangements	-0.10	*0.14*	-0.12	*0.13*	-0.30	*0.21*	-0.27	*0.20*	-0.29 *	*0.16*	-0.29 *	*0.15*	-0.67 ***	*0.21*	-0.66 ***	*0.21*
Sought debt and/or equity finance	-0.06	*0.14*	-0.04	*0.13*	-0.32	*0.20*	-0.35 *	*0.20*	-0.16	*0.15*	-0.18	*0.15*	-0.47 **	*0.22*	-0.54 **	*0.22*
Intercept	0.44	*0.38*	0.34	*0.36*	0.22	*0.54*	0.19	*0.51*	0.22	*0.44*	0.37	*0.42*	0.01	*0.60*	0.33	*0.56*
Log Likelihood	-180.52		-181.26		-179.71		-180.5		-203.38		-204.26		-192.17		-193.90	
Adjusted R-squared	0.122		0.114		0.202		0.193		0.142		0.133		0.286		0.267	
Number of observations (n)	170		170		138		138		170		170		138		138	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.3

Regression Results for Business Performance and Innovation Persistence: Operational Process Innovation in the Food Industry

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.07	*0.18*			0.16	*0.23*			0.17	*0.20*			0.36	*0.28*		
Persistent innovators	-0.01	*0.17*			0.04	*0.22*			0.24	*0.19*			0.17	*0.27*		
Regular innovators	-0.46 ***	*0.14*			0.28	*0.19*			-0.24	*0.17*			0.45 **	*0.22*		
Intermittent innovators	-0.09	*0.14*			-0.11	*0.19*			0.03	*0.17*			0.08	*0.22*		
Persistence (Categorical)			-0.024	*0.036*			0.050	*0.046*			0.030	*0.041*			0.103 *	*0.056*
Sub-industry (Non-AgriFF)	0.13	*0.13*	0.11	*0.13*	-0.59 ***	*0.17*	-0.58 ***	*0.17*	0.07	*0.15*	0.05	*0.15*	-0.20	*0.21*	-0.20	*0.21*
With collaboration	0.11	*0.11*	0.13	*0.11*	0.33 **	*0.14*	0.33 **	*0.14*	0.18	*0.13*	0.18	*0.13*	0.35 **	*0.17*	0.35 **	*0.17*
Market competition																
Minimal	-0.44 *	*0.25*	-0.28	*0.25*	0.10	*0.31*	0.03	*0.30*	0.11	*0.29*	0.23	*0.28*	0.39	*0.37*	0.31	*0.36*
Moderate	-0.42 *	*0.22*	-0.33	*0.22*	0.18	*0.29*	0.17	*0.28*	-0.07	*0.26*	-0.02	*0.25*	0.24	*0.35*	0.19	*0.35*
Strong	-0.18	*0.19*	-0.10	*0.19*	0.27	*0.25*	0.26	*0.24*	0.10	*0.22*	0.15	*0.21*	0.21	*0.29*	0.16	*0.29*
ICT Intensity																
Moderate	-0.07	*0.21*	-0.05	*0.21*	0.34	*0.26*	0.35	*0.26*	0.09	*0.24*	0.09	*0.24*	0.10	*0.31*	0.09	*0.31*
High	-0.27	*0.28*	-0.21	*0.28*	0.59	*0.37*	0.56	*0.37*	-0.33	*0.32*	-0.30	*0.32*	-0.26	*0.49*	-0.28	*0.49*
Most intense	-0.18	*0.23*	-0.17	*0.23*	0.43	*0.30*	0.44	*0.29*	-0.30	*0.27*	-0.31	*0.27*	-0.21	*0.35*	-0.22	*0.34*
Used STEM skills	-0.27 **	*0.11*	-0.20 *	*0.11*	-0.05	*0.14*	-0.06	*0.14*	-0.23 *	*0.12*	-0.18	*0.12*	0.02	*0.17*	-0.01	*0.17*
Market location (Local only)	0.22	*0.14*	0.25 *	*0.14*	-0.03	*0.20*	-0.05	*0.20*	0.06	*0.16*	0.09	*0.16*	0.14	*0.24*	0.09	*0.24*
With flexible working arrangements	-0.06	*0.11*	-0.03	*0.11*	-0.07	*0.15*	-0.07	*0.15*	-0.20	*0.13*	-0.18	*0.13*	-0.35 *	*0.19*	-0.33 *	*0.19*
Sought debt and/or equity finance	-0.08	*0.11*	-0.07	*0.11*	-0.30 **	*0.15*	-0.30 **	*0.15*	-0.18	*0.13*	-0.16	*0.13*	-0.26	*0.18*	-0.27	*0.18*
Intercept	0.48	*0.31*	0.26	*0.30*	0.05	*0.43*	0.07	*0.40*	0.21	*0.35*	0.07	*0.34*	-0.04	*0.52*	0.09	*0.49*
Log Likelihood	-249.97		-255.85		-217.40		-218.82		-283.20		-285.82		-263.38		-264.38	
Adjusted R-squared	0.109		0.062		0.152		0.139		0.111		0.090		0.127		0.118	
Number of observations (n)	232		232		183		183		232		232		189		189	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.4

Regression Results for Business Performance and Innovation Persistence: Marketing Methods Innovation in the Food Industry

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	-0.05	*0.22*			0.38	*0.32*			-0.21	*0.23*			0.19	*0.35*		
Persistent innovators	0.07	*0.22*			0.46	*0.35*			0.24	*0.23*			0.69 *	*0.36*		
Regular innovators	-0.07	*0.18*			0.06	*0.27*			0.15	*0.19*			0.10	*0.29*		
Intermittent innovators	-0.23	*0.15*			0.07	*0.24*			-0.02	*0.16*			-0.19	*0.27*		
Persistence (Categorical)			-0.009	*0.045*			0.100	*0.068*			0.002	*0.048*			0.093	*0.073*
Sub-industry (Non-AgriFF)	-0.04	*0.15*	0.01	*0.15*	-0.48 **	*0.24*	-0.46 *	*0.23*	-0.08	*0.16*	-0.04	*0.16*	-0.33	*0.26*	-0.25	*0.25*
With collaboration	0.05	*0.13*	0.06	*0.12*	0.45 **	*0.19*	0.43 **	*0.18*	0.04	*0.13*	0.05	*0.13*	0.35 *	*0.21*	0.38 *	*0.21*
Market competition																
Minimal	-0.35	*0.28*	-0.31	*0.27*	-0.28	*0.41*	-0.27	*0.41*	0.00	*0.29*	-0.01	*0.29*	-0.18	*0.47*	-0.05	*0.46*
Moderate	-0.23	*0.27*	-0.21	*0.27*	-0.27	*0.42*	-0.24	*0.42*	-0.08	*0.29*	-0.09	*0.29*	-0.34	*0.48*	-0.26	*0.48*
Strong	-0.15	*0.22*	-0.12	*0.22*	0.00	*0.35*	0.00	*0.34*	0.04	*0.23*	0.01	*0.23*	-0.03	*0.41*	0.04	*0.40*
ICT Intensity																
Moderate	-0.01	*0.23*	0.00	*0.23*	0.09	*0.31*	0.10	*0.31*	0.22	*0.24*	0.21	*0.24*	0.27	*0.32*	0.26	*0.32*
High	-0.20	*0.31*	-0.19	*0.30*	-0.10	*0.47*	-0.12	*0.46*	-0.13	*0.33*	-0.17	*0.32*	-0.23	*0.61*	-0.36	*0.61*
Most intense	0.00	*0.25*	0.02	*0.25*	0.03	*0.36*	0.02	*0.36*	-0.01	*0.27*	-0.02	*0.27*	-0.19	*0.37*	-0.17	*0.37*
Used STEM skills	-0.15	*0.12*	-0.09	*0.12*	-0.26	*0.19*	-0.23	*0.18*	-0.16	*0.13*	-0.16	*0.12*	-0.31	*0.21*	-0.22	*0.20*
Market location (Local only)	0.27 *	*0.15*	0.29 **	*0.15*	0.45 *	*0.25*	0.48 *	*0.24*	0.20	*0.16*	0.22	*0.16*	0.22	*0.27*	0.29	*0.26*
With flexible working arrangements	-0.03	*0.14*	0.00	*0.14*	-0.39 *	*0.23*	-0.38 *	*0.23*	-0.18	*0.15*	-0.21	*0.15*	-0.86 **	*0.24*	-0.87 ***	*0.24*
Sought debt and/or equity finance	-0.14	*0.14*	-0.13	*0.14*	-0.26	*0.22*	-0.25	*0.22*	-0.25 *	*0.15*	-0.20	*0.15*	-0.37	*0.24*	-0.32	*0.23*
Intercept	0.32	*0.37*	0.13	*0.34*	0.36	*0.56*	0.29	*0.51*	0.07	*0.39*	0.09	*0.37*	0.86	*0.59*	0.57	*0.55*
Log Likelihood	-217.13		-218.57		-217.45		-217.79		-229.58		-231.11		-217.68		-219.50	
Adjusted R-squared	0.069		0.055		0.207		0.204		0.099		0.085		0.241		0.222	
Number of observations (n)	196		196		156		156		196		196		148		148	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.5

Regression Results for Business Performance and Innovation Persistence: Goods and Services Innovation in the AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	-0.25	*0.57*			0.57	*0.80*			0.80	*0.56*			0.64	*1.27*		
Persistent innovators	0.14	*0.67*			0.32	*0.78*			-0.02	*0.66*			0.24	*1.09*		
Regular innovators	-0.64	*0.39*			0.42	*0.50*			0.06	*0.39*			1.11	*0.80*		
Intermittent innovators	-0.33	*0.30*			-0.01	*0.35*			0.09	*0.30*			0.24	*0.58*		
Persistence (Categorical)			-0.11	*0.11*			0.14	*0.13*			0.12	*0.11*			0.21	*0.22*
With collaboration	-0.01	*0.34*	0.07	*0.31*	0.53	*0.45*	0.48	*0.38*	-0.09	*0.34*	0.01	*0.31*	0.21	*0.75*	-0.02	*0.63*
Market competition																
Minimal	-0.39	*0.48*	-0.30	*0.47*	-0.37	*0.59*	-0.40	*0.56*	-0.13	*0.48*	-0.09	*0.46*	-0.05	*1.10*	-0.19	*1.03*
Moderate	-0.51	*0.48*	-0.40	*0.46*	-0.34	*0.64*	-0.36	*0.57*	-0.63	*0.48*	-0.53	*0.45*	0.33	*1.45*	-0.08	*1.27*
Strong	-0.45	*0.38*	-0.33	*0.35*	-0.24	*0.48*	-0.24	*0.45*	-0.20	*0.37*	-0.20	*0.34*	-0.34	*0.90*	-0.48	*0.82*
ICT Intensity (High to Most intense)	-0.33	*0.37*	-0.23	*0.36*	0.42	*0.50*	0.33	*0.45*	-0.50	*0.37*	-0.46	*0.35*	0.27	*0.83*	0.00	*0.76*
Used STEM skills	-0.24	*0.28*	-0.20	*0.27*	-0.64 *	*0.34*	-0.60 *	*0.32*	-0.47 *	*0.28*	-0.44 *	*0.26*	-0.39	*0.61*	-0.33	*0.57*
Market location (Local only)	0.29	*0.41*	0.28	*0.38*	0.67	*0.68*	0.57	*0.64*	-0.31	*0.40*	-0.24	*0.37*	1.51	*1.96*	0.63	*1.66*
With flexible working arrangements	-0.07	*0.30*	-0.03	*0.29*	-0.38	*0.41*	-0.44	*0.38*	-0.39	*0.30*	-0.45	*0.29*	-0.65	*0.71*	-0.96	*0.63*
Sought debt and/or equity finance	-0.04	*0.31*	-0.14	*0.29*	-0.38	*0.37*	-0.41	*0.35*	-0.20	*0.31*	-0.18	*0.29*	-0.67	*0.51*	-0.63	*0.48*
Intercept	0.64	*0.62*	0.39	*0.59*	0.41	*1.00*	0.55	*0.89*	1.20 *	*0.62*	1.07 *	*0.58*	-0.43	*2.57*	0.97	*2.05*
Log Likelihood	-93.09		-94.71		-61.46		-61.70		-92.82		-93.34		-54.74		-55.67	
Adjusted R-squared	0.144		0.105		0.281		0.273		0.169		0.156		0.329		0.295	
Number of observations (n)	71		71		50		50		71		71		37		37	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.6

Regression Results for Business Performance and Innovation Persistence: Organisational and Managerial Innovation in the AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.01	*0.42*			1.57 ***	*0.47*			0.23	*0.46*			1.79 **	*0.88*		
Persistent innovators	0.15	*0.36*			0.62	*0.46*			-0.14	*0.39*			0.61	*0.72*		
Regular innovators	-0.04	*0.24*			0.31	*0.27*			0.43	*0.26*			0.63	*0.44*		
Intermittent innovators	0.06	*0.21*			0.48 *	*0.27*			0.32	*0.23*			0.50	*0.45*		
Persistence (Categorical)			0.013	*0.073*			0.276 ***	*0.084*			0.074	*####*			0.33 **	*0.15*
With collaboration	0.22	*0.23*	0.23	*0.23*	1.45 ***	*0.30*	1.38 ***	*0.30*	0.11	*0.26*	0.10	*0.26*	1.26 **	*0.51*	1.27 **	*0.49*
Market competition																
Minimal	0.77	*0.51*	0.76	*0.50*	1.79 ***	*0.53*	1.75 ***	*0.53*	0.41	*0.56*	0.49	*0.56*	1.70 **	*0.80*	1.69 **	*0.78*
Moderate	-0.01	*0.33*	0.01	*0.31*	-0.08	*0.40*	-0.18	*0.37*	-0.04	*0.36*	-0.11	*0.35*	-0.29	*0.67*	-0.49	*0.59*
Strong	0.13	*0.23*	0.15	*0.22*	-0.01	*0.26*	0.01	*0.26*	0.12	*0.25*	0.10	*0.25*	0.33	*0.43*	0.29	*0.41*
ICT Intensity (High to Most intense)	-0.51 **	*0.25*	-0.52 **	*0.25*	0.01	*0.36*	-0.04	*0.36*	-0.29	*0.28*	-0.24	*0.28*	-0.20	*0.53*	-0.25	*0.52*
Used STEM skills	-0.04	*0.19*	-0.04	*0.18*	-1.05 ***	*0.26*	-0.98 ***	*0.25*	0.09	*0.21*	0.08	*0.20*	-0.56	*0.46*	-0.51	*0.44*
Market location (Local only)	-0.53 *	*0.31*	-0.51 *	*0.30*	0.11	*0.52*	0.13	*0.51*	-0.44	*0.34*	-0.38	*0.34*	-0.55	*0.81*	-0.66	*0.76*
With flexible working arrangements	-0.02	*0.18*	-0.03	*0.18*	-0.38	*0.24*	-0.42 *	*0.24*	-0.33	*0.20*	-0.31	*0.20*	-0.90 **	*0.36*	-0.93 **	*0.35*
Sought debt and/or equity finance	0.214	*0.181*	0.24	*0.17*	-0.69 ***	*0.23*	-0.68 **	*0.22*	0.14	*0.20*	0.07	*0.19*	-0.61	*0.40*	-0.61	*0.38*
Intercept	0.54	*0.42*	0.51	*0.41*	0.42	*0.60*	0.42	*0.58*	0.41	*0.46*	0.46	*0.46*	0.83	*0.98*	0.99	*0.91*
Log Likelihood	-103.64		-103.78		-69.12		-71.06		-112.58		-114.59		-74.56		-75.11	
Adjusted R-squared	0.114		0.111		0.633		0.610		0.115		0.077		0.454		0.442	
Number of observations (n)	95		95		66		66		95		95		53		53	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.7

Regression Results for Business Performance and Innovation Persistence: Operational Process Innovation in the AgriFF Subsector

Variables	Gross Output Growth (*Log*)				Value-Added Growth (*Log*)				Labour Productivity Growth (*Gross Output*)				Labour Productivity Growth (*Value-Added*)			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.05	*0.38*			0.77	*0.49*			0.52	*0.40*			1.15 *	*0.66*		
Persistent innovators	0.05	*0.27*			-0.30	*0.33*			0.54 *	*0.29*			-0.16	*0.46*		
Regular innovators	-0.83 ***	*0.24*			0.16	*0.28*			0.14	*0.26*			0.98 **	*0.40*		
Intermittent innovators	-0.10	*0.21*			-0.28	*0.25*			0.25	*0.23*			-0.09	*0.34*		
Persistence (Categorical)			-0.064	*0.068*			0.035	*0.079*			0.141 **	*0.069*			0.18	*0.11*
With collaboration	0.03	*0.22*	0.05	*0.23*	1.23 ***	*0.25*	1.21 ***	*0.26*	0.11	*0.24*	0.12	*0.24*	0.82 **	*0.36*	0.78 **	*0.37*
Market competition																
Minimal	-0.05	*0.44*	0.03	*0.45*	0.84 *	*0.46*	0.81 *	*0.45*	0.54	*0.47*	0.60	*0.46*	0.63	*0.63*	0.60	*0.65*
Moderate	-0.32	*0.32*	-0.35	*0.33*	0.32	*0.36*	0.44	*0.36*	0.00	*0.34*	0.00	*0.34*	0.08	*0.53*	0.17	*0.54*
Strong	-0.22	*0.23*	-0.18	*0.23*	0.41	*0.25*	0.47 *	*0.25*	0.30	*0.24*	0.30	*0.24*	0.45	*0.38*	0.43	*0.38*
ICT Intensity (High to Most intense	-0.36	*0.27*	-0.41	*0.28*	-0.02	*0.43*	-0.13	*0.42*	-0.38	*0.29*	-0.40	*0.28*	0.40	*0.71*	0.27	*0.72*
Used STEM skills	-0.28	*0.17*	-0.19	*0.18*	-0.41 **	*0.20*	-0.43 **	*0.20*	0.10	*0.19*	0.12	*0.18*	0.16	*0.32*	0.00	*0.32*
Market location (Local only)	0.02	*0.28*	0.09	*0.28*	0.49	*0.45*	0.50	*0.44*	-0.27	*0.30*	-0.24	*0.29*	-0.06	*0.66*	-0.09	*0.67*
With flexible working arrangements	-0.08	*0.19*	-0.06	*0.19*	-0.31	*0.22*	-0.20	*0.22*	-0.30	*0.20*	-0.32	*0.20*	-0.65 **	*0.32*	-0.46	*0.31*
Sought debt and/or equity finance	-0.22	*0.19*	-0.17	*0.19*	-0.14	*0.23*	-0.17	*0.23*	-0.22	*0.20*	-0.21	*0.20*	-0.05	*0.31*	-0.07	*0.32*
Intercept	0.78 *	*0.40*	0.56	*0.40*	-0.21	*0.57*	-0.37	*0.55*	0.18	*0.43*	0.15	*0.41*	0.07	*0.82*	0.05	*0.81*
Log Likelihood	-133.32		-140.02		-86.24		-89.37		-141.56		-142.06		-94.81		-99.04	
Adjusted R-squared	0.195		0.094		0.387		0.337		0.108		0.100		0.262		0.166	
Number of observations (n)	114		114		80		80		114		114		70		70	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.8

Regression Results for Business Performance and Innovation Persistence: Marketing Methods Innovation in the AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	-0.06	*0.51*			0.11	*0.48*			0.51	*0.51*			-0.06	*0.66*		
Persistent innovators	0.34	*0.73*			0.83	*0.93*			0.69	*0.74*			1.29	*1.22*		
Regular innovators	-0.45	*0.47*			0.03	*0.49*			0.89 *	*0.48*			-0.28	*0.68*		
Intermittent innovators	-0.74 **	*0.32*			-0.05	*0.39*			0.20	*0.32*			-1.49 **	*0.59*		
Persistence (Categorical)			-0.03	*0.12*			0.04	*0.11*			0.18	*0.11*			0.03	*0.18*
With collaboration	-0.14	*0.31*	-0.05	*0.31*	0.63 *	*0.32*	0.68 **	*0.30*	-0.17	*0.31*	-0.13	*0.30*	0.32	*0.48*	0.63	*0.49*
Market competition																
Minimal	0.34	*0.60*	0.42	*0.61*	-1.39 *	*0.69*	-1.40 **	*0.66*	-0.01	*0.60*	-0.09	*0.59*	-1.33	*0.82*	-0.85	*0.86*
Moderate	-0.44	*0.57*	-0.32	*0.56*	-0.39	*0.59*	-0.37	*0.56*	-0.66	*0.57*	-0.67	*0.55*	-0.65	*0.92*	-0.25	*1.00*
Strong	-0.39	*0.36*	-0.25	*0.35*	0.28	*0.35*	0.31	*0.34*	-0.16	*0.36*	-0.19	*0.34*	0.27	*0.52*	0.61	*0.56*
ICT Intensity (High to Most intense	-1.51 **	*0.59*	-0.98 *	*0.56*	1.39	*0.83*	1.51 **	*0.69*	-0.26	*0.60*	-0.30	*0.55*	-1.13	*0.92*	-0.04	*0.91*
Used STEM skills	-0.58 *	*0.33*	-0.19	*0.29*	-0.75 **	*0.36*	-0.73 **	*0.32*	-0.31	*0.34*	-0.37	*0.29*	-1.35 **	*0.58*	-0.37	*0.48*
Market location (Local only)	0.67	*0.43*	0.49	*0.42*	-0.60	*0.99*	-0.56	*0.94*	0.06	*0.43*	0.11	*0.41*	-0.82	*1.32*	-0.55	*1.45*
With flexible working arrangements	-0.35	*0.29*	-0.19	*0.29*	-0.65 *	*0.36*	-0.60	*0.31*	-0.16	*0.30*	-0.19	*0.28*	-1.38 ***	*0.48*	-1.46 ***	*0.52*
Sought debt and/or equity finance	0.20	*0.34*	-0.11	*0.33*	-0.48	*0.38*	-0.46	*0.33*	-0.45	*0.35*	-0.42	*0.32*	-1.24 **	*0.48*	-1.22 **	*0.51*
Intercept	0.79	*0.60*	0.24	*0.54*	1.70	*1.22*	1.55	*1.01*	0.50	*0.60*	0.56	*0.53*	3.88 **	*1.57*	2.04	*1.54*
Log Likelihood	-86.81		-90.40		-50.45		-51.01		-87.55		-88.72		-48.74		-54.79	
Adjusted R-squared	0.217		0.131		0.386		0.372		0.194		0.166		0.590		0.441	
Number of observations (n)	69		69		48		48		69		69		39		39	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.9

Regression Results for Business Performance and Innovation Persistence: Goods and Services Innovation in the Non-AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	-0.06	*0.22*			0.17	*0.37*			-0.19	*0.28*			0.01	*0.34*		
Persistent innovators	-0.02	*0.20*			-0.27	*0.34*			0.12	*0.26*			0.09	*0.31*		
Regular innovators	-0.36	*0.22*			0.07	*0.43*			-0.46	*0.28*			0.01	*0.38*		
Intermittent innovators	-0.28	*0.21*			-0.55	*0.36*			-0.12	*0.26*			-0.10	*0.33*		
Persistence (Categorical)			-0.021	*0.046*			0.0003	*0.076*			-0.029	*0.058*			0.015	*0.068*
With collaboration	0.19	*0.16*	0.20	*0.16*	-0.02	*0.27*	0.02	*0.27*	0.26	*0.20*	0.24	*0.20*	0.19	*0.24*	0.18	*0.23*
Market competition																
Minimal	0.63	*0.48*	0.75	*0.47*	0.26	*1.06*	0.09	*1.06*	0.46	*0.61*	0.71	*0.59*	-0.06	*0.36*	-0.05	*0.34*
Moderate	0.55	*0.46*	0.61	*0.45*	-0.11	*1.04*	-0.25	*1.04*	0.70	*0.59*	0.86	*0.57*	-		-	
Strong	0.71	*0.48*	0.74	*0.47*	-0.08	*1.07*	-0.25	*1.06*	0.73	*0.60*	0.85	*0.59*	-0.21	*0.32*	-0.23	*0.30*
ICT Intensity (High to Most intense)	-0.01	*0.16*	0.03	*0.16*	-0.15	*0.28*	-0.05	*0.28*	-0.24	*0.20*	-0.22	*0.20*	-0.08	*0.26*	-0.07	*0.24*
Used STEM skills	0.04	*0.18*	0.10	*0.17*	0.19	*0.31*	0.25	*0.29*	-0.21	*0.22*	-0.16	*0.21*	0.17	*0.26*	0.20	*0.24*
Market location (Local only)	0.25	*0.20*	0.27	*0.20*	-0.30	*0.35*	-0.38	*0.35*	0.26	*0.25*	0.30	*0.25*	-0.45	*0.29*	-0.46 *	*0.28*
With flexible working arrangements	-0.20	*0.18*	-0.13	*0.17*	0.27	*0.33*	0.36	*0.32*	-0.07	*0.22*	-0.03	*0.22*	0.08	*0.28*	0.10	*0.27*
Sought debt and/or equity finance	-0.05	*0.17*	-0.06	*0.17*	0.20	*0.29*	0.24	*0.29*	-0.18	*0.22*	-0.21	*0.21*	0.09	*0.27*	0.11	*0.26*
Intercept	-0.54	*0.50*	-0.78	*0.48*	0.30	*1.04*	0.28	*1.05*	-0.65	*0.63*	-0.93	*0.61*	0.37	*0.41*	0.34	*0.38*
Log Likelihood	-68.90		-71.07		-94.86		-96.88		-88.80		-90.72		-75.42		-75.54	
Adjusted R-squared	0.153		0.108		0.116		0.067		0.165		0.126		0.071		0.068	
Number of observations (n)	85		85		75		75		85		85		66		66	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.10

Regression Results for Business Performance and Innovation Persistence: Organisational and Managerial Innovation in the Non-AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.27	*0.28*			0.84	*0.56*			0.15	*0.35*			0.84	*0.55*		
Persistent innovators	0.03	*0.26*			-0.13	*0.55*			0.38	*0.33*			0.45	*0.52*		
Regular innovators	-0.05	*0.25*			0.88 *	*0.48*			0.34	*0.31*			1.20 **	*0.47*		
Intermittent innovators	0.04	*0.16*			-0.28	*0.32*			0.41 **	*0.20*			0.11	*0.31*		
Persistence (Categorical)			0.037	*0.054*			0.14	*0.11*			0.099	*0.069*			0.24 **	*0.11*
With collaboration	0.17	*0.16*	0.19	*0.15*	-0.01	*0.31*	-0.02	*0.31*	0.00	*0.20*	-0.07	*0.20*	-0.17	*0.32*	-0.28	*0.31*
Market competition																
Minimal	0.69	*0.48*	0.70	*0.47*	-0.05	*1.27*	0.33	*1.24*	0.80	*0.60*	0.65	*0.60*	0.99	*1.21*	1.05	*1.17*
Moderate	0.59	*0.46*	0.58	*0.45*	-0.42	*1.20*	-0.10	*1.20*	0.92	*0.58*	0.90	*0.58*	0.66	*1.14*	0.79	*1.13*
Strong	0.83 *	*0.46*	0.82 *	*0.45*	0.12	*1.21*	0.39	*1.21*	1.14	*0.58*	1.14 *	*0.58*	1.10	*1.16*	1.19	*1.15*
ICT Intensity (High to Most intense)	0.10	*0.16*	0.10	*0.15*	-0.43	*0.32*	-0.29	*0.31*	-0.28	*0.20*	-0.35 *	*0.19*	-0.74 **	*0.31*	-0.67 **	*0.30*
Used STEM skills	-0.18	*0.17*	-0.18	*0.16*	-0.40	*0.33*	-0.39	*0.33*	-0.24	*0.21*	-0.29	*0.21*	-0.26	*0.34*	-0.29	*0.34*
Market location (Local only)	0.26	*0.17*	0.28 *	*0.16*	0.56	*0.35*	0.42	*0.33*	0.56	*0.22*	0.60 ***	*0.21*	0.62 *	*0.35*	0.47	*0.33*
With flexible working arrangements	-0.09	*0.16*	-0.09	*0.15*	-0.15	*0.33*	-0.01	*0.33*	-0.02	*0.20*	-0.03	*0.19*	-0.25	*0.32*	-0.14	*0.31*
Sought debt and/or equity finance	0.07	*0.16*	0.04	*0.15*	0.43	*0.32*	0.35	*0.32*	-0.39	*0.21*	-0.38 *	*0.20*	0.16	*0.31*	0.12	*0.30*
Intercept	-0.86 *	*0.48*	-0.88 *	*0.47*	0.00	*1.23*	-0.42	*1.21*	-1.39	*0.60*	-1.24 **	*0.60*	-1.07	*1.18*	-1.12	*1.14*
Log Likelihood	-77.35		-77.68		-115.34		-118.48		-98.14		-100.04		-106.84		-108.80	
Adjusted R-squared	0.125		0.118		0.186		0.120		0.245		0.213		0.245		0.206	
Number of observations (n)	92		92		81		81		92		92		78		78	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.11

Regression Results for Business Performance and Innovation Persistence: Operational Process Innovation in the Non-AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.09	*0.19*			0.26	*0.37*			0.27	*0.26*			0.49	*0.39*		
Persistent innovators	0.00	*0.21*			-0.11	*0.41*			0.23	*0.28*			0.19	*0.41*		
Regular innovators	-0.11	*0.16*			0.15	*0.33*			-0.07	*0.22*			0.43	*0.32*		
Intermittent innovators	-0.19	*0.17*			-0.18	*0.33*			0.22	*0.23*			0.31	*0.34*		
Persistence (Categorical)			0.008	*0.040*			0.045	*0.078*			0.053	*0.054*			0.118	*0.081*
With collaboration	0.09	*0.13*	0.11	*0.12*	0.08	*0.24*	0.11	*0.24*	0.15	*0.17*	0.15	*0.16*	0.16	*0.25*	0.14	*0.24*
Market competition																
Minimal	0.58	*0.43*	0.61	*0.43*	0.40	*1.15*	0.31	*1.10*	0.59	*0.58*	0.71	*0.57*	0.82	*0.83*	0.76	*0.81*
Moderate	0.61	*0.43*	0.62	*0.42*	0.11	*1.14*	0.04	*1.10*	0.75	*0.57*	0.82	*0.56*	0.83	*0.82*	0.79	*0.81*
Strong	0.87 **	*0.43*	0.85 **	*0.42*	0.53	*1.14*	0.44	*1.10*	0.74	*0.57*	0.79	*0.57*	0.68	*0.85*	0.67	*0.84*
ICT Intensity (High to Most intense	0.01	*0.15*	0.03	*0.14*	-0.20	*0.30*	-0.17	*0.29*	-0.37 *	*0.20*	-0.35 *	*0.19*	-0.47	*0.29*	-0.46	*0.28*
Used STEM skills	-0.13	*0.14*	-0.11	*0.14*	-0.15	*0.28*	-0.17	*0.27*	-0.05	*0.19*	-0.03	*0.18*	0.21	*0.28*	0.16	*0.27*
Market location (Local only)	0.33 **	*0.14*	0.33 **	*0.14*	0.43	*0.28*	0.41	*0.28*	0.29	*0.19*	0.29	*0.19*	0.36	*0.29*	0.31	*0.28*
With flexible working arrangements	-0.03	*0.15*	-0.02	*0.14*	-0.05	*0.30*	-0.06	*0.29*	-0.11	*0.20*	-0.06	*0.19*	-0.19	*0.34*	-0.19	*0.34*
Sought debt and/or equity finance	0.00	*0.14*	0.00	*0.14*	0.16	*0.27*	0.18	*0.27*	-0.19	*0.18*	-0.18	*0.18*	0.17	*0.27*	0.15	*0.26*
Intercept	-0.84 *	*0.45*	-0.92 **	*0.44*	-0.53	*1.18*	-0.48	*1.11*	-0.79	*0.61*	-0.91	*0.59*	-1.03	*0.82*	-0.89	*0.79*
Log Likelihood	-82.49		-83.67		-129.39		-130.00		-113.65		-114.62		-119.87		-120.42	
Adjusted R-squared	0.126		0.107		0.069		0.056		0.157		0.142		0.131		0.120	
Number of observations (n)	106		106		94		94		106		106		88		88	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Table G.12

Regression Results for Business Performance and Innovation Persistence: Marketing Methods Innovation in the Non-AgriFF Subsector

Variables	Gross Output Growth *(Log)*				Value-Added Growth (*Log*)				Labour Productivity Growth *(Gross Output)*				Labour Productivity Growth *(Value-Added)*			
	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*	Coefficient	*SE*
Highly Persistent innovators	0.31	*0.19*			0.62	*0.42*			-0.22	*0.27*			0.19	*0.40*		
Persistent innovators	0.16	*0.17*			0.45	*0.39*			0.19	*0.24*			0.72 *	*0.37*		
Regular innovators	-0.04	*0.15*			-0.05	*0.34*			-0.12	*0.21*			0.03	*0.33*		
Intermittent innovators	0.21	*0.17*			0.13	*0.38*			-0.02	*0.24*			-0.05	*0.34*		
Persistence (Categorical)			0.053	*0.037*			0.127	*0.083*			-0.014	*0.052*			0.109	*0.079*
With collaboration	0.11	*0.11*	0.10	*0.11*	0.41	*0.25*	0.40	*0.24*	0.13	*0.16*	0.11	*0.16*	0.17	*0.25*	0.13	*0.25*
Market competition																
Minimal	1.59 ***	*0.55*	1.44 ***	*0.53*	0.09	*0.48*	0.01	*0.46*	1.18	*0.77*	1.19	*0.75*	0.10	*0.44*	0.08	*0.43*
Moderate	1.68 ***	*0.54*	1.59 ***	*0.53*					1.16	*0.77*	1.20	*0.75*				
Strong	1.80 ***	*0.53*	1.70 ***	*0.52*	0.37	*0.39*	0.32	*0.38*	1.25 *	*0.75*	1.27 *	*0.73*	0.10	*0.37*	0.07	*0.36*
ICT Intensity (High to Most intense)	0.08	*0.14*	0.03	*0.13*	-0.34	*0.31*	-0.40	*0.30*	-0.33 *	*0.19*	-0.39 **	*0.18*	-0.42	*0.28*	-0.48 *	*0.27*
Used STEM skills	-0.11	*0.13*	-0.10	*0.12*	-0.22	*0.30*	-0.16	*0.28*	-0.16	*0.19*	-0.11	*0.17*	0.01	*0.26*	0.09	*0.25*
Market location (Local only)	0.33 ***	*0.12*	0.33 ***	*0.12*	0.53 *	*0.28*	0.53 **	*0.27*	0.18	*0.17*	0.22	*0.16*	0.35	*0.29*	0.45	*0.28*
With flexible working arrangements	0.05	*0.17*	0.02	*0.16*	-0.13	*0.37*	-0.13	*0.35*	0.01	*0.24*	-0.05	*0.22*	-0.20	*0.31*	-0.27	*0.30*
Sought debt and/or equity finance	0.04	*0.12*	0.00	*0.11*	0.57 **	*0.27*	0.57 **	*0.26*	-0.10	*0.17*	-0.06	*0.16*	0.01	*0.30*	0.06	*0.29*
Intercept	-2.04 **	*0.58*	-1.87 **	*0.54*	-0.57	*0.61*	-0.54	*0.55*	-1.11	*0.82*	-1.09	*0.77*	-0.19	*0.56*	-0.22	*0.52*
Log Likelihood	-67.27		-68.78		-130.34		-130.98		-102.88		-103.90		-124.73		-126.04	
Adjusted R-squared	0.222		0.199		0.200		0.189		0.147		0.129		0.135		0.110	
Number of observations (n)	102		102		92		92		102		102		92		92	

Note: The asterisks, ***,** and *, denote significance at the 1%, 5% and 10% levels, respectively. All SEs are given to two-significant digits and the corresponding coefficients are given to the same number of digits behind the decimal points as their SEs.

Appendix H

2018 Australian Journal of Agricultural and Resource Economics Publication

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]