CHAPTER 1: INTRODUCTION TO THE STUDY

The study reported in this thesis examines the productivity and efficiency of not-for-profit charities, using The Gideons International in Australia (TGIA) as a case study. The main purpose of this introductory chapter is to establish the background of the study, highlight the rationale behind it, state the objectives and underlying research questions, and provide an outline of the thesis.

1.1 Background

This study was partly motivated by increasing demands from the NFP and charitable sector in Australia for greater recognition of that sector's contribution to the Australian economy (e.g. National Roundtable of Nonprofit Organisations 2009; Crosbie 2011). The study was also motivated by the perceived relative paucity of research on the sector, particularly on its efficiency and effectiveness, and by the opportunity to explore these aspects using TGIA as a case study.

CPA Australia, one of the major Australian professional accounting bodies, released in 2011 a guide to internal controls for NFP organisations (CPA Australia 2011). The release of that guide is one indication of the growing recognition of the contribution NFP organisations make to the Australian economy. From the guide it is apparent that performance and efficiency have been recognised as important foci for internal controls for charities and other NFP organisations. A standard chart of accounts for financial reporting by the NFP sector has also been introduced (Department of Finance, Finance Circular No. 2011/03).

The Australian Government recognised the important contribution of charities (IC 1995) and the NFP sector (Productivity Commission 2010) to the Australian economy some 20 years ago, and commissioned a number of major studies and/or other enquiries. The Australian Government also established the Australian Charities and Not-for-Profits Commission (ACNC) which was officially launched on Monday 10 December 2012 (ACNC Media Release, 10 December 2012).

In 2014 the current Australian Government has indicated its intention to abolish the ACNC in favour of a Centre for Excellence, because 'This Government believes that the role of government is to support civil society, not to control it or bind it in more red tape' (Ferguson 2012). Similarly, the New Zealand Charities Commission (NZCC) was established in 2005 and shut down in 2012 because 'A statement from the NZ Government says it has decided that its Charities Commission is unnecessary, carrying out a duplication of functions of Government, and has ordered its "disestablishment" ' (Pro Bono News 2012). Bill d'Apice, Partner with Sydney-based law firm Makinson d'Apice Lawyers, was quoted in March 2012 (well before the ACNC was launched on 10 December 2012) as saying 'With the ACNC Implementation Task Force conducting its public consultations, it will be interesting to see whether the public is of the view that the Federal Government's expenditure on a separate commission established to carry out some of the functions of the Australian Taxation Office and some new functions related to transparency and education, justifies the expenditure of the Federal Government in Australia' (Pro Bono News 2012). The New Zealand Charities Commission was set up for a period of four years and is the first Charities Commission of the nations of the British Commonwealth to have been disestablished (Pro Bono News 2012).

Former Director of Charity Services at the United Kingdom (UK) Charity Commission, David Locke, said at the time of the NZCC shutting down in 2012 (again well before the ACNC was launched on 10 December 2012) that it was 'against the flow' of charity regulation throughout the world (Civil Society News 2012). He was then living in Australia and working as part of the Australian ACNC implementation taskforce, responsible for seeing in the new regulator in the country. He added:

> I have been following the decision in New Zealand. This decision is against the flow of a number of other common jurisdictions that have recognised the need for independent regulation of this important sector. Scotland, Northern Ireland and Singapore have all established independent regulators in recent years. In Hong Kong the Law Commission has recommended the establishment of a Charity Commission. In the UK the British government did consider the future of the Charity Commission in 2010 as part of its review of arms length bodies. The government accepted that the Charity Commission of England and Wales carried out necessary functions and there was a need for the exercise of these functions to be independent of political interests. The issue of impartiality is in my view an important one. In Australia, the government is implementing a wide raft of reforms of the charitable and NFP

> sector and is delivering on a number of key recommendations from the Productivity Commission report of 2010. The establishment of the ACNC is one of the cornerstones of this important reform agenda. Here the government has recognised the need for the regulator to be an independent body that has its own Commissioner and appropriation and reports to Parliament.

One response to the above 'against the flow' assertion (Civil Society News 2012) was:

> The 'against the flow' assertion needs some critical evaluation. Relationships between the government, the not-for-profit sector and the community at large, move in cycles, at different paces in different countries. The developments in New Zealand might more accurately reflect a trend of civil society in each jurisdiction expecting higher value from their not-for-profit regulators. In England and Wales, the trend towards higher value may be seen in the reductions to the budget of the Charity Commission of England and Wales, under which it will presumably focus on delivering the best value to the community within its reduced resources. In Australia, the formation of the Australian Charities and Not-for-profits Commission (ACNC) with 'back office' support from larger government agencies also reflects a government looking to provide greater value to the community by avoiding duplication of 'overhead' costs. Efficiency initiatives in Scotland, Northern Ireland, Singapore and elsewhere also reflect this trend, probably accelerated by the fiscal pressures on all Governments since the global economic crisis. The circumstances in New Zealand need to be considered in this light. The changes in New Zealand do not necessarily diminish the availability of 'independent regulation' of the charitable sector in New Zealand, and are more likely indicative of a public expectation of greater value from regulators.

The above policy decisions and discussion would appear not to obviate the compelling reasons for having regulatory authorities like the ACNC in Australia and the NZCC in New Zealand in the first place. The policy decisions certainly do not appear to diminish the need for research on the charitable and NFP sector in Australia (and globally). The relative paucity of such research exists whether or not there is any type of regulatory authority or regulation in Australia (and globally).

The parent entity of TGIA is The Gideons International (TGI), which dates back to 1899 and operates globally from its international headquarters in the United States of America (USA). In Australia, TGI has operated through a self-supporting, locally incorporated association (TGIA, The Gideons International in Australia) since 1970, but TGI's work in Australia dates back to 1956. TGIA has been granted the status of an income tax exempt charitable institution (charity) under Australian taxation legislation and is registered with the ACNC. In a business sense, TGI can be described as a global

charity that distributes Bibles internationally through various outlets. All funding comes from private sources and there are no Government grants. In each country where it operates, TGI has a number of branches through which Bible distribution and fundraising of private donations is attributed. In Australia there were 133 branches as of 31 May 2013 (end of financial year for TGIA), spread across the six states, the Australian Capital Territory and the Northern Territory. All Bible distributions are carried out by volunteers who are members of TGIA/TGI.

From the national level in Australia, the hierarchical structure of TGIA extends to the branch level through state/territory levels and area levels. The number of members varies across branches, and a branch is effectively a bottom-line decision making unit (DMU) that is structured the same. Each branch effectively carries out the same service activities of Bible distribution and fundraising of private donations in a defined local geographical territory.

As is shown by the above summary, TGIA activities are characteristic of charities generally. Any charity will seek to do two things: to provide a service (service activities) and to raise funds (fundraising activities) to provide that service.

This thesis describes research into the productive efficiency of the service and fundraising operations of TGIA, a charitable not-for-profit (NFP) entity (charity) that operates in the private sector in Australia. The ultimate aim of the study was to identify the significant factors affecting the productivity and efficiency of a charitable institution, using TGIA as the case study organisation, with a view to showing that the study methods should be of use to other charitable institutions.

A measure of overall performance is total factor productivity (TFP), which is a productivity measure involving all factors of production in the economic sense (Coelli, Rao, O'Donnell and Battese 2005, page 3). It is common to measure TFP as the ratio of an aggregate output to an aggregate input (O'Donnell 2010). The thesis shows how the study has decomposed sources of TFP by following the methodology proposed by O'Donnell (2010, 2011).

The theory underlying the study is based on the concept of efficiency as proposed by Farrell (1957). Efficiency is a concept in which there is established a production frontier defining the relationship between inputs and outputs. The production frontier represents the maximum output attainable from each input level. A producer operating on the frontier is technically efficient whereas a producer operating below the frontier is not efficient (Coelli et al. 2005, page 3; O'Donnell 2011). The concepts of efficiency defined here are from economics and should not be confused with concepts of efficiency embodied in other studies; for example, the concept of efficiency based on accounting and financial ratios, or using proxy variables for efficiency in regression models (e.g. Weisbrod and Dominguez 1986; Trussel and Parsons 2003, 2007; Gordon, Knock and Neely 2009). The technical efficiency of a DMU is measured by reference to the distance from the established frontier.

As seems to be common among charities, TGIA, a registered charity in Australia, has a wealth of tabulated data and descriptive statistics at the entity and branch levels. However, there is a notable absence of mathematical programming and inferential statistical studies using this available information. This study tests, and confirms, that mathematical and statistical analysis of productive efficiency and its underlying concepts can extract very beneficial new information to add to that already collected by management (e.g. Vassiloglou and Giokas 1990; Dyson and Shale 2010). This new information has the potential to enhance the performance of charities and their contributions to the Australian economy as a whole.

The study focuses on three principal areas of TGIA, the case-study charity. The empirical analysis is carried out at the meta-frontier (all Australia/national) and group-frontier (five state regions) levels of TGIA. In presenting the study and its findings, the thesis focuses on three aspects of the theory and practice tested.

First, the thesis describes various productivity and efficiency performance measures of the Bible distribution (BDIST) operations and the fundraising of private donations (DON) operations by the branches of TGIA. (Note that TGI operates globally but this research is concerned only with the Australian branches and operations under the aegis of TGIA. The thesis uses the more contextual common term 'branch' to describe groups that are termed 'camps' by TGIA and TGI.)

Second, the thesis describes the development, application, testing and analysis of regression models using the Tobit regression method (Coelli et al. 2005, page 194), with the various productivity and efficiency performance measures obtained for BDIST and DON as the dependent variables respectively. Selected independent variables are used to explain variation in the dependent variables. This approach is justified by its adoption in previous studies along similar lines (see, for example, Cruz 2004; Borge and Haraldsvik 2005; Armagan 2008). One analyst (Callen 1994) used efficiency as an independent variable in regression models. That approach was not explored further because of a possibility that it may cause an endogeneity problem.

Third, the thesis focuses on the meta-frontier approach (MFA) of Battese and Rao (2002), Battese, Rao and O'Donnell (2004), O'Donnell, Rao and Battese (2008) and O'Donnell, Falah-Fini and Triantis (2011). This approach seems justified for at least the following three reasons:

(a) There have been previous studies using MFA such as those cited immediately above and Khrueathai, Untong, Kaosa-ard and Villano (2011), Ben-Naceur, Ben-Khedhiri and Casu (2009), and Boshrabadi, Villano and Fleming (2007). The application of MFA is still relatively in its infancy compared with, say, the thousands of studies of productivity and efficiency. The application in this thesis extends the work previously undertaken in the area of MFA.

(b) The mode of operation of TGIA, in terms of its hierarchical structure and availability of data, lends itself to the application of MFA. In particular, the meta or national level is already segmented into five state regions or groups with tabulations of data over time for all output, input and other variables included in the empirical analysis.

(c) It is anticipated that further insight could be gained into the TGIA's levels of productivity, and efficiency scores and the factors affecting them, by applying MFA.

The empirical analysis was carried out by first constructing balanced panel datasets from TGIA databases that contain data on the input, output and other variables used. A balanced panel dataset ensures compatibility with software applied in the analysis. Next, data envelopment analysis (DEA) was applied to the input/output datasets to

obtain the various productivity and efficiency scores as branch performance measures, using the decomposing productivity index numbers (DPIN) computer program. Then, various measures of productivity and efficiency were used respectively as single dependent variables in Tobit regression analysis (TRA). This was done to seek to explain the variation in each dependent variable caused by postulated independent variables, and it helped in determining the direction and significance of factors possibly affecting each measure for Bible distribution (BDIST) and fundraising of private donations (DON). Finally, MFA was applied to give more insight into factors affecting particular dependent variables at the national and group levels.

There is no shortage of data and tabulated descriptive statistics at all levels of TGIA. Cross-sectional, time series and panel data have been made available for the research described in this thesis, and ethical issues have been addressed. The structure of the TGI/TGIA organisation and the availability and other aspects of the data suit the research to which this thesis relates. For example, Dyson and Shale (2010) used DEA to examine the technical efficiency of four entities in the UK, two of which were NFP, and commented that 'there was no shortage of data so that the issues discussed are as far as possible not driven by lack of information'. Such a comment applies equally to this case study of TGIA.

It is against the background of the perceived importance of charities as an integral part of the wider NFP sector in Australia that this thesis seeks to make a contribution. There is an apparent gap in the published literature on the application and relevance of productive efficiency to charities using mathematical programming and econometric analysis. The thesis adds to existing literature in the topic areas. To the author's knowledge, the study makes an original empirical contribution as the first to apply DEA in the analysis of performance of not-for-profit organisation such as charitable institutions, examined the possible factors affecting these performance indicators and apply MFA to branches of a single NFP charitable entity (microeconomic level) and on charities in Australia in general. The thesis also contributes guidelines for TGIA management to manage its efficiency and productivity level. Previous published studies have focused only on entity-to-entity comparisons at an industry level (e.g. Weisbrod and Dominguez 1986; Callen 1994; Gordon, Knock and Neely 2009).

TGIA is part of the private charitable NFP sector in Australia (referred to collectively as ‘charities’), which is a subset of the much broader NFP sector. In making a case study of TGIA, it was anticipated that the method applied in the research will be extendable and applicable to measuring the branch performance of other individual charities and NFP entities, and thereby benefit the NFP sector in Australia as a whole in the future. Extensions to global models for charities operating internationally, similar to that in Pitkin (2013), will also be possible.

It is anticipated that the results and evaluation of the analyses will be an additional indicator, adding to information already established by TGIA and a guide to future directions for improving the performance of TGIA at all levels. The intention is to provide a more complete understanding of key issues in the application of productive efficiency analysis, and of factors affecting service and the fundraising operations of charities and the broader NFP sector in Australia. Suggestions are also made for further research.

1.2 Statement of the problem

There are two main aspects to the problem addressed in this thesis. These are: the performance of TGIA; and the provision of empirical evidence from the TGIA case study to support similar studies for branch operations of other charities and NFP entities.

The performance of TGIA is mapped year by year against predetermined goals at all levels of its operations. Emphasis in achieving satisfactory performance is placed on each branch as the basic DMU. All other things being equal, it is assumed that enhanced performance at TGIA branch level flows through to the higher levels in the TGIA hierarchy.

Performance measurement to date by TGIA appears to have relied on simple ratio and time series analyses at particular points in and over time, from year to year. The application of more sophisticated analysis embodied in, for example, the paradigms of applied mathematics, inferential statistics and econometrics, and the interpretation thereof, may lead to better outcomes for TGIA. This is important because the

environment in which TGIA operates becomes more challenging each year. It is hoped that TGIA will welcome the results from the analysis in this study, and will be able to use them to enhance the performance and performance management at TGIA.

Although there have been studies involving cross-charity/NFP entity comparisons at an industry level as cited in later chapters, there appears to be an absence of microeconomic studies making cross-branch comparisons of the performance of single charities/NFP entities using the methods applied in this study. The thesis also explores possible parallels with microeconomic studies of bank branches of single banks, in an attempt to gain insight in this area — recognising that charities are generally NFP while banks are generally for-profit. The thesis addresses the absence, to date, of microeconomic studies on charities, and it is anticipated that this demonstration of the value of empirical evidence on performance and performance management for TGIA will lead to similar studies for other private charities/NFP entities.

In view of the stated research problem, the thesis has four objectives and the related research questions can be summarised under each objective.

Objective 1

To measure the relative overall performance of TGIA branches' service activities of Bible distribution (BDIST) and fundraising of private donations (DON) in Australia for the period 2008 to 2013.

(a) What were the relative productivity levels of Bible distribution and fundraising of private donations of TGIA branches in Australia during the period 2008 to 2013 inclusive?

(b) Have these levels changed year by year from 2008 to 2013 inclusive?

Objective 2

To examine measures of efficiency of TGIA branches for the period 2008 to 2013.

(a) What were the relative levels of measures of efficiency of Bible distribution and fundraising of private donations of TGIA branches in Australia during the period 2008 to 2013 inclusive?

(b) Have these levels of measures of efficiency changed year by year from 2008 to 2013 inclusive?

Objective 3

To examine factors possibly affecting the performance of TGIA branches in Australia for the period 2008 to 2013.

(a) For the factors postulated as possibly affecting the levels of productivity and of measures of efficiency of Bible distribution and fundraising of private donations performance for TGIA branches in Australia for the period 2008 to 2013, what were the magnitude, statistical significance and direction of each factor?

Objective 4

To examine the application of the meta-frontier approach (MFA) to the performance of TGIA branches in Australia for the period 2008 to 2013.

(a) What were the meta-technology ratios (MTRs) that were used to obtain estimates of total factor productivity (TFP) and output technical efficiency (OTE) for Bible distribution and fundraising of private donations of TGIA branches in Australia for the period 2008 to 2013 inclusive?

(b) Have these MTRs changed year by year from 2008 to 2013 inclusive?

The research study is evidence-based and confined to the relationships existing between facts or data that are directly accessible to observation, particularly TGIA datasets. It therefore reflects an epistemology of objectivism and ontology of positivism. The study also draws on paradigms of mathematics, statistical analysis, econometrics, economics, management, business, management science and performance management.

The main argument is that the research, using the TGIA case study, will give new insights into the theory, application and extension of management science, performance management and benchmarking to charities in Australia. This argument is supported by the notable paucity of literature about similar studies in the topic area.

1.3 Outline of the thesis

In Chapter 2 (Overview of the Not-for-Profit and Charitable Sector and The Gideons International in Australia) the historic and contemporary developments in the NFP and charitable sector, and the history and mode of operation of TGIA, are presented. In Chapter 3 (Conceptual and Methodological Framework) a comprehensive discussion is provided on the historic, contemporary and emerging themes in productivity and efficiency research, and the framework used in the empirical analysis is described. In Chapter 4 (Review of Efficiency Studies on Charities and Not-for-Profit Entities) the literature related to productive efficiency for charities and NFP organisations is reviewed. In Chapter 5 (Empirical Models, Data Requirements and Data Sources) the analytical framework and empirical models are summarised. In Chapter 6 (Performance of TGIA) the most significant results are summarised and discussed. In Chapter 7 (Productivity Differences by State Group) MFA is applied to TGIA. In Chapter 8 (Summary and Conclusions) the research questions underlying the objectives of the study are answered, limitations and implications of the study are addressed and suggestions are made for further research. Use of EndNote X4.0.2 (Thomson Reuters 1998 to 2010) assisted with the keeping of the bibliographical records for the list of references at the end of the thesis.

CHAPTER 2: OVERVIEW OF THE NOT-FOR-PROFIT AND CHARITABLE SECTOR AND THE GIDEONS INTERNATIONAL IN AUSTRALIA

In this chapter an overview of the NFP and charitable sector and The Gideons International in Australia (TGIA) is provided. The historic and contemporary developments in the sector are addressed and the history and mode of operation of TGIA are described. The first section covers the structure, principles and fundamentals of operation, and other attributes of the NFP and charitable sector in Australia. In the second section, TGIA is described in terms of its history, structure, governance, Bible distribution, fundraising and funding sources, and other attributes.

2.1 Background

The focus in this section is on the charitable and NFP sector in Australia, to provide background to that sector in the Australian economy. The following review supports the importance of this sector in the Australian economy and justifies the study presented in this thesis.

The contribution of charities (generally NFP) is recognised as important in the context of the Australian economy, and prompted the Australian Government in 1994 to request a study by the Industry Commission (IC) on the Australian charities. The IC was then the Australian Government's independent research and advisory body on a range of economic, social and environmental issues affecting the welfare of Australians. Its role was to help governments make better policies in the long-term interest of the Australian community and the report on the study was published in June 1995 (IC 1995).

In commissioning a more recent study on the Australian NFP sector in 2009 by the Productivity Commission (PC), the Australian Government confirmed that the contribution of the NFP sector (of which charities are a subset) is still generally recognised as important in the context of the Australian economy. The PC succeeded

the former IC and has similar functions. The role of the PC is to help governments make better policies in the long-term interest of the Australian community (PC n.d).

At least one submission to the PC from a peak private charitable NFP body highlighted that only a small number of academics in Australia were doing research applicable to the sector, and that more was needed, including in the area of efficiency (National Roundtable of Nonprofit Organisations {NRNO} 2009). The NRNO submission states at page 7 that:

> Apart from the generous and useful work of a small number of academics who specialise in the not-for-profit sector in Australia, and somewhat limited work undertaken by the Australian Bureau of Statistics (ABS), by some government agencies and by sector organisations themselves, there appears to be little systematic collection and analysis of information about the not-for-profit sector as a discrete and important sector. This means there is likely to be considerable scope for better and more use of information on the contribution of the sector, which could then be used to inform policy which supports or removes impediments to the contribution of the sector and by the sector itself to improve and enhance its own efficiency and effectiveness.

The Productivity Commission (PC) (2010) report, which was published in January 2010 (Productivity Commission 2010), states that the PC 'was also asked to examine ways to improve the efficiency and effectiveness of the sector'. The need for ongoing consideration of efficiency in the NFP sector is mentioned a number of times. Charities are mentioned several times as a significant contributor to the NFP sector in Australia.

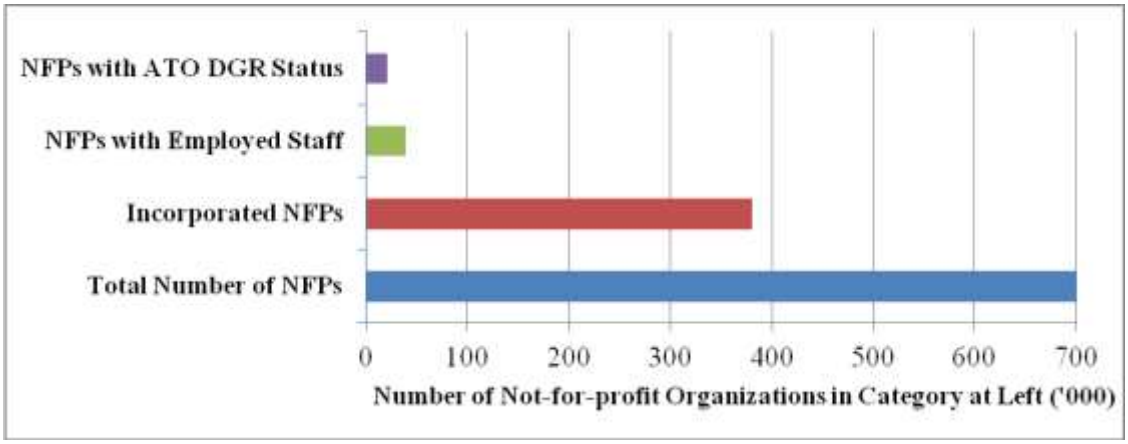
An article in *The Canberra Times* on 7 March 2011 by David Crosbie, Chief Executive Officer of the Community Council for Australia (CCA), cited the 2010 PC Report and other Australian Government enquiries and reviews on Australian charities and NFP organisations. He called for the key reforms emerging to be progressed (*The Canberra Times*, 7 March 2011, page 9).

A useful summary of the structure, principles and fundamentals of operation and other attributes of the NFP sector relevant to this study are given in an NRNO 2009 fact sheet. The fact sheet draws on statistics from the Australian Bureau of Statistics (ABS) and other sources (NRNO 2009).

2.1.1 Size of the not-for-profit sector

According to the Australian Bureau of Statistics (ABS 2009a), in 2009 there were an estimated 700,000 NFP organisations in Australia. Most were relatively small – which are those that are entirely dependent on volunteering e.g. localised community and special interest groups. Approximately 380,000 were incorporated (as a company limited by guarantee, association or cooperative, or under specialised legislation such as trade unions); about 38,000 employ staff; and approximately 20,000 have Deductible Gift Recipient (DGR) status with the Australian Taxation Office (ATO) in Australia (TGIA is not one of them) (ABS 2009a; ATO 2008). This is illustrated in Figure 2.1, which clearly shows that the NFP sector is of considerable size.

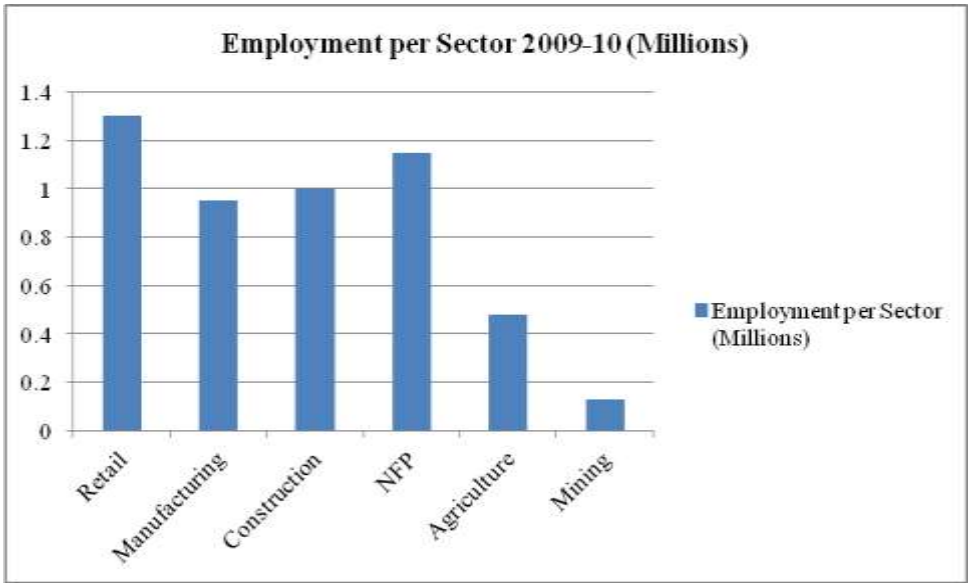
Figure 2.1 — Size of the Australian not-for-profit sector: 2009 (ABS 2009a)



2.1.2 Economic contribution

According to the National Roundtable of Not-for-Profit Organisations (NRNO 2009) and ABS (2009a) for the year ended 30 June 2007, Australia's 41,000 economically significant NFP organisations employed 890,000 people (8.6% of Australians in employment), had an income of $A76 billion, contributed $A34 billion (3.4%) to gross domestic product (GDP), and made an economic contribution equivalent to that of the government administration and defence industry and one and a half times the size of the economic contribution of the agriculture sector. Figure 2.2 (ABS 2009a) shows that the NFP sector also makes a significant contribution to the Australian economy in terms of paid employment. TGIA has fewer than 20 paid employees.

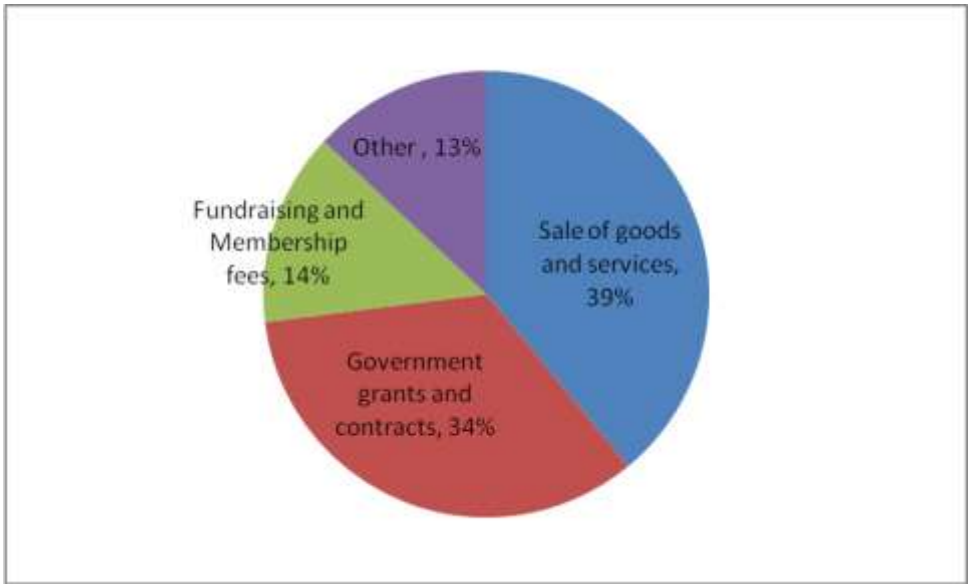
Figure 2.2 — Importance of the NFP sector: the economic influence of NFPs (ABS 2009a)



2.1.3 Sources of income

According to the ABS (2009a) for the year ended 30 June 2007, the NFP sector's main sources of income were the sale of goods and services (39% of income), government grants and contracts (34%), fundraising and membership fees (14%) and other sources (13%), as illustrated in Figure 2.3. TGIA receives nothing from government, nothing from services and very little from sale of goods/merchandise.

Figure 2.3 — Sources of income for the Australian not-for-profit sector (ABS 2009a)



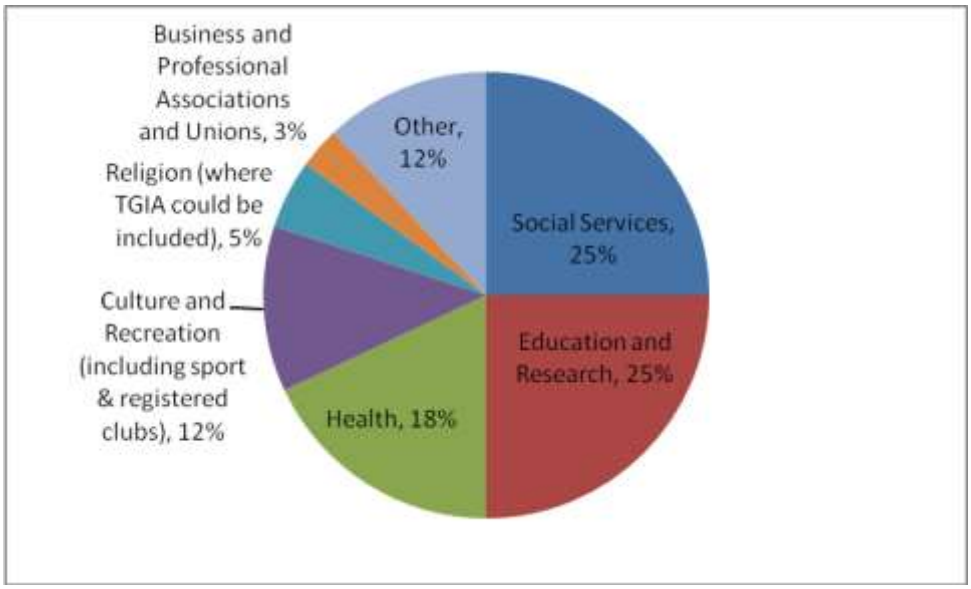
2.1.4 International comparisons

According to Salamon et al. (1999) in terms of its contribution to employment, Australia's NFP sector is of a size similar to that of the USA and the UK, larger than that of Canada, New Zealand and most European countries, and smaller than the NFP sector in the Netherlands and Ireland. The parent body TGI, of which TGIA is part, operates in over 190 countries internationally including many of those identified here.

2.1.5 Components of the sector

According to the ABS (2009a), organisations in the following fields accounted for approximately the following percentages of NFP sector employment for the year ended 30 June 2007: social services (25%), education and research (25%), health (18%), culture and recreation (including sport and registered clubs) (12%), religion (5%) (where TGIA could be included), business and professional associations and unions (3%) and other (12%) (see Figure 2.4).

Figure 2.4 — Components of the Australian not-for-profit sector



2.1.6 Philanthropy

According to Lyons and Passey (2005), in 2004, 13.4 million adult Australians donated $5.2 billion to NFP organisations (and $0.5 billion to government-owned entities). A further $2 billion was provided by 10.5 million Australians who bought raffle tickets or attended charity auctions and similar events. Not all donations can be claimed as a tax deduction (e.g. TGIA donations are not tax-deductible). In the year ended 30 June

2005, $1.5 billion was claimed. In the year ended 30 June 2004, over half a million Australian businesses provided $3 billion to NFP organisations as gifts of money, goods, services and sponsorship (Department of Family, Community Services and Indigenous Affairs 2005). For TGIA, thousands of donors have donated millions of dollars over many years.

2.1.7 Volunteering

According to the ABS (2009a), during 2006, 5.2 million Australians (34% of adults) volunteered 620 million hours of labour for NFP organisations of all sizes and a further 93 million hours were donated to government and for-profit entities. Of the 620 million volunteer hours, 52% were for organisations that rely entirely on volunteer labour and 48% were for NFP entities that also employ staff. This voluntary contribution was equivalent to an additional $13 billion donated to the NFP sector. It would be difficult to quantify hours volunteered for TGIA by its numerous volunteers. Volunteering for TGIA is a key issue in providing its services and fundraising.

2.1.8 Membership

According to Passey and Lyons (2005), in 2003 over 13 million Australians (86% of adults) belonged to at least one NFP association while 48% belonged to at least three organisations. Almost one million people held office in an NFP organisation. In TGIA there are thousands of members and many provide services on a voluntary basis.

2.1.9 More recent data

The PC (2010) report appears to be more up to date than the NRNO fact sheet (NRNO 2009), ABS data and other data cited above. It is notable that the PC report (PC 2010) cites, several times, research by the preparer of the NRNO 2009 fact sheet (Adjunct Professor Mark Lyons, University of Technology, Sydney). The PC report lists a number of recent (2009) characteristics of, and recommendations for, the NFP sector in Australia.

- The NFP sector is large and diverse, with around 600,000 organisations.
- The ABS has identified 59,000 economically significant NFPs, contributing $43 billion to Australia’s GDP and 8% of employment during 2006–07.

- The NFP sector has grown strongly with average annual growth of 7.7% from 1999–2000 to 2006–07.
- 4.6 million volunteers work with NFPs with a wage equivalent value of $15 billion.
- More Australians are volunteering, but for fewer average hours, so total hours grew only slowly (2% per annum over the seven years to 2006–07).
- Most areas have seen a decline in volunteering, although there has been strong growth in the number of volunteers with culture and recreation organisations.
- The level of understanding among the wider community of the sector's role and contribution is poor and deserves attention.
- A nationally agreed measurement and evaluation framework would add significantly to this understanding.
- Current information requirements imposed on NFPs for funding and evaluation purposes are poorly designed and unduly burdensome.
- Reform is needed to meet 'best practice' principles.
- A significant advance would be to establish a Centre for Community Service Effectiveness to improve knowledge on good evaluation practice, and assemble and disseminate evaluations based on the agreed measurement framework.
- The current regulatory framework for the sector is complex, lacks coherence and sufficient transparency, and is costly to NFPs.
- A national registrar for NFPs should be established to consolidate Commonwealth regulations, register and endorse NFPs for concessional tax status, register cross-jurisdictional fundraising organisations, and provide a single portal for corporate and financial reporting.
- Legislative proposals to reduce reporting burdens associated with companies limited by guarantee are welcome and needed if more NFPs are to adopt Commonwealth incorporation.
- A separate chapter in the Corporations Act dealing with NFP companies should be introduced, as should rules on the disposal of assets.
- More generally, states and territories should seek to harmonise Incorporated Associations legislation in these and other key areas.
- Jurisdictional and agency differences have also resulted in a lack of consistency and comparability in financial reporting requirements for NFPs.

- Australian governments should, as a priority, implement the agreed Standard Chart of Accounts.
- Fundraising legislation differs significantly between jurisdictions, adding to costs incurred by the NFP sector. Harmonisation of fundraising legislation through the adoption of a model Act should be an early priority for governments.

The Productivity Commission (PC 2010) described charities (usually NFP) as organisations with a charitable purpose, as defined in common law and classified according to the *Pemsel* case (1891) under the headings of relief of poverty, advancement of education, advancement of religion, and other purposes beneficial to the community.

The Commission described an NFP as an organisation that imposes the rule that no profits will be distributed to its members. NFPs engage in a diverse range of activities (PC 2010). The activity estimates produced by the ABS in the satellite account (ABS 2009b) are based on the International Classification of Not-for-profit Organisations (ICNPO), which divides the sector into 12 broad categories.

PC (2010) further stated that, measured by organisation numbers, the largest sector among NFPs is religion. The broad category encompassing environment, development and housing, law, advocacy, philanthropic and international organisations (environmental and others) is also significant, as is the category of culture and recreation services. However, when ranked by measures of activity levels, a different picture emerges.

Measured in terms of gross value added (GVA) (that is, on a national accounts basis), education and research make up 27% of the sector's activity, with the other categories around the 16 to 19% level — other than associations, which make up 5% of GVA. Measured by employment, the largest categories are social services and education and research; however, this is the number of employees rather than full time equivalent (FTE) so the differences from GVA in part reflect the different rates of full-time employment across the activity areas. When the value of volunteer time is factored in, the largest category is culture and recreation. This reflects the fact that volunteers in

culture and recreation organisations make up 45% of the sector total. Social services and education and research are also significant categories when the value of volunteer time is included.

According to PC (2010), the trends over time are only indicative, as the allocations of NFPs to the ICNPO classifications are not identical over the two satellite accounts. The categories are also fairly broad, masking the different contribution of activities, especially in the environment and other categories. The dominant change since 1999–2000 is a relative decline in the sector share for both GVA and employment of culture and recreation, and growth in environment and other categories.

When volunteer hours are considered, the extent of change in the sector becomes more apparent. Volunteer hours have fallen in all categories except health and culture and recreation, where they have grown strongly. While this may reflect reclassification issues, it is consistent with the anecdotal evidence that some organisations (notably community services) are finding it more difficult to recruit and retain volunteers. Further, for most activity areas the decline in volunteer hours is offset by strong employment growth.

The 2009 estimate of 700,000 NFPs in Australia (see 2.1.1 above) compares with around 520,000 in 1995–96 (Lyons and Hocking 2000). Researchers obtained these data from government agencies responsible for registration and peak bodies within the sector. Trading cooperatives (around one-third of all cooperatives) are usually excluded from the definition of NFPs because they are able to distribute surpluses to members. Although financial and insurance mutual organisations do not distribute profits, they are excluded from the internationally agreed statistical classification for the sector.

Little information is available on those organisations that have chosen not to register their formation through incorporation. Lyons and Hocking (2000) extrapolated the results of a survey of associations in a single New South Wales local government area to provide estimates for Australia. Given the narrow sample on which they were constructed, the authors warned that these ‘estimates should be treated with caution’. A

similar method has recently been applied to provide estimates of unincorporated organisations in New Zealand and Canada (Sanders et al. 2008).

More recent data on incorporated entities suggest that growth has occurred in all categories, with the exception of cooperatives which have fallen significantly over the 12 years to 2007–08. However, caution should be exercised in interpreting data on these organisations because it can be difficult to identify those that are no longer operating.

How large is the sector? To estimate economic activity for the NFP sector satellite account, the ABS draws on the database maintained by the ATO. Of the approximately 180,000 NFPs on the ATO register, the ABS (2009a) identified 58,779 as economically significant organisations. The differences between ATO and ABS numbers resulted from two factors. First, differences existed in the definitions of NFPs. For example, in accordance with the international statistical convention, the ABS excluded bodies corporate, building societies and credit unions. Second, ABS only identified economically significant organisations. All NFPs with turnover greater than $150,000 per annum must be registered for GST. Organisations with turnover below this threshold may choose to be registered. Around 60% of NFPs registered for GST had turnover below the threshold. To avoid double-counting, the ABS accounted for those organisations which had more than one entry on the ATO registry (July 2009).

According to information provided by the ATO (30 November 2009), approximately 61,000 NFPs lodged business activity statements (TGIA would be one of them) or income tax returns (TGIA is income tax exempt), made PAYG wage payments (TGIA would have done that) or paid superannuation guarantee amounts (TGIA would have done that). This is slightly higher than the number of economically significant organisations identified by the ABS. The PC report showed the relationship between the various estimates of NFP numbers (in Figure 4.1, PC 2010 page 60; not reproduced here). It compared the narrower ABS estimates (a subset of ATO data) with the broader estimates based on the approach of Lyons and Hocking (2000), which attempted to enumerate unincorporated entities. By their nature, unincorporated organisations are closely related to the household sector, undertaking activities

designed to meet local needs and relying on the volunteer contributions of community members.

Credit unions and building societies undertake activities that are more closely aligned to those undertaken by the business sector. These organisations were and are excluded from the ABS definition but are included in that of the ATO.

The first comprehensive attempt to measure the scale and contribution of the sector in Australia was undertaken by the Australian Not-for-profit Data Project. The project was a collaboration between the ABS and the Centre for Australian Community Organisations and Management (CACOM) at the University of Technology, Sydney (UTS). The project produced data for 1995–96 on the number and type of organisations, employment and volunteers, expenditure and revenue. It also provided estimates of the NFP sector's contribution to national income.

More recent estimates of economic contribution were provided in the 2006–07 Not-for-profit Institutions Satellite Account (ABS 2009b), which updated previous estimates for 1999–2000 (ABS 2002). The data were produced in accordance with the Handbook on Not-for-profit Institutions in the System of National Accounts (UN 2003), which provided an internationally accepted framework for measuring the economic contribution of the sector. In the national accounts for the economy, production estimates for the various sectors (such as health and community services, education, and cultural and recreational services) included the contribution of NFPs where these services were provided by employees. National accounts do not include an explicit valuation of the contribution of volunteers (see also Callen 1994).

The output of market NFPs is assessed as the sum of the total value of goods and services sold, bartered or used for payments in-kind (including to employees), plus the total value of changes in inventories of finished goods and work-in- progress intended for one or more of the above uses. The output of non-market NFPs is calculated as the sum of intermediate consumption of goods and services, compensation of employees, consumption of fixed capital, and taxes less subsidies on production (e.g. payroll tax) other than those on products.

Included as Appendix 1 is another and more current assessment that provides further evidence of the size of the sector. This is reproduced, with permission, from the "Guide to giving: The Australian directory of not for profit organisations 2014", page 9, Pro Bono Australia, Melbourne, Australia. The information contained therein confirms that the sector continues to be large.

Although there are some uncertainties, estimates, definitions and exclusions related to the data discussed above, a reasonable conclusion at the end of this section is that the NFP sector (including charities) in Australia is significant. The sector is perceived to be in need of reform in many ways, including improvement in efficiency and effectiveness.

2.2 Reports from other countries

The UK Government launched a review of the NFP sector in the UK in 2002 (Dunn and Riley 2004). This UK review also recognised the growing importance of the NFP sector, and specifically identified charities as the driver for more general reforms to the NFP sector in the UK. There is also evidence from the USA that despite the rapid expansion of the NFP sector and its contribution to US society, the number of detailed economic analyses of the efficiency of NFP organisations remain relatively limited (e.g. Song and Yi 2010).

2.3 Summary and conclusions on the sector

In this section a scenario of the NFP sector in Australia has been presented, giving context for the research work reported in this thesis. Clearly, the contribution of the NFP sector, including the significant subset 'charities', is well-recognised by the Australian and other governments despite recent changes in government policy in Australia and New Zealand. The need for reform in relation to the NFP sector has been recognised by the Australian Government and by at least two major industry bodies in Australia (NRNO and CCA) — no matter what government policy environment exists. In the next section TGIA is described in the context of the charitable NFP sector.

2.4 The Gideons International in Australia (TGIA)

In order to put TGIA in context as part of the charitable NFP sector in Australia a detailed description of TGIA is given in this section, under the headings of history, structure, governance, fundraising and funding sources, Bible distribution and other attributes.

2.4.1 History of TGIA and TGI

The Gideons International (TGI) is an NFP International Association of Christian business and professional men, having its origin in the USA in 1899. The organisation is supported by an Auxiliary of the wives of Gideon members.

The history of TGIA dates back to 1956 when Bible distributions occurred in Melbourne, Victoria, prior to the 1956 Olympic Games in that city. Meetings of interested men in Australia took place at the time and branches were formed. The National Association in Australia (TGIA) was formed in 1959. By 1966, one million Bibles had been distributed in Australia by members of TGIA. In a tradition that still continues, the Australian Prime Minister or Australian Governor-General of the day is presented with a commemorative Bible marking each millionth Bible distribution milestone in Australia. In 2010 a commemorative Bible, marking the milestone of the 14 millionth Bible distributed in Australia, was presented to the Australian Governor-General.

The National Office (headquarters) of TGIA has been in Canberra since 1970 and TGIA was incorporated under the *Associations Incorporations Act of the Australian Capital Territory (ACT)* in 1971. By 1973, TGIA owned its own building in Mawson, ACT, from which the National Office continues to operate. By 1977, TGIA had become a fully self-supporting National Association of TGI. By 1981, there were 100 branches in Australia across most states and territories. In 1982, the first Australian Guide Book for TGIA was published and the 2002 version of that guide book is the source of the information in this section (The Gideons International in Australia Incorporated 2002). Article 9 of the Constitution of TGIA contained in this guide book clearly stipulates that TGIA is an NFP organisation.

Since 1982 there have been changes in organisation and structure at TGIA. Nevertheless, TGIA continues its main operational function of distributing Bibles in Australia.

2.4.2 Structure of TGIA

In the business and management context, TGI/TGIA is probably best known for its work in distributing Bibles globally, to various outlets (at financial year end 31 May 2013, in over 190 countries and in over 90 languages). It could be aptly described as an international network for Bible distribution. At 31 May 2013, the organisation had its international headquarters in the USA, servicing 12 areas in the USA as well as countries that are not fully self-sufficient in terms of funds available for Bible distribution and administration. It has 10 'Qualified' National Associations/Countries that are fully self-sufficient, including Australia. There are also five 'Supported' National Associations/Countries. The remaining countries — split into global regions and called International Outreach Countries (IOCs) — are mainly serviced from the USA. The funding for the distribution of Bibles in IOCs is assisted by contributions received by an International Outreach Fund (IOF). The IOF is funded by contributions from National Associations, including TGIA, and other sources.

At 31 May 2013, there were 133 branches in Australia and 11,594 branches globally. It would be possible to carry out the research in this thesis at any level of the TGI/TGIA hierarchy by specifying the constituents as DMUs. It is considered that the structure at all levels of TGI/TGIA provides an ideal case study for the research areas to which this thesis relates. However, the focus in this study is solely on branches in Australia.

2.4.3 Governance of TGIA

At the global level, the governance of TGI appears to rest ultimately with the members of the International Association at an Annual General Meeting held at each Annual International Convention. At the Australian level, the governance of TGIA appears to rest first with the members of the Australian National Association at an Annual General Meeting held at each Annual National Convention; and then ultimately at the global level with TGI.

From a practical and day-to-day perspective, global-level management at TGI rests with a representative international TGI Cabinet (Board of Directors) through a Cabinet-appointed International Executive Director who acts as the Official Secretary and is responsible to the Cabinet for the overall administration of TGI. Similarly, management of TGIA rests with a representative National TGIA Cabinet through a Cabinet-appointed National Executive Director who acts as the Official Secretary and is responsible to the Cabinet for the overall administration of TGIA.

The general cabinet structure pervades the TGI/TGIA organisation. For example, there are five 'State' Cabinets in Australia and each branch in Australia has its own local Cabinet charged with directing branch activities. At each cabinet level there is a President, Vice-President, Treasurer, Secretary and Chaplain together with other Cabinet members peculiar to the respective levels. Generally, Cabinet members can only serve consecutively for three successive years. Guide books containing policies, procedures, a constitution, by-laws and numerous manuals assist cabinets and administrators in managing the TGI/TGIA organisation.

2.4.4 Bible distribution by TGIA

For the year ended 31 May 2013, TGIA distributed 306,800 Bibles in Australia. Global distribution by TGI for the same year was 84.6 million. Bibles are distributed around the world to hotels, motels, schools and various other outlets.

Internal assessments and estimates by TGIA/TGI suggest that there is a potential market for at least 1 million Bibles to be distributed in Australia each year and 100 million globally. Goals projecting out to 2020 reflect this potential.

2.4.5 Fundraising by and funding sources of TGIA

(a) Fundraising by TGIA

The word 'fundraising' does not appear to have a place in official TGI/TGIA literature. A proxy term 'promotion' is generally used to encompass both 'fundraising' for and 'advertising' of TGI/TGIA services, with a view to generating funds to provide those services (e.g. see Callen 1994).

Promotion activities aimed at generating funds can include: presentations at churches; sale of cards for Christmas, births, weddings and other occasions which concurrently generate donations (Gideon Card program, in TGIA terminology); programs targeting members and others to include TGIA as a beneficiary in a will; encouraging offerings from members at branch meetings and State and National Conventions; programs targeting the general public for donations; and ad hoc appeals to members for specific projects such as National Office building renovations.

(b) Funding sources of TGIA

The permitted sources of funds are clearly established by the TGIA Constitution and By-laws (The Gideons International in Australia Incorporated 2011). These sources are membership dues, donations, legacies (bequests) and other sources as determined by TGIA's National Cabinet.

To carry out its work, TGI/TGIA receives funds from Gideon and Auxiliary members' dues and offerings (at 31 May 2013 the organisation had 300,673 members globally and 3,420 in Australia), donations from the general public, donations from churches and church congregations, bequests and investment income. All contributions to the organisation are from private sources. There is no government funding. TGIA is self-sufficient financially in terms of its administration and Bible costs in Australia. It also regularly contributes funds to assist with the global activities of TGI.

2.4.6 Other attributes of TGIA

The organisation's financial year starts on 1 June each year and runs to 31 May in the following year. All year-to-year data used in analyses reported in this thesis relate to annual figures to 31 May in a particular year.

Although TGIA and TGI fit within the charitable NFP sector at the Australian (under several pieces of legislation) and global levels, the services they provide are unique. The organisations appear to be the only ones providing this type of service (Bible distribution) in these ways, and to the outlets they target internationally.

2.5 Summary and conclusions on TGIA

In this section a detailed description of TGIA and its relation to the NFP charitable sector has been given. From the above details on TGI/TGIA organisation's activities, it is readily apparent that TGI/TGIA activities are characteristic of charities generally, in that any charity will seek to do two things: to provide a service (service activities) and to raise funds (fundraising activities) to provide that service.

Outputs vary from charity to charity, but this twofold categorisation of output appears to apply generally for the activities of all charities. For the TGI/TGIA organisation, the two outputs are Bible distribution (from service activities) and donations/voluntary income (from fundraising activities). Inputs also vary from charity to charity but a simple categorisation for inputs appears more challenging for charities collectively. Voluntary labour is a common input for charities as indeed it is for TGI/TGIA. In terms of TGIA/TGI inputs, there is always sufficient potential to increase outputs. Full coverage of outputs and inputs appears later in this thesis.

2.6 Overall summary and conclusions from this chapter

In this chapter an overview of the NFP and charitable sector and TGIA has been given, and clearly shows that TGIA has a place in the context of the sector. In the next chapter the conceptual and methodological framework of analyses reported in this thesis is covered.

CHAPTER 3: CONCEPTUAL AND METHODOLOGICAL FRAMEWORK

In this chapter the conceptual and methodological framework underlying the study is provided. The historic, contemporary and emerging themes in productivity and efficiency research as a topic area are summarised. There is a brief introduction to the topic, and discussion follows on basic concepts, methods of productivity and efficiency measurement, and the framework for the empirical analysis.

3.1 Introduction

In the discipline of productivity and efficiency analysis, the seminal paper by Farrell (1957) is the starting point for the two main streams of productivity and efficiency measurement. These streams are data envelopment analysis (DEA), which is a non-parametric approach, and stochastic frontier analysis (SFA), which is a parametric approach. The basic concepts of measuring productivity and efficiency are grounded in Farrell (1957).

3.2 Basic concepts of productivity and efficiency measurement

As already stated in Chapter 1, the concept of productivity being discussed in this thesis is total factor productivity (TFP), which is a measure of productivity involving all factors of production in the economic sense (Coelli et al. 2005, page 3). It is common to measure TFP as the ratio of an aggregate output to an aggregate input (O'Donnell 2010). 'Technical efficiency' is a concept from economics in which there is established a production frontier defining the relationship between inputs and outputs. The production frontier represents the maximum output attainable from each input level. The technical efficiency of a decision-making unit (DMU) is measured by reference to the distance from the established frontier. This is illustrated graphically in Figures 3.1 and 3.2 later in this chapter.

From a time perspective, a topic-related paper by O'Donnell (2010) includes references ranging from 1823 to 2010. From an abundance perspective, since the pioneering paper by Farrell (1957), frontier estimation of efficiency has occupied substantial literature on that topic. Coelli et al. (2005) has become a universal

introductory reference book on the topic. Although literature on the topic appeared to be more abundant up to 2005, the plethora has continued. More recent work has included stochastic approaches to non-parametric estimation, decomposition, and uncertainty (e.g. O'Donnell 2008, 2010; Dyson and Shale 2010). The now seminal paper by Farrell (1957) listed only ten references, including only one paper (Debreu 1951) that appeared to have any direct relevance to Farrell's work. Numerous papers since 1957 refer back to Farrell (1957) as a significant landmark; for example, Zhu and Peyrache (2013) and O'Donnell (2014).

3.3 Methods for efficiency measurement

There are two main approaches used in the measurement of efficiency – these are the DEA-based approach and the stochastic frontier analysis (SFA) approach. Charnes, Cooper and Rhodes (1978) are generally credited with the development of the original DEA model under constant returns to scale (CRS) (CCR model) while Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) pioneered the use of SFA. In this section, these two concepts are briefly discussed.

3.3.1 DEA — a non-parametric approach

(a) Basic concepts of DEA

In the data envelopment analysis (DEA) methodology, efficiency is defined as the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights structure is calculated by means of mathematical programming and assuming constant returns to scale (CRS).

From their landmark paper, Charnes et al. (1978; CCR) are credited with being the pioneers of DEA. In their words, 'This paper is concerned with developing measures of "decision making efficiency" with special reference to possible use in evaluating public programs'. The paper introduced a nonlinear (non-convex) programming model (CCR model) to provide a scalar measure of efficiency of each DMU assuming CRS. The paper itself contains no evidence of any empirical application of the CCR model and develops a theoretical non-parametric framework for measuring efficiency, which continues to be applied. The CCR model does not appear to have inspired much empirical activity using DEA between 1978 and the next landmark in 1984 (see

Emrouznejad, Parker and Tavares 2008, page 153, Figure 1). In 1984, Banker, Charnes and Cooper (1984) developed a model with variable returns to scale (VRS) considerations, as addressed later in this thesis.

Data envelopment analysis (DEA) measures the relative efficiency of DMUs using traditional outputs and inputs as variables, with no assumed functional relationship between the variables. It is a mathematical programming technique grounded in the concepts of linear programming (LP), rather than an econometric technique like the parametric SFA discussed later. DEA generally assumes a set of DMUs carrying out the same activities using a homogeneous set of outputs and inputs. In this study TGIA branches are the basic DMUs and they display these characteristics.

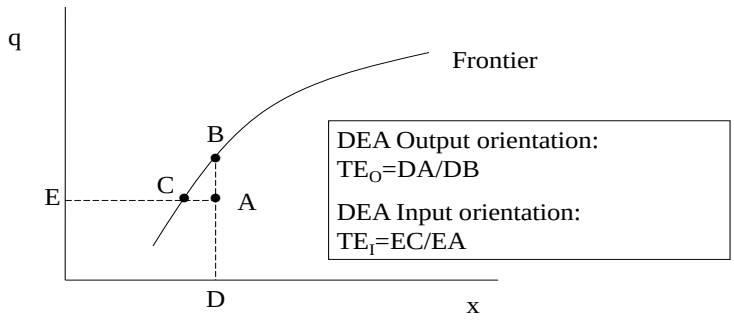
Although an advantage of DEA is its ability to handle multiple outputs and multiple inputs, it is generally introduced more simply; for example, by considering the case of a single output and a two inputs as in Coelli et al. (2005, pages 165–167). In the context of the case study of TGIA, the application of DEA focuses on two models, each with one output and two inputs (Bible distribution model and fundraising model). Appendix 2 presents an introduction to DEA in the TGIA context using LP concepts.

Under DEA, the measurement of productivity and efficiency is a relative concept. Relativity implies comparison. To get an appropriate and justifiable comparison, say in the context of the branches of TGIA, one branch must be compared with others. It must also be remembered that DEA sits on a platform of LP. In the context of TGIA, it involves solving a separate linear program for each TGIA branch to calculate the productivity and efficiency scores for each branch relative to the whole set of branches, by formulating an objective function for each branch and using the outputs and inputs of the other branches as constraints. Interpretation of the DEA results tells the user whether or not a branch can improve its performance relative to the set of branches with which it is being compared.

Conceptually, DEA is one of a set of frontier measurement techniques. It has the benefit of not assuming a particular functional form or shape for the frontier. Figure 3.1 illustrates the concept of technical efficiency. Technically efficient DMUs have data points on the frontier representing an efficiency score of 1. The LP models

underlying DEA are formulated so that the technical efficiency score for each DMU is limited to the range 0 to 1: DMUs with a score of 1 are efficient and lie on the frontier; DMUs with a score of less than 1 are inefficient and lie below the frontier. Inefficiency of a particular DMU is also a measurement of the distance the score is below the frontier.

Figure 3.1 — Technical efficiency (from Coelli et al. 2005, Figure 6.3, page 174)



The conceptual explanations above are consistent with other topic-related books, journals, reports and publications such as:

(a) Fizel and Nunnikhoven (1992) who explained the concepts of DEA and technical efficiency in the context of an application to for-profit and non-profit nursing homes (e.g. pages 430–432).

(b) Steering Committee for the Review of Commonwealth/State Service Provision (1997, page 9).

(c) Forsund and Sarafoglou (2002) in which the authors examined the origins of DEA (e.g. pages 25–26).

(d) papers listed by Emrouznejad et al. (2008) in their bibliography of around 4,000 DEA applications over three decades.

(e) *The Users' Guide to DPIN 3.0* (O'Donnell 2011).

Decision-making unit (DMU) A in Figure 3.1 is technically inefficient, while DMUs B and C are technically efficient. It is possible to define input-orientated or output-orientated technical efficiency scores. The output-orientated technical efficiency score of DMU A is TE_O=DA/DB. If this is, say, 0.80, it indicates that the firm is producing

20% below its potential output, given the inputs it has available. The input-orientated score is TE_I=EC/EA. It would also be 0.80, suggesting it can produce the same output with 20% less inputs.

As stated above, DEA calculates the efficiency of an organisation within a group relative to observed best practice within that group. The organisations can be whole entities (e.g. TGIA/TGI), separate entities within the organisation (e.g. TGI national associations, countries, etc.) or disaggregated business units within the separate entities (e.g. TGIA/TGI branches, countries etc.) — for example, see Steering Committee for the Review of Commonwealth/State Service Provision 1997, DEA Information Paper, page 9).

The curve plotting the minimum amounts of the input required to produce the output quantity is known as a frontier isoquant or efficient frontier. It is a smooth curve representing theoretical best practice as in Figure 3.1. Producers can gradually change input combinations given current technological possibilities.

The point of operation marked for DMU A in Figure 3.1 would be technically inefficient because more inputs are used than are needed to produce the level of output designated by the frontier isoquant. The points for DMU B and DMU C are technically efficient points.

Technical efficiency is usually measured by checking whether inputs need to be reduced in equal proportions to reach the frontier. This is known as a 'radial contraction' of inputs because the point of operation moves along the line from the origin to where a DMU (e.g. a TGIA branch) is now.

If a DMU has two inputs (like a TGIA branch in this study), the model described above aims at obtaining the maximum rate of reduction with the same proportion, i.e. a radial contraction in the two inputs that can produce the current outputs (a single output in the TGIA case). In contrast, non-radial models put aside the assumption of proportionate contraction in inputs and aim at obtaining the maximum rate of reduction in inputs that may discard varying proportions of the original input resources (Avkirin, Tone and Tsutsui 2006).

The technical efficiency scores take a value between 0 and 1 where a value of 1 indicates full efficiency. TE_O and TE_I are usually similar, and will be identical if the technology exhibits CRS. A CRS technology is (approximately) one in which an *X*% increase in all inputs causes output to increase by *X*%. These technical measures of efficiency can be generalised to multi-input and multi-output models. The feasible production set is the set of all input–output combinations that are feasible. This set consists of all (non-negative) points on or below the production frontier.

Microeconomic production theory portrays a DMU's input and output combinations using a production function. The maximum output which can be achieved with any possible combination of inputs can be shown by estimating a production function; that is, a production technology frontier can be constructed (Seiford and Thrall 1990). Analysts use DEA and frontier techniques to test how to use this principle in empirical applications while overcoming the problem that it is never possible to observe all the possible input–output combinations for DMUs.

DEA has been recognised as a valuable analytical research instrument and a practical decision support tool. DEA has been credited for not requiring a complete specification for the functional form of the production frontier nor the distribution of inefficient deviations from the frontier. Rather, DEA requires general production and distribution assumptions only. However, if those assumptions are too weak, inefficiency levels may be systematically underestimated in small samples. In addition, erroneous assumptions may cause inconsistency with a bias over the frontier. Therefore, the ability to alter, test and select production assumptions is essential in conducting DEA-based research. However, the DEA models currently available offer a limited range of alternative production assumptions only.

(b) Mechanics of DEA estimation

(i) One-stage approach with DEA

In the case of applications of basic DEA to any dataset, the one-stage approach involves measuring the efficiency scores relative to other DMUs, usually with standard software (e.g. data envelopment analysis program (DEAP), decomposing productivity index numbers (DPIN) and LIMDEP econometric software). Although some authors

make speculative commentary as to reasons for the levels of efficiency score, there is generally no attempt to statistically test for the significance of factors that might be affecting the efficiency scores.

(ii)Two-stage approach with Tobit regression (TRA)

For DEA, a two-stage approach has generally been preferred. This involves measuring the efficiency scores using basic DEA as the first stage followed by a second-stage regression of these scores on factors that might be perceived as influencing the level of the scores across DMUs (e.g. environmental variables). Second-stage Tobit regression has been preferred because it can account for truncated data (Coelli et al. 2005, page 194).

(c) The importance of orientation with DEA: output and input

DEA can be applied with an input or output orientation. Under an input orientation, the proportion by which inputs can be reduced is examined without outputs diminishing. Under an output orientation, the proportion by which outputs can increase using the same level of inputs is examined. For CRS DEA, the technical efficiency scores will not vary from one orientation to another. For VRS DEA, the technical efficiency scores may vary from one orientation to another.

In the context of The Gideons International in Australia (TGIA), a DEA input orientation would enable the calculation of the radial proportion by which inputs can be reduced for non-efficient branches (scores less than 1) and still achieve the same level of output. In the case of an output orientation, DEA would enable the calculation of the radial proportion by which the level of output can be increased for non-efficient TGIA branches while maintaining the same level of input. The selection of orientation can be based on whether the user of DEA perceives there is greater control over inputs or outputs. For a detailed discussion of DEA orientation see, for example, Coelli et al. (2005, pages 180–181) and Coelli and Perelman (1999).

On the one hand, TGIA could be seen to have more control over input. TGIA seeks to maximise voluntary labour, and could, for example, limit the level of voluntary labour through a tighter selection process of members. The activities of voluntary labour may then move in a particular direction that could affect the level of output (Bible

distribution (BDIST) and donations procured (DON)). On the other hand, and more emphatically, TGIA seeks to maximise its outputs BDIST and DON as prime objectives, but can be limited in this endeavour, for example, by insufficient voluntary labour and external factors.

In the context of the TGIA case study, a DEA VRS output orientation would appear to be appropriate because TGIA's goal as a charitable NFP service entity is clearly to maximise its output with the best use of its available input resources. Previous studies that justify this approach include Basso and Funari (2004, page 202); Marco-Serrano (2006, page 172); Varela, de Andra de Martins and Favero (2010, page 117); Ahmad, Mohammad and Mohammad (2013, page 123) and Hribernik and Kierzenkowski (2013, page 7). It was therefore decided to focus on an output orientation using DEA VRS for this TGIA case study, and specifically on TFP and OTE. The DPIN computer program, with its underlying DEA algorithms, was used to calculate all productivity and efficiency scores for TGIA. It is noted, however, that DPIN automatically provides the results of both output and input orientations as a matter of course.

Although the number of Tobit regressions performed was much higher than reported, the reporting of results from Tobit is on the factors affecting TFP and OTE obtained from the DEA VRS output orientation. Such an approach is justified by the overall objectives of TGIA to maximise its output by improving its productive efficiency. Additionally, the results reported later in the thesis suggest that this is a sound approach in hindsight because little would appear to be lost by not following up on what factors influence measures other than TFP and OTE given the close relationship between TFP and TFPE, and the generally high magnitude of other efficiency scores (output scale efficiency (OSE), etc.). The close relationship between TFP and TFPE exists because TFPE is the ratio of TFP (observed total factor productivity) to the maximum TFP possible in each period (usually denoted by TFP*) (O'Donnell 2011, page 17). This would appear to imply that the level of TFP scores would be reflected in the level of the TFPE scores. In the context of TGIA for example, it was found that low TFP scores were reflected in low TFPE scores.

(d) Slacks, peers and targets with DEA

In the DEA framework, outputs are defined as goods and/or services provided to entities or persons outside the DMU (Steering Committee for the Review of Commonwealth/State Service Provision 1997, page 14). Inputs are defined as traditional factors affecting outputs and such traditional inputs are assumed to be under the control of the DMU (Coelli et al. 2005, page 190). Slacks are defined as the extra amount by which an input (output) can be reduced (increased) to attain technical efficiency after all inputs (outputs) have been reduced (increased) in equal proportions (i.e. radially) to reach the production frontier. This is a feature of the piece-wise linear production frontier derived when using DEA (Steering Committee for the Review of Commonwealth/State Service Provision 1997, page 15).

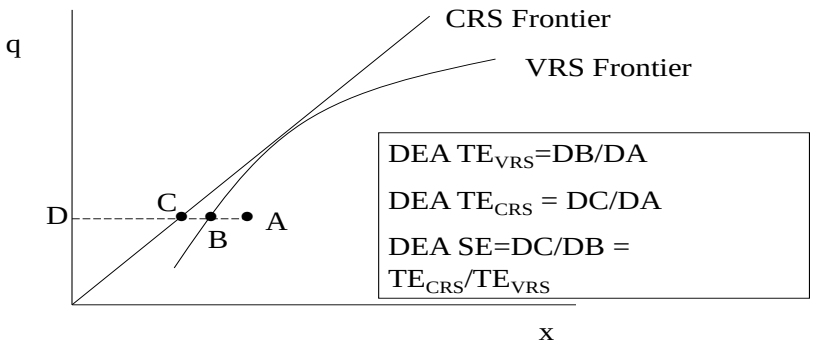
DEA not only allows managers to determine relative efficiency levels, it also provides details on which other operating units should be studied in order to improve efficiency levels (these are known as peers), and what input and output levels are achievable if the operating unit is fully efficient (these are known as targets) (Coelli et al. 2005, page 166).

For TGIA, therefore, it was possible to identify slacks (input and output), peers and targets for each branch. The results from doing this are summarised in Chapter 6 and presented in more detail in the appendices.

(e) Returns-to-scale considerations with DEA

Banker, Charnes and Cooper (1984; BCC) are credited with the development of the basic DEA model under VRS. Figure 3.2 illustrates the concept of technical efficiency.

Figure 3.2 – Scale efficiency (SE) (from Coelli et al. 2005, Figure 6.3 page 174)



A production technology exhibits CRS if a *Z*% increase in inputs results in *Z*% increase in outputs. For the VRS model, a production technology exhibits increasing returns to scale (IRS) if a *Z*% increase in inputs results in a more than *Z*% increase in outputs. A production technology exhibits decreasing returns to scale (DRS) if a *Z*% increase in inputs results in a less than *Z*% increase in outputs.

Banker et al. (1984) extended the CCR model to create the BCC model by introducing a new separate variable 'which makes it possible to determine whether operations were conducted in regions of increasing, constant or decreasing returns to scale (in multiple input and multiple output situations)' (page 1078). They contributed to the literature on DEA by providing further theoretical models for estimating relative technical and scale efficiencies for DMUs with reference to an efficient production frontier. Their main contribution was to define a scale efficiency measure as the ratio of the aggregate efficiency to the measure of technical efficiency. The reader is again referred to the DEA and the LP concepts set out in Appendix 2.

Banker et al. (1984) did not report an empirical application of the BCC model but the effect of the BCC model has been similar to that of the CCR model in that it continues to be applied in empirical work. The concept of the VRS DEA model and scale efficiency was covered well by Coelli et al. (2005, pages 172–174).

A simple consideration for justification of why it is important to consider VRS is given in the DEA report of the Steering Committee for the Review of Commonwealth/State Service Provision (1997, page 16). The report suggests that the assumption of CRS is inappropriate if it is likely that the size of service providers (e.g. TGIA branches) will influence their ability to produce services efficiently. The less restrictive VRS frontier allows the best-practice level of outputs to inputs to vary with the size of the organisations in the sample.

The use of the VRS specification permits the calculation of technical efficiency devoid of scale efficiency effects (Coelli 1996). Some previous studies that have considered both the CRS and VRS models have generally found that technical efficiency scores tend to be higher or more generous under the VRS model. Tofallis and Sargeant (2000) gave an elementary non-mathematical introduction to DEA and demonstrated one way in which it could be applied to assess charities. They used what they called 'the more generous assessment provided by the variable returns to scale model' of DEA.

Asogwa, Penda and Lawal (2011) used DEA to study farm resource management in Nigeria. They tested the hypothesis that there was no significant difference between CRS and VRS efficiency scores among the Nigerian farmers. They found that most farmers operated very far away from the efficiency frontier. They also found that on average VRS scores were significantly higher than CRS scores, suggesting that the hypothesis they tested should be rejected.

In Karimzadeh (2012) a good justification for the use of VRS in applications of DEA was provided, as follows. VRS refers to increasing or decreasing efficiency based on size. CRS means that producers are able to linearly scale the inputs and outputs without increasing or decreasing efficiency. The assumption of CRS may be valid over limited ranges but its use must be justified. CRS efficiency scores will never be higher than VRS efficiency scores. In a CRS (or CCR) model, the input-oriented efficiency score is exactly equal to the inverse of the output-oriented efficiency score. This is not necessarily true for inefficient DMUs in the case of other assumptions about returns to scale. The CRS version is more restrictive than the VRS and yields usually a fewer number of efficient units and also lower efficient score among all DMUs.

The CCR model has developed the Farrell (1957) efficiency measurement concept from several inputs and one output to several inputs and several outputs. In this model using a linear combination, different inputs and outputs are changed into one virtual input and output which the ratio of these virtual combinations of outputs to inputs will be the estimation of efficiency boundary for the measurement of relative efficiency given that the yield is constant. The BCC model assumes a variable output with respect to the scale. In the model, the technical efficiency is decomposed to pure technical efficiency and scaled efficiency in order to measure the output to scale as well as efficiency itself. Recently Aldeseit (2013) examined the performance of dairy farms in Jordan, using DEA. He found that on average VRS scores were higher than CRS scores.

In the context of the research presented in this thesis, the above discussion would appear to provide justification and compelling reasons for using the VRS DEA model in the TGIA case study. Such an approach was therefore taken.

(f) Accounting for environmental variables with DEA

Accounting for environmental variables (EVs) or factors with DEA is covered particularly well by Coelli et al. (2005, pages 190-195) and other published literature. EVs in this context can be defined as those variables outside the direct control of managers in the production process (e.g. ownership differences, location characteristics, labour union power, government regulations) (Coelli et al. 2005, pages 190-191).

Coelli et al. (2005) suggested four possible ways to handle EVs, but acknowledge that these are not the only methods:

(i) If the values of the EV can be ordered from least to most detrimental effect on efficiency, the efficiency of the *i*-th DMU is compared with those DMUs in the sample that have a value of the EV that is less than or equal to that of the *i*-th DMU (Banker and Morey 1986).

(ii) If there is no natural ordering of the EV, then use a three-stage method proposed by Charnes, Cooper and Rhodes (1981):

1. Divide the sample into two categorised sub-samples and solve DEAs for each sub-sample.
2. Project all observed data points onto their respective frontiers.
3. Solve a single DEA using the projected points and assess any difference in the mean efficiency of the two sub-samples.

(iii) Include the EV(s) directly into the LP formulation.

(iv) Use the two-stage method. The first stage involves solving a DEA problem using only the traditional inputs and outputs. The second stage involves regressing the efficiency scores from the first stage on the EVs using Tobit regression.

Coelli et al. (2005) recommended the two-stage approach in most cases. The several reasons given include ease of calculation, and the fact that it facilitates hypothesis testing and can accommodate more than one variable.

There are many journal articles that demonstrate how environmental factors are accounted for under the DEA framework. Lan and Lin (2003) investigated the technical efficiency and service effectiveness of 76 selected railways in the world during the period 1999–2001. The scores were regressed on several environmental variables. The Tobit regression results indicated that percentage of electrified lines, population density and per capita gross national income were factors significantly influencing the efficiency; while the effectiveness was significantly influenced by the average length per ton carried and per capita gross national income. Drake, Hall and Simper (2005) assessed the relative technical efficiency of institutions operating the Hong Kong banking system that had been significantly affected by environmental and market factors in years leading up to their study. Tobit regression results indicated differential impacts of environmental factors on the technical efficiency of different size groups and financial sectors. Zhao and Wang (2014) analysed China’s 2011 industrial electrical energy efficiency step by step using a DEA optimisation model. The results from second-stage Tobit regression showed that the external environment had a significant impact on electrical energy efficiency.

Further examples of studies that include EVs are: an inter-country comparison of agriculture in 43 countries (Kudaligama and Yanagida 2000); railways in Europe (Coelli and Perelman 2000); electricity distribution in South America (Estache, Rossi and Ruzzier 2002); dairy farms in New Zealand (Jaforullah and Premachandra 2003); banking in Italy (Angelidis and Lyroudi 2006); and the life insurance industry in Turkey (Kasman and Turgutlu 2007).

The theme common to the above examples is that the two-stage approach to accounting for environmental variables was generally preferred. In the TGIA case study presented in this thesis, the two-stage approach outlined above was used to assess the direction, magnitude and significance of factors possibly affecting TFP and various measures of efficiency of TGIA branches.

(g) Extensions of DEA

(i) DEA in the presence of uncertainty

Dyson and Shale (2010) and O'Donnell, Chambers and Quiggin (2010) presented from different perspectives the theme of allowing for uncertainty when using DEA. There have been some prior publications on the subject, but these two brought together well the concepts and extensions of DEA in the presence of uncertainty.

Dyson and Shale (2010) discussed a number of applications of DEA and the nature of uncertainty in those applications. They then reviewed the key approaches to handling uncertainty in DEA, imprecise DEA (IDEA), bootstrapping, Monte Carlo simulation (MCDEA) and chance-constrained (CCDEA), and considered the suitability for modelling the applications of each approach. Implicit in this approach was the application of stochastic methods in the DEA context. Based on their experience the authors suggested that from the literature emerge generic data categories and sources of uncertainty that may have wide applicability, and they presented these in their paper. The authors stated that the most common of these and their characteristics were not exclusive or exhaustive. They summed up their tabulation by saying that in real-world applications there could be uncertainty in any of the inputs and outputs, that where data exhibited uncertainty they would envisage both symmetrical and skewed distributions, often in the same application, and these distributions would typically be constructed

subjectively. They tentatively concluded that, given their focus on real units and best practice, with the sources of uncertainty in both inputs and outputs of those units, IDEA was a relatively simple and useful step in the direction of incorporating uncertainty into DEA and Monte Carlo simulation as the most flexible and comprehensive approach.

O'Donnell, Chambers and Quiggin (2010) presented a more theoretical approach to handling efficiency measurement in the presence of uncertainty using both DEA and SFA. They made the point that in a stochastic decision environment, differences in information can lead rational decision makers to make different production choices despite facing the same stochastic technology and the same markets. Therefore, productivity and efficiency measurement in such a setting can be seriously and systematically biased by the manner in which the stochastic technology is represented. They gave the example of conventional production frontiers implicitly imposing the restriction that information differences have no effect on the way risk-neutral decision makers utilise the same set of inputs. The result is that rational and efficient ex ante production choices can be mistakenly characterised as inefficient informational differences and can be mistaken for differences in technical efficiency. O'Donnell et al. (2010) used simulation methods to illustrate the type and magnitude of empirical errors that can emerge in efficiency analysis as a result of overly restrictive representations of production technologies.

In summing up their research and findings, O'Donnell et al. (2010) stated that conventional efficiency analysis and most modern production economics were concerned with estimating non-stochastic behaviour and non-stochastic technologies. They claimed that stochastic elements of the decision environment were typically only recognised when and if it was econometrically convenient and that this practice placed strong and as yet untested a priori restrictions on stochastic technologies. If the restrictions were invalid, then the application of standard methods of efficiency analysis to data arising from production under uncertainty could give rise to spurious findings of efficiency differences between DMUs.

In discussing their results, O'Donnell et al. (2010) pointed out that they had intentionally considered a case where all DMUs faced exactly the same decision environment (that is, DMUs faced a common stochastic technology and the same input and output markets). They added that DMUs only differed in their subjective beliefs about that decision environment, and those differences in beliefs led DMUs to prepare rationally for that stochastic world in different ways. The empirical outcome was seriously-biased efficiency scores as estimated by either standard input-oriented DEA or output-oriented SFA methods. Although O'Donnell et al. (2010) did not consider output-oriented DEA or input-oriented SFA measures of efficiency, they contended that seriously biased results could also occur in these cases even if all DMUs had exactly the same belief structure.

O'Donnell et al. (2010) said that when it is realised that real-world data typically reflect multiple sources of behavioural differences across DMUs, then it is apparent that, in attempts to estimate or approximate a supposed common frontier technology, serious problems can emerge from the practice of ignoring the interplay of these other sources with the truly stochastic nature of many production technologies. An important implication of their results is that it is necessary to consider the findings of virtually all previous empirical studies of efficiency to determine whether the results may have been affected by a failure to take appropriate account of uncertainty. O'Donnell et al. (2010) claimed that in some cases it could be necessary to qualify policy recommendations derived from findings of widespread inefficiency and, more importantly perhaps, develop robust techniques that would make it possible to disentangle differences in technical efficiency from differences caused by the stochastic nature of production.

The major finding by O'Donnell et al. (2010) was that the incorporation of an appropriate representation of uncertainty is a matter of major urgency if empirical efficiency analysis is to remain relevant to a fundamentally uncertain economic world. O'Donnell et al. (2010) concluded that results derived from a non-stochastic approximation of a stochastic world clearly cannot be regarded as reliable.

In the TGIA case study presented in this thesis, the focus was on basic DEA. This is similar to what Dyson and Shale (2010) described as their original studies using basic DEA before they turned to the study of uncertainty that might be present using the same entities as in their original studies. However, the world of Bible distribution and fundraising of donations is reasonably certain for TGIA which operates in a limited and well-defined market. With this in mind, it was considered that little would be gained by pursuing any detailed consideration of uncertainty for TGIA in this thesis.

(ii) Stochastic DEA

DEA is usually presented as being non-stochastic, leaving SFA with its parametric attributes and stochastic error terms to overcome a sometimes perceived disadvantage of DEA. However, some authors have addressed another theme, that of stochastic DEA.

Applications of DEA in stochastic environments continue as an emerging theme from the original work by Charnes, Cooper and Rhodes (1978; CCR). DEA had originally been recognised generally as a non-stochastic/non-parametric technique only. A number of papers have been published on DEA in stochastic environments and examples are given below.

Post, Cherchye and Kuosmanen (2002) claimed to have developed a new non-parametric model for efficiency estimation. They addressed the limitations of standard DEA and specifically allowed for stochastic disturbances. They proposed an alternative non-parametric approach and introduced stochastic disturbances analogous to SFA. In contrast to SFA, they did not specify the distribution functions for the inefficiency terms and the disturbances, so as to preserve the non-parametric nature of DEA. The authors obtained powerful statistical and computational results but believed their paper constituted a mere starting point for developing a new non-parametric approach.

They saw many routes for future research. They suggested that future research could focus on exploiting the insights developed in the paper for other uses including estimation of elasticities of scale and substitution, selecting target or benchmarking points for inefficient DMUs, and forecasting effects of adjusting input–output mix or

production scale, among other uses. They stated that the paper left many important questions unanswered but the powerful statistical and computational results derived in the paper should provide a strong stimulus to direct further research effort towards this technique.

Ruggiero (2004) stated that the ability to estimate efficiency reliably with DEA was hampered in the presence of measurement error and other statistical noise. He added that a main and legitimate criticism of all deterministic models was the inability to separate out measurement error from inefficiency, both of which were unobserved. He considered one DEA panel data model of efficiency estimation, which averaged cross-sectional efficiency estimates across time and worked relatively well. He showed that this approach led to biased efficiency estimates, and provided an alternative model that corrected this problem. The two approaches were compared using simulated data for illustrative purposes. The alternative approach introduced by Ruggiero (2004) was performed using DEA on average data because averaging the data accounts for measurement error prior to the performance analysis. He stated that as a result, the approach provides a much better measure of efficiency.

Ruggiero (2004) performed three simulation analyses and the results provided evidence that averaging the data worked better in accounting for measurement error. He acknowledged that a limitation of both approaches was the assumption that DMUs' efficiency was constant across time. He also stated that, while potentially limiting, it was important to consider that this assumption is also used in the panel data stochastic frontier models. He therefore suggested that an interesting extension of his paper would be to compare the alternative approach to the stochastic frontier using simulated data.

Khodabakhshi (2010) considered the concept of chance-constrained programming approaches to develop an output-oriented super-efficiency model in stochastic DEA. He stated that the output-oriented super-efficiency model was one of the classic models in DEA widely used by practitioners and that, in many real applications, data were often imprecise. He added that a successful method for addressing uncertainty in data was to replace deterministic data by random variables, leading to stochastic DEA. Therefore, he developed an output-oriented super-efficiency model in stochastic data

envelopment analysis, and derived its deterministic equivalent which was a nonlinear program. He showed that the deterministic equivalent of the stochastic super-efficiency model could be converted to a quadratic program. The sensitivity analysis of the proposed super-efficiency model was also discussed with respect to changes in parameter variables. Finally, data related to seventeen Iranian electricity distribution companies were used to illustrate the methods developed in his paper.

In the context of the TGIA case study reported in this thesis, further consideration of stochastic DEA did not proceed. This was for similar reasons given in (i) above in relation to DEA in the presence of uncertainty.

(iii) Bootstrapping with DEA

It is appropriate to examine the work of Simar and Wilson (1998, 2000, 2007, 2011) and Wilson (2006) on bootstrapping in non-parametric (e.g. DEA) frontier models. It is also appropriate to consider applications of their suggested approach in studies by other authors.

Simar and Wilson (1998) provided a general methodology of bootstrapping in non-parametric frontier models. They demonstrated that non-parametric measures of efficiency have a statistical basis. They suggested that their bootstrap estimates offered by their methodology presented several possible enhancements to typical DEA applications.

Simar and Wilson (2000) proposed a general methodology for bootstrapping in frontier models, extending the more restrictive method proposed by Simar and Wilson (1998) by allowing for heterogeneity in the structure of efficiency. They asserted that despite a small but growing literature on the statistical properties of DEA estimators, most researchers had used these methods while ignoring the sampling noise in the resulting efficiency estimators, and continued to do so. Their empirical example demonstrated that ignoring the statistical properties of DEA estimators and the uncertainty surrounding DEA estimates could lead to erroneous conclusions. They claimed to have provided a general, computationally tractable method for adapting bootstrap methods to the problem of non-parametric efficiency estimation. They stated that their method could be used to assess uncertainty about distance to the true production frontier from a

relatively small number of points in the production set, cleverly chosen to reflect the location of most of the data, or of at least the most interesting part of the data.

Wilson (2006) developed a computer program called FEAR that could carry out the type of approach suggested by Simar and Wilson (1998, 2000) and in subsequent publications cited below. As this approach was not applied in the TGIA study for reasons discussed below, FEAR was also not used.

Simar and Wilson (2007) stated that, of the many papers reporting studies in which non-parametric estimates of productive efficiency were regressed on environmental variables in two-stage procedures to account for exogenous factors, none had described a coherent data-generating process (DGP). This statement cannot be disputed. They claimed that conventional approaches to inference employed in these papers were invalid because of complicated, unknown serial correlation among the estimated efficiencies. They first described what they called a 'sensible DGP for such models'. They proposed single and double bootstrap procedures to permit valid inference, and said the double bootstrap procedure improved statistical efficiency in the second-stage regression. They examined the statistical performance of their estimators using Monte Carlo experiments and concluded that truncated regression using the double bootstrap was the preferred choice over second-stage Tobit regression.

Simar and Wilson (2011) once more examined the widespread practice where DEA efficiency estimates are regressed on some environmental variables in a second-stage analysis. They stated that 'We attempt to clear up some of the confusion that has developed' since their earlier work. Again they did not recommend the use of second-stage regressions involving DEA efficiency scores. However, they stated that if one chose to do so, the issues that had been raised in the paper should be considered carefully. The issues they raised have certainly been noted in the context of this TGIA study. Finally, they issued a stern warning to 'let the buyer beware — caveat emptor'.

The bootstrapping approach discussed above has been applied in studies since it was first recommended. Alexander, Haug and Jaforullah (2007) conducted a two-stage (DEA and regression) analysis of the efficiency of New Zealand secondary schools. Using Simar and Wilson's double bootstrap procedure, they drew robust conclusions

about a system that had undergone extensive reforms with respect to ideas high on the educational agenda such as decentralised school management and parental choice. They found that school type affected school efficiency and teacher quality.
Cullmann, Schmidt-Ehmcke and Zloczysti (2009) assessed the relative efficiency of knowledge production in the Organisation for Economic Cooperation and Development (OECD) using the single bootstrap procedure suggested by Simar and Wilson (2007). The empirical evidence supported their hypothesis that barriers to entry (aimed at reducing competition) reduced research efficiency by attenuating the incentive to innovate and to allocate resources efficiently.

Curi, Guarda, Lozano-Vivas and Zelenyuk (2013) investigated the effects of home-country banking regulations on the performance of foreign banks in Luxembourg's financial centre. The two-stage bootstrap method proposed by Simar and Wilson (2007) was applied to bank panel data covering 1999–2009. The analysis generated policy implications for bank regulators in both home and host countries and provided insight into the choice between establishing a branch or a subsidiary when developing cross-border activities through financial centres.

Huang and Eling (2013) analysed the efficiency of non-life insurance companies in four of the fastest-growing markets in the world — the BRIC (Brazil, Russia, India, China) countries. They found that the environment strongly affected the efficiency of non-life insurers operating in the BRIC countries. They identified three drivers of efficiency in a second-stage regression that followed Simar and Wilson (2007). The results enhanced their understanding of the insurance industry in the BRIC countries, their economic environment, and their efficiency.

Lee and Worthington (2014) stated that between 2001 and 2005 the US airline industry faced financial turmoil. At the same time, the European airline industry entered a period of substantive deregulation. During this period and because of these combined events, opportunities opened for low-cost carriers to become more competitive in the market. To help assess airline performance in the aftermath of these events, Lee and Worthington (2014) provided new evidence of technical efficiency for 42 national and international airlines in 2006 using the DEA bootstrap approach first proposed by Simar and Wilson (2007). In the first stage, technical efficiency scores were estimated

using a bootstrap DEA model. In the second stage, a truncated regression was employed to quantify the economic drivers underlying technical efficiency. The results highlighted the key role played by non-discretionary inputs in measures of airline technical efficiency.

The debate on the appropriateness of their method continued after Simar and Wilson (2011) (SW). Tziogkidis (2012) gave a critique of the SW approach, challenging some fundamental assumptions in the SW bootstrap DEA approaches which had been widely used in the literature. He stated at the end (page 27):

> To sum up, the bootstrap DEA introduced by Simar and Wilson (1998) is a consistent procedure and a valuable tool for applying statistical inference in DEA. However, their assumption of equality between the bootstrap and DEA biases is practically implausible. Therefore, it should be avoided correcting twice for bootstrap bias or using the 'enhanced' confidence intervals of Simar and Wilson (2000). Regarding the question of whether we should smooth the empirical distribution, we propose that it should be avoided as it is a very technical procedure and results can be very sensitive to the choice of the smoothing parameter. Instead, the simple bootstrap is always consistent and has a very good performance in terms of moments, hence the term 'naïve' is an unfair characterisation and should not be used.

The final recommendation by Simar and Wilson (2011) has, however, been noted and addressed (page 216):

> We do not recommend the use of second-stage regressions involving DEA efficiency scores. However, if one chooses to do so, the issues that have been raised here should be considered carefully. Regardless of whether one adopts the model considered by SW, the BN model, or some other model yet to be presented one should carefully consider what restrictions are necessary, and whether these are reasonable. Ideally, restrictions should be tested. In addition, one should carefully consider how valid inference can be made. To do these things, one must have a coherent, well-defined statistical model. Finally, let the buyer beware—caveat emptor.

In the TGIA case study presented in this thesis, the author, being a 'buyer', has certainly 'been aware'. However, in the context of the TGIA study, use of the two-stage approach using DEA and Tobit regression still appears justified because such an approach continues to be main stream and was applied recently by Khan and Shah (2015); Novignon (2015); Park, Ko, Jung and Lee (2015); Alboghdady (2014); Alrafadi, Kamaruddin and Yusuf (2014); Bangi (2014); Das and Das (2014); Li

(2014); Lubis, Daryanto, Tambunan and Purwati (2014); Luik, Viira and Värnik (2014); Nargis (2014); Yakob, Yusop, Radam and Ismail (2014); Zhao and Wang (2014); Al-Bagoury (2013). Moreover, the use of Tobit in the context of this study is justified, given that this is so far the only study that has considered the measurement of efficiency in the TGIA sector – in line with the previous studies in the not-for-profit organisations. Nevertheless, it is acknowledged that the use of the bootstrapped (SW) approach will be a good basis for the extension of this study, owing to the critique put forward by Tziogkidis (2012) which appears to sound a note of 'caveat emptor' even for the SW approach.

(h) Applications of DEA

The approach taken in this section is to focus selectively on a number of DEA studies. The literature is far too voluminous to cover the whole range.

Farrell (1957) succinctly expressed his purpose in writing his landmark paper: namely, 'to provide a satisfactory measure of productive efficiency … and to show how it can be computed in practice' (page 253). He was responding to the importance of measuring productive efficiency to economic theorists and economic policy makers, to his perception that a greater focus was needed on the theoretical side of such measurement, and to provide a measure that took into account all inputs while avoiding index number problems. He extended and applied theoretical models for measuring productive efficiency to agricultural data, concluding that it would be interesting to compare his results with other agricultural production functions. His final comment was: 'Unfortunately, differences both in method and definition of variables are so large that such comparisons cannot at all easily be made' (page 278). Such a comment appears to reflect great insight by Farrell (1957) and its sentiments still appear to be true. The paper was well-received at the time it was presented and, as mentioned earlier, continues to be a significant landmark — making a pioneering contribution to the literature on productive efficiency at the time it was written.

Developments between 1957 and the next landmark papers by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) on SFA, and Charnes, Cooper and Rhodes (1978) on DEA, were slow (Coelli et al. 2005, page 162). After 1978, the number of publications on frontier efficiency measurement (DEA and SFA)

proliferated. In their 2008 bibliography, Emrouznejad et al. (2008, page 153, Figure 1) indicated an exponential growth pattern in DEA publications from 1978 onwards after Charnes et al. (1978). There have also been numerous studies using SFA since Aigner et al. (1977) and Meeusen and van den Broeck (1977). For example, the list of references in Coelli et al. (2005, pages 327–339) and the list of publications and working papers on the website of the Centre for Efficiency and Productivity Analysis (CEPA) at the University of Queensland (in 2011 and before, by O'Donnell and other authors) indicate that SFA is still in use with no sign of the research abating in this area. Table 3.1 gives some examples of DEA and SFA studies by sector over the past few decades.

Just as Farrell (1957) had written his pioneering paper and as Charnes et al. (1978) went on to pioneer DEA, Aigner et al. (1977) and Meeusen and van den Broeck (1977) pioneered SFA in their papers written independently and concurrently. By the end of 1978, frontier measurement and analysis of efficiency had been set on a course that continues to this day, embracing the non-parametric stream (DEA) and the parametric stream (SFA). The basic concepts and models evident in the pioneering papers already discussed have been applied empirically to varying degrees in the examples that are discussed later in this chapter.

There have been many books published in the area of productivity and efficiency analysis but for this thesis Coelli et al. (2005) provided much initial inspiration for the research. It has been consistently referred to even though there is much other literature in the topic area that has been reviewed and cited. It is considered that the book required at least the acknowledgment and prominence given.

Table 3.1 — Some examples of DEA and SFA studies by certain sectors

Sector	DEA	SFA	Both DEA and SFA
Agriculture	Armagan (2008); Błażejczyk-Majka, Kala and Maciejewski (2011)	Battese and Coelli (1992); Battese and Coelli (1995); Chen and Song (2006); Boshrabadi, Villano, and Fleming (2007); Cabrera, Solís and del Corral (2010); Barnes, Revoredo-Giha and Sauer (2011)	Wadud and White (2000); Jaforullah and Premachandra (2003); Zhang and Garvey (2008); Ismail, Idris and Hassanpour (2013); Helali, Tsagli and Kalai (2014)
Banking, Finance and Insurance			Weill (2004); Jakata and Mutasa (2014); Metica, Garcia, Bool and Sunga (2015)
Business Services and Economics			Deliktas and Balcilar (2002); Kox, van Leeuwen and van der Wiel (2010)
Education	Bessent and Bessent (1980); Taylor and Harris (2004)		Chakraborty, Biswas and Lewis (2001)
Energy			Ajodhia, Petrov and Scarsi (2004)
Health	Callen and Falk (1993); Varela, de Andra de Martins and Favero (2010)		Banker, Conrad and Strauss (1986)
Higher Education			Sav (2012)
Manufacturing			He and Chen (2008)
Mining			Shi and Grafton (2010)
Transportation			Lan and Lin (2003); Lin and Tseng (2005); Michaelides, Belegri-Roboli, Karlaftis and Marinos (2009)
Not-for-profit and Charity	Callen (1994); Tofallis and Sargeant (2000); Basso and Funari (2004); Udbye (2011); Pitkin (2013)	Song and Yi (2010)	

Coelli et al. (2005) provide content on the four principal methods involved in productivity and efficiency analysis: econometric estimation of average response models, index numbers, data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Basic concepts for each method are included with a balance of empirical examples, together with presentations on appropriate computer programs that have been developed to carry out the analysis. The book contains a comprehensive list of references for each method. It is considered that the final chapter of the book, which sets out the authors' conclusions, provides an excellent basis on which to develop the topic areas covered in general terms and more specifically in the TGIA case study. The

research presented in this thesis for the TGIA case study applied some of the concepts and computer programs covered in the book.

The DEA models developed by Charnes et al. (1978), assuming CRS, and Banker et al. (1984), assuming VRS, have been applied and extended to cover multi-industry situations with cross-sectional and panel data as demonstrated by examples below. Sensitivity comparisons of efficiency scores calculated by the non-parametric DEA and the parametric SFA have become common.

Bessent and Bessent (1980) used DEA to analyse the relative efficiency of a range of elementary schools in an urban school district in the USA, thereby introducing the application of DEA to the field of educational administration. They demonstrated that DEA could identify individual school units that are less efficient than other comparable units, setting down a procedure for using DEA results as management information for the improved efficiency of schools.

Sherman (1984) applied DEA to a group of teaching hospitals, providing meaningful insights into the location and nature of hospital inefficiencies. He suggested DEA as a basis for directing management efforts toward increasing efficiency and reducing health care costs.

Bowlin (1987) evaluated DEA for measuring and evaluating the operational efficiency of US Air Force organisations. The study used DEA to locate possible inefficiencies in the performance of US Air Force real-property maintenance activities. The author concluded that this type of efficiency analysis had value for the Air Force in measuring, evaluating and enhancing operational efficiency.

Camm and Grogan (1988) used DEA to assign handicaps to runners in a race with age and gender as inputs. Runners could then compare themselves with others in a race. This application of DEA permitted a superior method for race awards.

Maindiratta (1990) considered applying DEA analysis in hospitals to explore whether even greater savings would be possible if the task were to be optimally apportioned to a number of smaller DMUs. Size efficiency was introduced to measure the potential

for further input reductions, and then compared and contrasted to scale efficiency. The existence of a largest radially size-efficient output scale was established as a ray property of the production frontier.

Fizel and Nunnikhoven (1992) employed DEA to generate efficiency indices for individual nursing homes relative to a best-practice frontier. Their results supported the property rights hypothesis that for-profit homes are inherently more efficient than non-profit ones.

Miliotis (1992) applied DEA to electricity distribution districts in Greece. The results were calculated using assumptions and compared with productivity indices and with measures of efficiency produced by econometric methods. Miliotis (1992) concluded that DEA scores appeared to be more reliable than simple productivity indices. He also concluded that 'comparison of the different cases explains the reason for low efficiencies, which can be due to the management of controllable inputs, the design of the supply system or other environmental factors' (Miliotis 1992 page 549).
Hjalmarsson and Veiderpass (1992) used DEA to examine the efficiency of electricity retail distribution in Sweden in a multiple-input multiple-output situation. They extended the basic DEA model using different assumptions about returns to scale.

Burgess and Wilson (1993) assessed the efficiency of 89 Veterans Affairs (VA) hospitals in the USA over 3 years. The authors stated that the US hospital industry is characterised by multiple outputs and the lack of information on prices, making the DEA approach beneficial. They were surprised at the number of VA hospitals out of the 89 that were sitting on the efficiency frontier with no inefficiency.

McCarty and Yaisawarng (1993) examined technical efficiency in 27 New Jersey USA school districts. Only three were found to be fully efficient. The authors went on to use regression analysis to explain variations in efficiency scores as a function of inputs outside the control of schools (EVs).

Sharma, Leung and Zaleski (1997) used a single-output multiple-input model in their study of productive efficiency of 53 swine producers in Hawaii. Only 10 were found to be fully efficient. The authors claimed that if all producers operated at full efficiency,

thereby increasing industry output, then this could obviate the necessity to import live hogs into Hawaii.

Carrington, Puthucheary and Rose (1997) outlined the way in which the New South Wales (NSW) Treasury had used DEA to assist in improving the NSW Police Service. One of the authors' conclusions was that results suggested that, on average, police patrols could maintain the same level of output with 13.5% fewer inputs.

The above examples of DEA applications covering the 20 years from 1978 to 1998 show that DEA has been applied widely and successfully across many sectors and industries. Ten years later, Emrouznejad et al. (2008) presented a DEA bibliography listing thousands of publications on the topic during the 30 years since the work of Charnes et al. (1978). Some more recent examples of the application of DEA are cited below.

Sun (2002) used DEA to measure the relative efficiency of the 14 police precincts in Taipei City, Taiwan. The results indicated how DEA could be used to evaluate these police precincts from commonly available police statistical data for the years 1994–1996. The analysis indicated that differences in operating environments, such as resident population and location factors, did not have a significant influence upon the efficiency of police precincts.

Oni, Nkonya, Pender, Phillips and Kato (2009) used DEA and Tobit regression to examine agricultural productivity trends and patterns in Nigeria as well as the drivers of such trends during the period 1995–2006.

Varela, de Andra de Martins and Favero (2010) applied DEA to measure variations in the performance of small municipalities in the State of São Paulo, Brazil. The correlation analysis of DEA score was used to verify possible associations between technical efficiency and the funding profile of expenses with health care. The results showed that 6.41% of the municipalities were considered efficient. They also showed that the level of municipality dependence on inter-governmental general purpose grants and the national health funding specific purpose grants had negative correlation with efficiency scores.

Błażejczyk-Majka, Kala and Maciejewski (2011) applied DEA to economic results recorded in the years 1989–2007 by average farms representing selected regions of the European Union. The resulting individual dynamics of technical efficiency changes were divided into four homogeneous groups to facilitate identification of differences in production technology. These differences were then explained by classical analysis of basic factors used in agricultural production.

Giannoccaro, Prosperi, Alcón and Martin-Ortega (2013) used DEA to assess the eco-efficiency of an eventual water pricing reform in the irrigated agricultural system of Capitanata, in Italy. Overall, findings pointed out that a pricing system based on 'per area' and 'output' would lead to the highest eco-efficiency, although this was not valid under any water pricing charge. The authors suggested that the enforcement of water saving via pricing did not imply a higher eco-efficiency, mainly in the case of environmental efficiency. They claimed that the DEA approach appeared useful in the assessment of water pricing policies where conflictive economic and environmental goals arise. They concluded that DEA provided a methodology to support policy makers in the design of water policy pricing aimed at the enhancement of efficiency, both economic and environmental.

In a study by Rahbari, Mahmoudi and Ajabshirchi (2013), DEA was applied to analyse the efficiency of producers, to discriminate between efficient and inefficient farmers, and to identify wasteful uses of energy in order to optimise the energy inputs for greenhouse tomato production in Esfahan province of Iran. The researchers collected data from 30 tomato producers by using a face-to-face questionnaire.

Karagiannis and Lovell (2013) considered productivity measurement based on radial DEA models with multiple constant inputs. They showed that in this case the Malmquist and the Hicks–Moorsteen productivity indices coincided and were multiplicatively complete, and the choice of orientation for the measurement of productivity change did not matter. Also, there was a unique decomposition of productivity change containing three independent sources, namely technical efficiency change and the magnitude and output bias components of technical change. They also

showed that an aggregate productivity index was given by the simple arithmetic mean of individual productivity indices.

The studies cited in this sub-section, summarised by sector in Table 3.2, represent the proverbial ‘tip of the iceberg’ of achievements in the DEA topic area since its inception decades ago. However, they appear to be reasonably representative and provide at least two key messages to inform the research undertaken for TGIA.

First, there is no doubt that DEA is an extremely powerful technique that has been diversely and successfully applied in numerous studies. Use of DEA appears well-justified in the measurement of productivity and efficiency, and different themes continue to emerge in its application. That some of these applications have been in the charity/NFP sphere lends further support to its application in the TGIA context.

Second, a theme common to some of the studies cited is that management can be in a better position to enhance performance of the DMUs as a result both of DEA studies and of examination of the factors affecting technical efficiency as a result of subsequent regression analysis.

The potential for providing information useful to management, leaders and governing bodies has always been a key motivation for undertaking the study of TGIA. Chapter 8 of this thesis specifically addresses the findings of the TGIA study and their implications for TGIA/TGI management.

Table 3.2 — Examples of DEA studies by sector

Sector	Study
Agriculture	Sharma et al. (1997); Oni, Nkonya, Pender, Phillips and Kato (2009); Błażejczyk-Majka, Kala and Maciejewski (2011); Giannoccaro, Prosperi, Alcón and Martin-Ortega (2013); Rahbari, Mahmoudi and Ajabshirchi (2013); Lubis, Daryanto, Tambunan and Purwati (2014); Alboghdady (2014); Luik, Viira and Värnik (2014)
Banking and Finance	Alrafadi, Kamaruddin and Yusuf (2014); Li Li (2014); Nargis (2014); Khan and Shah (2015)
Defence	Bowlin (1987)
Education	Bessent and Bessent (1980); McCarty and Yaisawarng (1993)
Higher Education	Al-Bagoury (2013); Bangi (2014); Das and Das (2014)
Insurance	Yakob, Yusop, Radam and Ismail (2014)
Energy	Miliotis (1992); Hjalmarsson and Veiderpass (1992)
Government services/Police	Carrington et al. (1997); Sun (2002)
Health	Sherman (1984); Maindiratta (1990); Fizel and Nunnikhoven (1992); Burgess and Wilson (1993); Varela, de Andra de Martins and Favero (2010); Novignon (2015)
Sport	Camm and Grogan (1988)
Taxation	Park, Ko, Jung and Lee (2015)
Theoretical	Karagiannis and Lovell (2013) (no empirical study reported)

From the above summaries it is clear that DEA has been used successfully in thousands of studies over decades and across numerous sectors. DEA appears well justified in the measurement of productivity and efficiency, and different themes continue to emerge in its application.

3.3.2 SFA — a parametric approach

As mentioned above, the parametric-based approach, SFA, is another way to measure productivity and efficiency for DMUs. In this section discussion focuses mainly on basic SFA, measuring inefficiency and accounting for environmental factors.

(a) Basic SFA concepts

The basic conceptual coverage of stochastic frontier analysis (SFA) is included for completeness only. This is because SFA is one of the major streams that have emerged as having wide application in studies of productive efficiency since Farrell (1957). For SFA, a one-stage approach is applicable given that any assumed models (e.g. Cobb–Douglas and translog) have parameters calculated for the variables that permit hypothesis testing for significance.

Aigner et al. (1977) formulated and applied a linear model to introduce SFA:

$$y_i = f(\boldsymbol{x}_i;\boldsymbol{\beta}) + v_i + u_i \qquad i = 1,\ldots, N, \qquad \text{(Equation 3.1)}$$

where y_i is the maximum output obtainable from $\boldsymbol{x_i}$, a vector of (non-stochastic) inputs, and $\boldsymbol{\beta}$ is an unknown parameter vector to be estimated. The error component v_i represents the stochastic symmetric disturbance or error term (noise) usually included in regression models. The v_i are assumed to be independently and identically distributed as $N(0, \sigma^2_v)$. The error component, u_i, represents a stochastic one-sided disturbance or error term associated with technical inefficiency. The u_i are assumed to be distributed independently of v_i, and to satisfy $u_i \leq 0$.

Aigner et al. (1977, page 21) were motivated to develop their model because ‘Previous studies of the so-called frontier production function have not utilised an adequate characterisation of the disturbance term for such a model’.

The Aigner et al. (1977) model was a breakthrough because it included separate error components associated with noise $\{v_i\}$ and technical inefficiency $\{u_i\}$. Earlier models used for example by Aigner and Chu (1968) and Afriat (1972) had not included either of these two components. Schmidt (1976) added a one-sided disturbance

component to those earlier models, but Aigner et al. (1977) appear to have been among the first to include v_i and u_i.

Aigner et al. (1977) built on and extended previous studies that used models that did not recognise v_i and u_i. They applied their model to two empirical examples, the first using data from the US primary metals industry, and the second using data from US agriculture. In their conclusions they stated that tests of their model on each dataset indicated relatively small one-sided components (u_i) of the disturbance thus suggesting high levels of efficiency relative to a stochastic frontier.

The authors' contribution to the then existing literature was to extend the theory and application of parametric frontier models in efficiency measurement and analysis. The authors suggested that additional research was required to evaluate the performance of moment estimators based on least-squares residuals mentioned in the paper. The paper has led and continues to lead to the prominent application of SFA in numerous studies (e.g. Song and Yi 2010; Cabrera, Solís and del Corral 2010; Battese and Coelli 1992; Pitt and Lee 1981).

Concurrently with Aigner et al. (1977), Meeusen and van den Broeck (1977) considered and applied a Cobb–Douglas model of the form below, to introduce SFA:

$$y_t = A \prod_j x_t^{\beta j}{}_j \, e^{-zt} \, e^{-vt} \qquad t = 1,\ldots,T. \qquad \text{(Equation 3.2)}$$

where A is total factor productivity (TFP), e^{-zt} is an efficiency measure distributed in the interval (0,1), and e^{-vt} is a disturbance measure in the usual regression sense, distributed in the interval $(0,\infty)$.

Like the linear model of Aigner et al. (1977; ALS), the Meeusen and van den Broeck (1977; MVB) model appears to have been a breakthrough because it also included separate error components associated with noise and efficiency. Earlier models used by Aigner and Chu (1968) and Afriat (1972) were also cited by Meeusen and van den Broeck (1977) as not including either of these two components. In carrying out their work, Meeusen and van den Broeck (1977) had also built on and extended previous studies that used models that did not recognise noise or disturbance measures. They

applied their model to data from the 1962 French Census of Manufacturing Industries as a first verification of the model. Meeusen and van den Broeck (1977) made a contribution to existing literature by extending the theory and application of parametric frontier models in efficiency measurement and analysis. They acknowledged that the choice of the Cobb–Douglas functional form was debatable and suggested therefore that it would be useful to compute the sensitivity of their results with respect to that choice.

(b) Measuring inefficiency with SFA

Coelli et al. (2005, page 242) expressed the independently proposed ALS and MVB models as the stochastic frontier production function model of the form

$$\ln q_i = \boldsymbol{x}_i' \boldsymbol{\beta} + v_i - u_i \qquad i = 1,\ldots, I\,. \qquad \text{(Equation 3.3)}$$

Coelli et al. (2005, page 244) stated that much of SFA is directed towards the prediction of inefficiency effects (u_i). They showed that $\mathrm{TE}_i = \exp(-u_i)$ represents the most common output-oriented measure of technical efficiency, being the ratio of observed output to the corresponding stochastic frontier output. This technical efficiency takes a value between 0 and 1. It measures the output of the *i*-th DMU relative to the output that could be produced by a fully efficient DMU using the same input vector.

The parameters of Equation 3.1 are estimated as a first step in predicting TE_i. With appropriate assumptions concerning v_i and u_i, Coelli et al. (2005, page 245) deferred towards estimating the model using the method of maximum likelihood (ML) because ML estimators (MLEs) have many desirable asymptotic properties. Following this first step, for which computer software like FRONTIER 4.1 (Coelli 1996) and LIMDEP (Greene 2007) are generally used, the same software then calculates and tabulates efficiency scores.

The theoretical algebra and other mathematics that leads to the efficiency measurements using SFA models is not reproduced here because it is not intended to apply SFA in this current study. Papers by Battese and Coelli (1992, 1995), amongst others, cover measurement methods in great detail.

(c) Estimation of production technologies with SFA

SFA is a method of frontier estimation that assumes a given functional form for the relationship between inputs and output. The unknown parameters of the function need to be estimated using econometric techniques once the functional form has been specified. Examples of functional forms are the linear, Cobb–Douglas, quadratic, normalised quadratic, translog, generalised Leontief and constant elasticity of substitution. In practice, Cobb–Douglas and translog appear to be the most popular.

(d) Accounting for environmental variables with SFA

Coelli et al. (2005, pages 281–284) addressed the issue of SFA and environmental factors, as summarised here.

(i) Exogenous variables that characterise the environment in which production takes place will often influence the ability of a manager to convert inputs into outputs.

(ii) It is useful to distinguish between non-stochastic variables that are observable at the time of making key production decisions (e.g. government regulation) and unforeseen stochastic variables that are viewed as sources of production risk (e.g. weather).

(iii) Non-stochastic variables are incorporated directly into the non-stochastic component of the production frontier using a one-stage or two-stage approach (e.g. Pitt and Lee 1981) or by allowing the variables to directly influence the stochastic component of the production frontier (e.g. Kumbhakar, Ghosh and McGuckin 1991).

(iv) Stochastic variables (e.g. production risk) are treated simply by appending another random variable to the frontier model to represent the combined effects of any variables that are unobserved at the time input decisions are made.

Coelli et al. (2005) warned potential users about limitations and cautions associated with the above approaches. Unlike in the case of DEA and environmental variables, where a specific recommendation is made for treating environmental variables following a two-stage approach using Tobit regression, Coelli et al. (2005, page 194) do not appear to make such a definitive recommendation in the case of SFA.

(e) Sensitivity comparisons between DEA and SFA

Sensitivity comparisons of efficiency scores calculated by the non-parametric DEA and the parametric SFA have become common. Table 3.1 listed some examples, which are discussed below.

Wadud and White (2000) compared estimates of technical efficiency obtained from SFA and DEA using farm-level survey data for rice farmers in Bangladesh. They modelled technical inefficiency effects as a function of farm-specific socioeconomic factors, environmental factors and irrigation infrastructure. The results from both SFA and DEA indicated that efficiency is significantly influenced by the factors measuring environmental degradation and irrigation infrastructure.

Deliktas and Balcilar (2002) estimated the level of efficiency, efficiency change, technical change and TFP change in transition economies based on panel data for 130 countries for the period 1991–2000 using SFA and DEA. They stated that DEA was mainly used for confirmatory analysis and supplemented SFA. They found that there was no technological progress, but over the whole period there was technological regress. Their results suggest that, on average, change in technical efficiency was outweighed by the technical regress. In order to evaluate the robustness of their results, they estimated technical efficiency, technical change and TFP indexes for the same dataset using VRS DEA. They stated that the estimates of technical efficiency of each country, for any given period in the output-oriented DEA with VRS, would be higher than or equal to that in the output-oriented CRS DEA, because VRS DEA is more flexible (Wadud and White 2000). In order to see whether the SFA and DEA rankings of the countries are analogous, they computed the Spearman rank correlation coefficient between the rankings of countries by these two methods in terms of efficiency levels for all countries and also for the transition countries. They found that the DEA results were highly confirmatory to the results obtained by SFA.

Jaforullah and Premachandra (2003) used data from the New Zealand dairy industry for the year 1993 to estimate farm-specific technical efficiencies and mean technical efficiency using three different estimation techniques under both CRS and VRS in production. The approaches used were the econometric stochastic production frontier (SPF = SFA), corrected ordinary least squares (COLS) and data envelopment analysis

(DEA). Mean technical efficiency of the industry was found to be sensitive to the choice of estimation technique. In general, the SFA and DEA frontiers resulted in similar mean technical efficiency estimates, but higher than the COLS production frontier.

Zhang and Garvey (2008) stated that the main objective of their paper was to conduct a sensitivity analysis for different frontier models and compare the results obtained from the different methods of estimating a multi-output frontier for a specific application. The methods included SFA and DEA. The results indicated that there were significant correlations between the results obtained from the alternative estimation methods.

Kox, van Leeuwen and van der Wiel (2010) empirically investigated whether a lack of competition determined the poor productivity performance of European business services. They used detailed panel data for 13 European Union countries over the period 2000–2005. They applied parametric (SFA) and non-parametric (DEA) methods to estimate the production frontier and subsequently explain the distance to this frontier by market characteristics, entry and exit dynamics, and national regulation. They applied DEA both as a robustness check on the SFA results and as a method that allowed looking deeper into the issue of scale efficiency. The global stochastic frontier model (GSF) and DEA models came up with similar findings.

Ismail, Idris and Hassanpour (2013) compared technical efficiency of paddy farming in the east coast and west coast of Peninsular Malaysia by using DEA and SFA. Primary data were collected using a set of structured questionnaires with 230 farmers. The results indicated that the differences in methodologies employed produced different efficiency estimates. The DEA result showed that efficiency score was 56%, which is lower than the efficiency score obtained using the SFA at 69%. The authors suggested that with these large differences in technical efficiency results, recommendations for policy purposes should not depend on only one method.

The common theme emerging from the above examples of comparisons between SFA and DEA appears to be that DEA was used to confirm the results from SFA, and generally the results were confirmed with the exception of Ismail, Idris and Hassanpour (2013). Although not used in the TGIA study presented in this thesis, and

despite the exception noted in at least one previous study, it can be expected that in the TGIA context use of SFA would provide confirmation of the results from DEA and that it would not change the general findings from this current study of TGIA.

Leaving aside the SFA component, the study by Deliktas and Balcilar (2002) had some striking similarities to the approach taken in the TGIA study, particularly for the first-stage DEA. Their study used output-oriented VRS DEA with panel data over several years (as the TGIA study has done) with a similar number of DMUs (130 countries compared with 121 branches in the case of TGIA).

3.3.3 Productivity differences and technology gaps

(a) Meta-frontier concepts

The meta-frontier approach (MFA) has been applied in conjunction with DEA, SFA and, more recently, TFP (O'Donnell, Fallah-Fini and Triantis 2011). Battese and Rao (2002) considered a stochastic meta-frontier function to investigate the technical efficiencies of firms in different groups that might not have the same technology. They presented a decomposition of output involving the technology gap and technical efficiency ratios for firms in a group relative to the best practice in the industry. The paper provided a concise summary of basic meta-frontier concepts developed up to 2002, as follows (Battese and Rao 2002, page 87):

> The metaproduction function was first introduced by Hayami (1969) and Hayami and Ruttan (1970, 1971). Hayami and Ruttan (1971, p. 82) stated 'The metaproduction function can be regarded as the envelope of commonly conceived neoclassical production functions'. In their discussion of agricultural productivity across various countries, Ruttan, Binswanger, Hayami, Wade and Weber (1978, p. 46) state, 'We now define the metaproduction function as the envelope of the production points of the most efficient countries.' The concept of a metaproduction function is theoretically attractive because it is based on the simple hypothesis that all producers in different groups (countries, regions, etc.) have potential access to the same technology. Following the seminal work of Hayami and Ruttan (1970), Mundlak and Hellinghausen (1982) and Lau and Yotopoulos (1989) employed the approach to compare agricultural productivity across countries. Some econometric advantages of applying the metaproduction function are discussed by Lau and Yotopoulos (1989), but the lack of comparable data and the presence of inherent differences across groups are the major limitations of the approach. Boskin and Lau (1992) used a new framework for the analysis of productivity and technical progress, based on direct econometric estimation

> of the aggregate metaproduction function. The concept of a *stochastic metafrontier* function, used in this paper, operationalises the standard metaproduction function approach. The stochastic metafrontier model has an error term that comprises a symmetric random error and a non-negative technical inefficiency term, as in the stochastic frontier production function model, originally proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). However, a stochastic metafrontier function may not envelop the separate production frontiers for the different groups involved. It is possible to use *non-stochastic* approaches to construct metafrontier functions. A stochastic metafrontier model was adopted by Gunaratne and Leung (2001) and Sharma and Leung (2000) in studies of the efficiency of aquaculture farms in several countries. Sharma and Leung (2000) used the Battese and Coelli (1995) model for the technical inefficiency effects in the stochastic metafrontier function in their empirical analysis of data on carp pond culture in South-Asian countries.

Since 2002, these concepts have been further developed and applied. Battese, Rao and O'Donnell (2004) examined a meta-frontier production function for estimation of technical efficiency (TE) and technology potentials of DMUs operating under different technologies. Boshrabadi, Villano and Fleming (2007) reported on an analysis of technical efficiency and environment–technology gaps in wheat farming in Iran. Chen and Song (2006) used SFA and a meta-frontier approach to examine technical efficiency and the technology gap in agriculture between regions and China as a whole. O'Donnell, Rao and Battese (2008) applied DEA and SFA to agricultural data to examine meta-frontier frameworks for the study of DMU-level efficiencies and technology ratios.

Barnes and Revoredo-Giha (2009, 2011) used MFA to estimate technical efficiency for the agricultural sectors in several European countries and compared efficiency estimates among them. They stated that the use of this type of analysis was justified because a frontier, which represents the best available technology within a particular region/country, cannot be strictly compared across other regions/countries unless they operate under the same production set. They found that when compared against a meta-frontier, which represented the European Union technology set, all countries suffered in terms of their technical efficiency scores.

Nkamleu, Nyemeck and Gockowski (2010) used SFA and MFA to investigate productivity potentials and efficiencies in cocoa production in West and Central Africa

by examining the technology gap between regions and West and Central Africa as a whole. The methodology enabled the estimation of national technology gap ratios (TGRs) — now more commonly called MTRs (meta-technology ratios) — by using a decomposition result involving both the national production frontiers and the (regional) meta-production frontier. Empirical results were derived using a comprehensive dataset collected during one of the larger surveys of cocoa farmers in four West and Central African countries. The data and analysis supported the view that technical efficiency in cocoa production is globally low, and the technology gap played an important part in explaining the ability of the cocoa sector in one country to compete with cocoa sectors in other countries in the West and Central Africa region.

Ben-Naceur, Ben-Khedhiri and Casu (2009) examined the effect of financial-sector reform on bank performance in selected Middle Eastern and North African (MENA) countries in the period 1994−2008. They evaluated bank efficiency in five countries by means of DEA and employed a meta-frontier approach to calculate efficiency scores in a cross-country setting. They then employed a second-stage regression to investigate the impact of institutional, financial, and bank specific variables on bank efficiency. Overall, the analysis showed that, despite similarities in the process of financial reforms undertaken in the five MENA countries, the observed efficiency levels of banks vary substantially across markets, with one country consistently outperforming the rest of the region. They stated that differences in technology seemed to be crucial in explaining efficiency differences.

Barnes, Revoredo-Giha and Sauer (2011) applied a regional approach to measure technical efficiencies on dairy farms which employed the deterministic meta-frontier approach. They constructed six super regions for the UK and applied SFA to construct six regional frontiers and a pooled (UK) dataset for comparison. A likelihood ratio test rejected the null hypothesis that these regions operated under a common frontier, which could indicate bias in previous attempts to measure dairying efficiency at the country level. The meta-frontier presented estimates against a common technology and mean scores ranged from below 0.50 for the English regions and Northern Ireland, to 0.52 for Wales and 0.56 for Scotland. The authors suggested that the paper promoted the application of the deterministic meta-frontier approach for similar sub-country studies.

O'Donnell, Fallah-Fini and Triantis (2011) showed how the MFA framework could also be used to make total factor productivity (TFP) comparisons within and across groups. Previously, they observed, MFA had been used extensively for evaluating the technical efficiency of heterogeneous production units that could be classified into different groups. The paper appeared to be the first to explore meta-frontiers in the context of TFP and decomposition. DEA was applied and DPIN 3.0 was used in the analysis. O'Donnell, Fallah-Fini and Triantis (2011) concluded that the productivity decomposition methodology developed in their paper could be applied in any empirical context where the standard meta-frontier methodology would normally be applied. They further concluded that estimated MTRs of the type reported in their paper would be of particular interest to managers and policy makers who have some capacity to change the production environment.

A common theme that emerges from previous studies using MFA is that technology gaps between meta and group levels appear to be identified consistently. This has potential benefits for managers and policy makers who can then examine MTRs in an attempt to identify causes and implement action aimed at improving performance at all levels.

To explore the method and conceptual framework of the meta-frontier approach in the context of TGIA, the focus is on the DEA approach to meta-frontiers in this thesis because only DEA was used in the TGIA case study. The discussion below draws heavily on the DEA aspects of Battese, Rao and O'Donnell (2004) and O'Donnell, Rao and Battese (2008). Appendix 3 sets out the basic mathematical concepts embedded in MFA.

In MFA studies meta-technology ratios (MTRs) are computed for each individual DMU. Note that it is also possible to calculate a regional measure of MTR, obtained using the mean of values calculated for each DMU in a particular region and relating the regional mean to the mean of the meta-frontier results.

In the context of TGIA in this thesis, MFA has been applied to the OTE situation. The extension to TFP in O'Donnell, Fallah-Fini and Triantis (2011) has also been considered.

(b) Possible sources of productivity differences for TGIA

Possible reasons why technology gaps may exist in TGIA could include the following.

(i) Technology might not be equally accessible for all branches because of urban, non-urban and remote location. Action to promote better accessibility could prove beneficial.

(ii) There are more influential people and motivators and centres of influence in some places than in others. For example, in some branches there may be only one or two really active members. Encouraging more members to increase participation and representation at hierarchical levels above the branch level could be advantageous.

(iii) One or more states could have an advantage because of the size of their membership.

(iv) Geographical locations relative to each other at levels above branch level of TGIA's operations. For example, it might not be as easy for members, who are generally volunteers, in the Western state region to take part in national activities held in the Northern state region because of financial, work and time constraints.

(v) At present there is decentralisation of functions from national through to state, area and branch levels at TGIA. For example, benefits might be gained if the number of levels were reduced i.e. more centralisation of functions than currently such as move to a two tiered network only, national and branch levels.

(vi) The demographic mix of members may vary at all levels.

(vii) What was happening internally and externally at TGIA/TGI year by year for the period 2008 to 2013? For example, this could have impacted more on some constituents at each level than others e.g. between branches and/or between state regions; it may recur unless something is done to mitigate the risk to TGIA if it should happen again.

Some or all of the above possible sources of productivity differences for TGIA could lead to the MTRs having values less than 1. The reasons suggested for technology gaps in this chapter are examples only, and the list is not intended to be exhaustive. TGIA may have already embarked on exploring some of these areas, such as by survey of members, or by communication and promotion. Another consideration, and only for donations procured (DON), could be the effect on TGIA of the global economic crisis between 2008 and 2013 that might have put negative pressure at all levels on the fundraising of private donations, and which may recur.

3.3.4 Decomposition of measures of productivity and efficiency

(a) Theoretical background

O'Donnell (2008) summarised the position at that time on the decomposition of productivity, both conceptually and in terms of empirical applications. Indeed, one of the aims of his paper was to present the numerous productivity and efficiency concepts, models and measures, as at 2008, within a coherent unifying framework. He claimed that the framework he proposed was both conceptually and mathematically simple. This simplicity was achieved by defining index numbers in terms of aggregate quantities and prices. The idea of defining index numbers in terms of aggregates has been around for a long time. More than 25 years ago, for example, Caves, Christensen and Diewert (1982, page 73) recognised that 'a key development in the economic theory of index numbers has been the demonstration that numerous index number formulas can be explicitly derived from particular aggregator functions'.

O'Donnell (2008) suggested that there were essentially two main approaches to decomposing TFP growth at the time. In the bottom-up approach, researchers defined generic measures of efficiency and technical change and then combined them to form a TFP index — see, for example, Balk (2001). In the top-down approach, they started with a recognisable TFP index and then attempted to decompose it in a meaningful way — see, for example, Fare, Grosskopf, Norris and Zhang (1994); Ray and Mukherjee (1996) and Kuosmanen and Sipiläinen (2009). O'Donnell (2008) combined the main features of both approaches. He started with input and output aggregator functions that were consistent with axioms from index number theory, then built up to measures of efficiency and technical change, and eventually to recognisable TFP

indexes. Such TFP index numbers are said to be complete. Because of the manner of their construction, they could be easily decomposed into meaningful measures of technical change and efficiency change.

O'Donnell (2008) stated that TFP had often been defined as the ratio of an aggregate output to an aggregate input and that this definition naturally led to TFP indexes that could be expressed as the ratio of an output quantity index to an input quantity index. According to O'Donnell (2008), such index numbers were multiplicatively complete; complete indexes could be shown to satisfy important axioms from index number theory. The paper formally defined what is meant by completeness and demonstrated, among other things, that any complete TFP index could be decomposed into measures of technical change, technical efficiency change, mix efficiency change, and scale efficiency change. This was a key message from the paper. O'Donnell (2008) also demonstrated that measures of price change were not necessary for the decomposition of a concept that was defined in terms of quantities only (as in the TGIA case study).

Lowe and Färe–Primont indexes are economically ideal in the sense that they satisfy all economically relevant axioms and tests from index number theory, including an identity axiom and a transitivity test (O'Donnell 2010, 2011). This means they can be used to make reliable multi-temporal (i.e. many periods) and/or multilateral (i.e. many firms) comparisons of TFP and efficiency.

The TGIA study used the Standard Edition of the DPIN 3 computer software written by O'Donnell (2011). The default TFP index in the Standard Edition of DPIN 3 is the multiplicatively complete Färe–Primont index (O'Donnell 2011).

(b) Components of productivity indicators — efficiency and technology

In relation to the components of productivity change, O'Donnell (2008) focused on measures of efficiency that are common in the economics literature and can be expressed in terms of aggregate quantities in input-oriented decompositions of TFP change.

(i) Input-orientated technical efficiency (ITE), which measures the difference between observed TFP and the maximum TFP that is possible while holding the

input mix, output mix and output level fixed. The production possibilities set is mix-restricted in the sense that it only contains (aggregates of) input and output vectors that can be written as scalar multiples.

(ii) Input-orientated scale efficiency (ISE), which measures the difference between TFP at a technically-efficient point and the maximum TFP that is possible while holding the input and output mixes fixed (but allowing the levels to vary).

(iii) Residual mix efficiency (RME), which measures the difference between TFP at a point on a mix-restricted frontier and the maximum TFP possible when input and output mixes (and levels) can vary. It is the component that remains after accounting for pure technical and scale efficiency effects.

(iv) Input-orientated mix efficiency (IME), which measures the difference between TFP at a technically efficient point on the mix-restricted frontier and the maximum TFP that is possible while holding the output level fixed.

(v) Residual input-orientated scale efficiency (RISE), which measures the difference between TFP at a technically mix-efficient point and TFP at the point of maximum productivity. The term scale is used because any movement around an unrestricted production frontier is a movement from one mix-efficient point to another, so any improvement in TFP is essentially a scale effect. However, the term residual is also used because, even though all the points on the unrestricted frontier are mix-efficient, they may nevertheless have different input and output mixes. Thus, what is essentially a measure of scale efficiency may contain a residual mix effect. The term residual is also appropriate in the sense that if there is interest in decomposing the difference between TFP at an observed point and TFP at the point of maximum productivity, then RISE is the component that remains after accounting for pure technical and pure mix efficiency effects.

(vi) TFP efficiency (TFPE), which measures the difference between observed TFP and the maximum TFP possible using the available technology.

O'Donnell (2008) also presented several output-orientated decompositions of TFPE. Output technical efficiency (OTE), output scale efficiency (OSE), residual output scale efficiency (ROSE), output mix efficiency (OME) and residual mix efficiency (RME) are output-orientated measures of technical, scale and mix efficiency that are analogous to the input-orientated measures. Such decompositions provide a basis for

an output- (as in the TGIA study) or input-orientated decomposition of any multiplicatively complete TFP index.

(c) Development of approaches

Over the past few decades, the notion of distance functions has become prominent and has proved very useful in describing technology in a way that makes it possible to measure productivity and efficiency. The notion was introduced independently by Malmquist (1953) and Shephard (1953). Distance functions allow description of multi-input and multi-output technology without the need to specify a behavioural objective (Coelli et al. 2005).

The following is a general definition of the output distance function (Grosskopf 2003):

$$D(x, y) = \inf\{\theta : (y / \theta, x) \rightarrow T\} \qquad \text{(Equation 3.4)}$$

where the technology is defined as T = {(x, y) : x can produce y} and $y \in \Re^{M+}$ is the vector of outputs, and $x \in \Re^{N+}$ is the vector of inputs. Since the interest is in productivity growth, time t needs to be incorporated. The convention of t and t + 1 to denote two adjacent periods is used. For example $D_t(x_t, y_t)$ refers to an output distance function which evaluates period t data relative to the technology in period t, T_t.

In a key development, Caves, Christensen and Diewert (1982; CCD) proposed definitions of productivity growth called Malmquist productivity indexes based on distance functions. They then proceeded to derive an index number equivalent of the defined Malmquist productivity measure which did not require estimation of distance functions. They showed that under certain conditions the Malmquist index is equivalent to the Tornqvist productivity index. According to CCD, a productivity index based on a distance function could be defined as a ratio of a Malmquist output quantity index to a Malmquist input quantity index, which would mimic the structure of the Tornqvist, Fisher, Laspeyres and Paasche index number definitions of productivity and fit more naturally with the average product concept of productivity as ratios of output to input. Diewert (1992) referred to this as the Hicks–Moorsteen index, and Bjurek (1994), Grifell-Tatjé and Lovell (1999) and Diewert (1993) adopted and implemented this approach.

In CCD it was suggested that the Malmquist productivity indexes could also be related to another quantity-type index, namely the Fisher index. Balk (1993), following Fare and Grosskopf (1992), showed that the Malmquist output-based productivity index is approximately equal to the Fisher productivity index. Diewert (1992) demonstrated, given that the technology takes a particular quadratic form and that some optimising conditions hold, that the Fisher productivity index is equal to both the distance function and index number CCD Malmquist productivity indexes. The general conclusion from these equivalence results was that these indexes were all special cases of Malmquist productivity indexes (Grosskopf 2003).

Grosskopf (2003, page 8) posed a question: 'What is the motivation for decomposing productivity growth into various subcomponents?' This was because of a then current interest in productivity overall because of the revival of the economic profession's interest in the sources of economic growth. At the centre of the revived debate were productivity, technical change and deviations from best practice. Grosskopf observed that the ability to disentangle productivity changes into components associated with certain factors may prove to be the most important application of these indexes. She also suggested that the motivation for finding sources or decompositions was deep-seated in economics. Nishimizu and Page (1982) made the first decomposition of the Malmquist productivity index, using a parametric approach to decompose the index into technical change and efficiency change. This had the intuitive appeal of identifying sources of productivity growth in terms of catching up and innovation, which could be given policy content. Fare, Grosskopf, Lindgren and Roos (1989, 1994) followed up on this idea but implemented it using non-parametric LP techniques to estimate the distance functions.

Since then, there have been a number of proposed alternative decompositions of the Malmquist productivity index, particularly in the DEA context, by authors including Ray and Desli (1997), Simar and Wilson (1998), Grifell-Tatjé and Lovell (1999) and Balk (2001). Balk's (2001) decomposition included input and output mix terms. Other directions (and decompositions) have evolved from the basic models discussed above and a more up-to-date discussion appeared in O'Donnell (2011).

According to O'Donnell (2011), DEA estimation and decomposition of Malmquist indexes was widespread in the productivity literature (Lovell 2003, page 438). He suggested that, except in restrictive special cases, DEA estimates of Malmquist indexes were unreliable measures of productivity change. The widespread use of DEA to estimate Malmquist indexes according to O'Donnell (2011) could be attributed to three main factors. First, it could be computed without the need for price data; all that was needed was an estimate of the production technology. However, there are now at least two other indexes that can also be used to measure productivity change without the need for price data, namely a Hicks–Moorsteen index proposed by Bjurek (1996) and a Färe–Primont index proposed by O'Donnell (2011). Like the Malmquist index, these productivity indexes require an estimate of the production technology.

Second, Fare, Grosskopf, Lindgren and Roos (1989, 1994) showed that the Malmquist index could be decomposed into a measure of technical change and a measure of technical efficiency change. Indeed, until recently it seemed that the Malmquist index was the only productivity index that could be exhaustively decomposed into the measures of technical change and efficiency change that policy makers needed. However, O'Donnell (2008) demonstrated that all theoretically meaningful productivity indexes could be exhaustively decomposed into such measures. Grifell-Tatjé and Lovell (1995) argued that, irrespective of how it was estimated, the Malmquist index ignored productivity changes associated with changes in scale. DEA estimates of the Malmquist index could also fail to capture productivity changes associated with changes in scope (i.e. changes in output mix and input mix).

Finally, Lovell (2003, page 438) attributed the popularity of the Malmquist index in part to the fact that DEA LPs for computing and/or decomposing it had been incorporated into at least two software packages. The DEAP 2.1 software is especially popular because it is available free-of-charge. O'Donnell (2011) developed DEA LPs for computing and decomposing Hicks–Moorsteen and Färe–Primont indexes. These LPs have been incorporated into an edition of the DPIN 3 software that is also available free-of-charge.

O'Donnell (2011) also suggested that within the large class of productivity indexes that can be broken into recognisable components, some indexes were more reliable than others. For example, the Färe–Primont index could be used to make reliable multi-lateral and multi-temporal comparisons (i.e., comparisons involving many firms and time periods) but the Hicks–Moorsteen index could only be used to make reliable binary comparisons (i.e. comparisons involving only two firms or two time periods). This was because the Hicks–Moorsteen index fails the transitivity test of Fisher (1992). Transitivity means that a direct comparison of the productivity of two firms/periods will yield the same estimate of productivity change as an indirect comparison through a third firm/period. This suggests that the Färe–Primont index, which is embedded in the DPIN 3 software, is ideally suited to carrying out the relevant analysis in the context of decomposition in the TGIA study in this thesis.

(d) Decomposition of productivity index numbers (DPIN)

The measurement of decomposition has been greatly enhanced by the work of O'Donnell (2008) and the availability of the computer software, DPIN, developed by O'Donnell (2010, 2011). The TGIA case study uses the approach of O'Donnell (2008, 2010, 2011) because it appears sound and is up-to-date.

O'Donnell (2008) examined the decomposition of multiplicatively complete TFP index numbers into measures of technical change, technical efficiency change, mix efficiency change and scale efficiency change. He developed a conceptual framework for the development of the DPIN computer program (O'Donnell 2010, 2011).

The original DPIN 1.0 program used DEA programs written by O'Donnell (2010) to compute and decompose the Hicks–Moorsteen TFP index. The DPIN 3.0 (2011) program uses DEA programs to compute and decompose a number of TFP indexes that are multiplicatively complete. DPIN 3.0 (2011) can calculate a range of indexes. The TGIA case study focused on the Färe–Primont TFP index, which has properties ideal for the purpose.

O'Donnell (2010) stated that the DPIN program methodology and software can be used in the following circumstances:

(i) To analyse balanced panel data.

(ii) When no price data are available (i.e. when only input and output quantity data are available).

(iii) For DMUs that operate in any market environment.

(iv) For DMUs that have any behavioural objective.

(v) When the technology exhibits CRS or VRS.

(vi) Either to allow for technical regress or to prohibit technical regress.

O'Donnell (2011) stated that the DPIN computer program uses the aggregate quantity framework developed by O'Donnell (2008) to compute and decompose productivity index numbers. He added that the O'Donnell (2008) methodology does not rely on the availability of price data and does not require any assumptions concerning either the degree of competition in product markets or the optimising behaviour of firms. Thus, DPIN can be used to analyse the drivers of productivity change even when prices are unavailable and/or industries are non-competitive. The program uses DEA LPs to estimate the production technology and levels of productivity and efficiency. The program then decomposes changes in productivity into measures of (a) technical change (measuring movements in the production frontier); (b) technical efficiency change (movements towards or away from the frontier); (c) scale efficiency change (movements around the frontier surface to capture economies of scale); and (d) mix efficiency change (movements around the frontier surface to capture economies of scope).

In the study of TGIA, and indeed for TGI and other charities, DPIN would appear to provide an ideal platform because the characteristics listed above from O'Donnell (2010) generally exist for such organisations. In particular, charities tend to operate in an environment where price information is generally unavailable and only quantities are available (Burgess and Wilson 1993; Callen and Falk 1993). Such is the definitely the case for TGIA and TGI.

Literature on the application of DPIN is limited because the development of that computer program is relatively new. However, the number of empirical applications is growing, including those reviewed below.

In Laurenceson and O'Donnell (2011) DPIN 3 was used to examine the decomposition of provincial productivity change in China. The authors stated that productivity and efficiency change lie at the heart of some of the key development challenges facing China's economy, the world's largest developing economy and second largest overall. Laurenceson and O'Donnell (2011) computed and decomposed provincial-level Hicks–Moorsteen TFP indexes for the period 1978 to 2008. On average across provinces, they found evidence of moderate TFP growth, as well as large changes in its components, over the sample period. They documented considerable heterogeneity from province to province both with respect to the rate of TFP growth and its components. They also discussed policy implications for China's economy, emerging from the findings of the study, and suggested that a broad policy suite will be needed.

O'Donnell, Fallah-Fini and Triantis (2011) used DPIN 3 in a meta-frontier framework to demonstrate how MFA can also be used to make TFP comparisons within and across groups.

Pitkin (2013) used DPIN to calculate TFP and various efficiency scores in a study of the factors affecting the productivity of global charities across nine countries.

Tozer and Villano (2013) decomposed the productivity growth of a group of grain producers in the Northern Agricultural Region of Western Australia into technical change and measures of efficiency at the farm level. They used DPIN 3 in their study to determine measures for ITE, ISE, IME and RISE.

Hadley, Fleming and Villano (2013) considered the relative importance of input mix as a source of inefficiency in a study to calculate a Hicks–Moorsteen productivity index using panel data for a sample of specialised pig producers in England and Wales. The index was then decomposed into measures of technology, technical efficiency, scale efficiency and mix efficiency for an input orientation. DPIN 3 was also used in this study.

Although still in relative infancy in its empirical application, the DPIN 3 computer program already has sufficient credibility and validity to justify its application to TGIA, and indeed later to TGI and other charities. So far as is known by this author of this thesis, there has been no previous empirical application of DPIN to the charitable NFP sector in Australia or at the global level, other than in Pitkin (2013).

(i) DEA-based approach

DPIN can be employed using a DEA-based approach. Such was the case in all studies discussed in the previous section (Laurenceson and O'Donnell 2011; O'Donnell, Fallah-Fini and Triantis 2011; Pitkin 2013; Tozer and Villano 2013; Hadley, Fleming and Villano 2013).

(ii)SFA-based approach

DPIN can also be employed using an SFA-based approach, as O'Donnell demonstrated (O'Donnell 2012) showing that SFA methodology can be used to decompose a new TFP index that satisfies most, if not all, economically relevant axioms and tests from index number theory. To illustrate, O'Donnell (2012) drew inferences concerning returns to scale and measures of TFP and efficiency change in US agriculture. The results indicated that the primary drivers of agricultural productivity change in California have been technical progress and improvements in scale efficiency (SE). The results were consistent with the US results obtained by O'Donnell (2010) using DEA methodology and an OECD agricultural dataset.

O'Donnell (2012) showed how to compute and decompose TFP indexes in an econometric framework when only quantity data are available (i.e., when there are no prices). The methodology did not rely on assumptions concerning the optimising behaviour of firms (e.g. cost minimisation) or the degree of competition in product markets (e.g. perfect competition), except insofar as they may be necessary to determine which variables in the model are determined endogenously and which are not. Nor does the methodology rely on any particular assumptions concerning the functional form of the output or input distance functions or the distribution of random inefficiency effects (e.g. time-varying, half-normal). Thus, the method appears to be applicable in many empirical contexts where main stream efficiency estimation methods are now used.

(e) Application of DPIN in the TGIA study

The application of DPIN in the TGIA study reflects the DEA-based approach. DPIN was used as a tool in the TGIA study and all DEA productivity and efficiency scores obtained came from DPIN. It was an opportunity to put DPIN to the test in the TGIA context and to demonstrate its capabilities and extend its application, given that it is a recent software development with relatively few published applications in practice.

The DPIN software permits uploading of datasets from Microsoft Excel .csv format, which were relatively easy to compile from the constructed .xls format in TGIA databases. It provides, as a matter of course, a range of productivity and efficiency scores. In effect, DPIN was used merely as a tool to achieve two of the objectives of the TGIA case study and to solve or understand the research questions underlying those objectives.

The panel data available for TGIA branches provide quantities only; typically there are no cost and price data for NFPs/charities such as TGIA. This, as well as other criteria identified above for the use of DPIN, and the empirical examples cited, justifies the use of DPIN for calculating the DEA VRS productivity and efficiency scores in this study. Note that the standard DPIN 3 version has a default setting of VRS. The technical regress setting for DPIN 3 was selected in all cases for the TGIA case study. It was considered that this gave more flexibility and would facilitate identification of years in which scores were lower than previous years. This should then provide an opportunity to consider the factors that may have caused such an outcome.

3.4 Framework for empirical analysis

3.4.1 Advantages and disadvantages of DEA and SFA

Coelli et al. (2005, pages 312 and 313) listed some of the advantages and disadvantages of DEA. A main advantage was that with DEA there was no need to specify a mathematical form for the production function. DEA had proved to be useful in uncovering relationships that remain hidden from other methodologies. It was capable of handling multiple inputs and outputs and of being used with any input–output measurement. The sources of inefficiency could be analysed and quantified for every evaluated unit. A disadvantage of DEA was that results were sensitive to the

selection of inputs and outputs (Berg 2010). The best specification could not be tested (Berg 2010). Another disadvantage was the number of efficient firms on the frontier tended to increase with the number of input and output variables (Berg 2010).

Other authors have addressed the issue of advantages and disadvantages of DEA consistent with the above discussion. According to Tofallis (2001), DEA had the advantages of clearly identifying the efficient units and easily incorporating multiple outputs, but it did not provide a single formula to model the efficient frontier and it suffered from the problems associated with slacks.

Basso and Funari (2004) asserted that the main advantage of using the DEA methodology in evaluating the efficiency of a set of DMUs was that DEA could consider multiple inputs and multiple outputs simultaneously. In the evaluation process the assessed units are assumed to adopt the same input structure to provide the same outputs.

Coelli et al. (2005, page 312) stated that two advantages of SFA over DEA are that SFA accounts for noise and can be used to conduct conventional tests of hypotheses. They stated that disadvantages include the need to specify a distributional form for the inefficiency term and the need to specify a functional form for the production function.

3.4.2 Application to TGIA

In this section a summary of the framework used for the empirical application, using TGIA data, of the chosen methods and concepts identified to this point of the thesis has been provided. The empirical application using these methods and concepts, including specific details of how they were applied, is the subject of later chapters.

The following two cases were considered separately:

(a) Bible distribution (BDIST): the service activities of TGIA; the actual physical distribution in Australia of Christian Bibles of different shapes and sizes to various outlets including hotels, motels and schools, carried out by members of the Gideons and the Auxiliary.

(b) Fundraising of private donations (DON): the fundraising activities of TGIA; the actual physical receipt of private donations in Australia from various sources including the general public, Gideon and Auxiliary members, churches and other organisations.

For each case, this section defines, discusses and justifies the choice of traditional output and input variables included for first-stage DEA using DPIN. Balanced panel datasets for each case were compiled. Relevant data issues and measurement issues were addressed (see e.g. Coelli et al. 2005, pages 133–160). This was also done for TGIA-related (internal) variables and for environmental variables (external to TGIA) which were examined in the second-stage Tobit regression using LIMDEP, with DEA productivity and efficiency scores obtained from DPIN as the dependent variable. There is an overlap of BDIST and DON inputs and variables. The empirical application was conducted as follows, for BDIST and DON respectively.

(a) Data construction at national/meta and group levels

The national level is the set of all TGIA branches in Australia. The group level is the subset of five TGIA state regions, with each state region having a certain number of branches.

Panel datasets at all levels were constructed from available TGIA data, i.e. panel data for branches of TGIA that have data for all six years (2008–2013), using Microsoft Excel 2003 spreadsheets in .xls and .csv formats . Of the 133 branches at financial year end 31 May 2013, 121 qualified.

(b) First stage — obtaining productivity and efficiency scores with DEA (using the DPIN computer program)

DPIN applied DEA to the constructed panel datasets, producing productivity and efficiency scores from DPIN for each individual TGIA branch for tabulation in Microsoft Excel 2003 spreadsheets.

(c) Second stage — examining factors possibly affecting the scores in the first stage with Tobit regression analysis (TRA) (using the LIMDEP computer program)

In the second stage, Tobit regression analysis, from LIMDEP, tested for factors affecting the productivity and efficiency of TGIA branches, with the productivity and efficiency scores from the first stage as the dependent variable. The steps are summarised in Table 3.3.

Table 3.3 — Summary of steps in the empirical application

Step	**First Stage (DEA)**	**Second Stage (TRA)**
Model formulation	BDIST and DON	BDIST and DON
Levels	National/Meta State/Region/Group	National/Meta State/Region/Group
Data construction	Microsoft Excel 2003 xls and csv panel datasets	Microsoft Excel 97–2003 xls and csv panel datasets
Underlying platform	Linear programming	Tobit regression
Time period	6 years 2008 to 2013 inclusive	6 years 2008 to 2013 inclusive
Main software	DPIN 3.0, DEAP 2.1	LIMDEP 9
Main issues addressed	Gaps in data and zero values	Endogenous variables and correlation between variables
Main outcome	Calculation of productivity and efficiency scores	Calculation of the significance, direction and magnitude of factors postulated to be affecting productivity and efficiency

3.4.3 Justification of the choices of methods

(a) Data envelopment analysis (DEA)

DEA and the mechanics of its application are longstanding and in continuous use, and thousands of studies have empirically tested them, with undoubted success. Callen and Falk (1993, page 53) made one of the few studies that reports an application of DEA to charities/NFPs, in relation to productivity and efficiency measurements methods. They supported the idea that DEA is ideally suited to studies where price and cost information is not readily available as is generally the case with charities/NFPs (as mentioned above).

DEA is also well suited to applications where the DMUs (TGIA branches in this case study) have a homogeneous set of outputs and inputs, and generally carry out the same activities by the same methods (e.g. Basso and Funari 2004, page 204). For the study presented in this thesis, heterogeneity (although mentioned above) is not relevant because even though the number of members varies across TGIA branches, each branch is effectively a bottom-line DMU and is structured the same as the others. Branches effectively carry out the same service activities of Bible distribution and fundraising for donations in their defined local geographical territory. This is another reason why the use of DEA was justified in the TGIA study.

Dyson and Shale (2010) favoured DEA over SFA in their study of efficiency measurement of predominantly NFP organisations in the presence of uncertainty. They stated that from their perspective the distributional assumptions required and other factors made an SFA approach unattractive in the context of their research targeting NFPs. Similarly this is the case for the study of TGIA in this thesis.

(b) Tobit regression analysis (TRA)

The use of TRA in the second stage of this study is justified by numerous studies using second-stage Tobit regression in the context of DEA efficiency measurement. Cruz (2004) studied state colleges and universities (SCUs), using DEA to determine the factors of technical inefficiency for transformational leadership assessment, and accountability using Tobit analysis. The findings indicated that the age of the institution and the dummy variable for research allocation were determinants of

technical efficiency. The author suggested that the results of the study could provide a helpful step toward further productivity studies of SCUs.

Garza-Garcia (2011) analysed the developments and main determinants of bank efficiency in the Mexican banking industry during 2001–2009. They applied DEA to obtain efficiency estimates and then ran a Tobit model to find its main determinants. The Tobit analysis suggested that main determinants of increased bank efficiency were loan intensity, GDP growth and foreign ownership; on the other hand, the analysis found that non-interest expenses, non-performing loans and the inflation rate reduce bank efficiency.

Nargis and Lee (2013) applied DEA to field-level survey data from a sample of 199 Boro rice farmers in the north–central part of Bangladesh for the year of 2010. A second-stage Tobit regression showed that the variation in efficiency scores was related to farm-specific attributes such as education, family size, seed type, land tenancy, extension services, irrigation machine type, and sources of energy. The evidence suggested that farmers in Bangladesh fail to exploit the full potential of technology, and might reduce their use of inputs if there was wider adaptation and spread of improved agricultural mechanisation.

Based on the preceding review of literature and the arguments put forward on pages 50 and 51, this study therefore used TRA approach as the method for analysing the magnitude, direction and significance of factors affecting the efficiency of TGIA. The efficiency scores are obtained from DEA in the first stage of analysis. While the Simar and Wilson (2011) approach and its ‘caveat emptor’ suggestion and the limitations of TRA are acknowledged, the application of second-stage TRA is still main stream in the literature. Therefore, the use of TRA is used on the grounds of supported by the literature and for ease of comparison of results for firms exhibiting similar characteristics to that of TGIA.

3.5. Summary and conclusions

In this chapter the conceptual and methodological framework underlying the study of TGIA has been provided. The historic, contemporary and emerging themes in productivity and efficiency research as a topic area in itself have been summarised. The topic has been introduced, and basic concepts, methods of productivity and efficiency measurement and the framework for the empirical analysis have been discussed.

More recently a method sitting on a platform of bootstrapping introduced by Simar and Wilson (1998, 2000, 2007, 2011) (SW) and Wilson (2006) has gained some support over the two-stage approach using Tobit regression described in this chapter. However, given that most of the literature that motivates the formation and development of the empirical models addressed in this thesis use the Tobit approach, it was opted to follow suit for ease of comparison of results. In this context, the limitation of the Tobit analysis is acknowledged. This has been flagged in Chapter 8 as an area for further analysis. This would include the estimation of bootstrapped DEA along with SFA, in order to examine the significance of estimated coefficients of the variables. The SW or bootstrapped DEA approach would also be taken into account in the publication of journal papers.

A reasonable conclusion from the discussion in this chapter is that research in the whole topic area of productivity and efficiency measurement is still very active with no sign of abating. The methods have been empirically proved over a long period, and extensions continue to emerge. Further application to TGIA and other charities would therefore appear to be well justified. In the next chapter a detailed review of related studies specifically on NFPs and charities is given, to contextualise the study of TGIA within the framework set out in this chapter.

CHAPTER 4: REVIEW OF EFFICIENCY STUDIES ON CHARITIES AND NOT-FOR-PROFIT ENTITIES

In this chapter the literature related to productive efficiency for charities and NFP organizations is reviewed, via an overview followed by a deeper consideration of the limited literature in this area.

4.1 Review of literature

4.1.1 An overview of fundraising by charities and not-for-profit entities

The small amount of published work on productive efficiency in charities and NFPs is notable. Callen (1994) used DEA to measure the technical efficiency of charities. Basso and Funari (2004) also used DEA for evaluating the technical efficiency of (NFP) museum institutions, but they did not extend their work to consider the factors affecting technical efficiency by using regression models with technical efficiency scores as the dependent variable.

The published work on factors affecting fundraising by charities has more recent foundations. Cullis, Jones and Thanassoulas (1984) examined this topic, but Weisbrod and Dominguez (1986) is the paper to which recent authors refer. A recent paper by Gordon, Knock and Neely (2009) draws on and extends this work. The key messages from these papers are stated later in this chapter.

4.1.2 NFP organisations, charities, cross-entity comparisons and studies of bank branches

This review considers some NFP organisations that are not officially labelled as charities. Such NFP organisations resemble NFP charities because they fundraise to collect private donations and they provide a service funded by the donations, just as is done by charities (e.g. Song and Yi 2010).

The studies on charities and other NFP organisations reviewed involve cross-entity comparisons at the industry level. The author could find little or no evidence in the literature of previous studies on efficiency, productivity or fundraising of branches of

the same charity; nowhere near the extent to which this study considers TGIA branches. Given that TGIA is a Christian/religious charity, the most similar study was by Udbye (2011) who used 2009 data from a US nationwide Christian/religious church organisation to assess operational productivity and efficiency utilising DEA. He used DEA models assuming VRS and an output orientation. However, Udbye (2011) used cross-sectional data and only one stage, whereas the TGIA study uses panel data and is two-stage.

Although banks are generally commercial and 'for-profit' in nature, it was considered that some insight at least might be gained from studies on the productivity and efficiency of branches of single banks that employed DEA for the analysis (e.g. Vassiloglou and Giokas 1990; Athanassopoulos 1998; Camanho and Dyson 1999, 2005; Portela, Thanassoulis and Simpson 2004; Yang 2009). The context here is that the TGIA case study involves studying branches of a single charity, albeit 'non-profit', and the only other branch-level comparisons using a single entity based on a DEA model that came to light in the hope of gaining insight involved banks.

4.1.3 Productivity and efficiency of charities and not-for-profit organisations

Song and Yi (2010) also observed that literature appears to be limited on the specific application of productivity and efficiency analysis to charities . They stated that despite the rapid expansion of the private NFP sector (including charities) in the USA, research on the efficiency of that sector is limited.

(a) Productivity and efficiency

It would appear reasonable to comment that any published research on productivity and efficiency of charities is indeed important because of the limited literature on the topic. In the study presented in this thesis, the central focus was the measurement of productivity and efficiency of both Bible distribution and fundraising by TGIA. Generally previous research on productivity and efficiency of charities has only taken place in conjunction with fundraising models.

(b) Fundraising efficiency of charities and NFPs

There is a stream of literature that focuses on the theme of the fundraising efficiency of charities and NFPs. The papers reviewed in this section consider donations and voluntary contributions, referred to collectively as 'fundraising'.

Studies reported tend to focus on developing and testing regression models for fundraising although some have applied DEA. In the context of the study of TGIA, this stream of literature has been reviewed to demonstrate that previous studies of charities and NFPs generally do not appear to have considered the areas of service activities, TFP or branch-level comparisons. It appears that the current study of TGIA could be the first to consider all these areas in the one study.

Cullis, Jones and Thanassoulas (1984) posed the question: 'Are Charities Efficient "Firms"?' when addressing the efficiency of UK charities. They asserted without discussion that they had been motivated by increasing public concern about the activities of UK charities, and perceived a need to apply economic analysis to a sample of (UK) charities. They examined the relationship between charitable, fundraising and administrative expenditures using two-stage least squares (TSLS) regression with a system of three structural equations, specifying the functions in natural logarithmic form and using annual data for the period 1977–1982.

Within acknowledged limitations of their empirical work, Cullis et al. (1984) stated that interpretation of their results was not obvious, and claimed that their results suggested allocative inefficiency in terms of underutilisation of fundraising. They regarded their work as a 'screening test' that gave cause for concern. Their main recommendations were: firstly, for further research, possibly case studies on UK charities; and secondly, an improvement in the provision of public data for analysis. Note that the concept of efficiency here is not technical efficiency, but rather the use of proxy variables for accounting ratio measures of efficiency based on the administrative and fundraising expenses of charities.

Weisbrod and Dominguez (1986) estimated a demand function for the output of private NFP organisations to examine the factors influencing charitable contributions to these organisations. Using sample data drawn from US IRS Form 990 tax returns for the

years 1973–1976, they tested the hypothesis that voluntary giving is responsive to conventional variables and found their results to be strongly supportive.

Tofallis and Sargeant (2000) used an elementary non-mathematical approach to DEA, to show how DEA could be applied to charities in assessing the efficiency with which fundraising and administrative expenses are used to generate voluntary income (donations). They did this to respond to a perceived gap in the application of DEA to the voluntary sector. Charities are characterised by the use of voluntary labour to carry out their activities, hence the term ‘voluntary sector’.

Tofallis and Sargeant (2000) examined cross-sectional data for the year 1997 on the level of spending on administration and fundraising in relation to voluntary income generation for a sample of UK charities. They used a DEA model with VRS because it gives a more generous assessment of technical efficiency, and they chose an input orientation because each charity is able to control its expenditure and the output of voluntary income (donations) is not under control. They were disturbed by the distribution of efficiency scores because only 15% of the sample had efficiency scores above 50%, and 43% had scores below 20%. Only 4% were 100% efficient.

This brief summary of results suggests that the findings of Tofallis and Sargeant (2000) should have sounded alarm bells for non-efficient charities in the UK to examine their efficiency. The fact that the results suggested shortcomings in charities’ efficiency could be viewed as a significant contribution to the sparse literature on the application of productivity and efficiency analysis to charities.

However, such statements need to be tempered by the two caveats stated by Tofallis and Sargeant (2000) under a section of their paper titled ‘Further Work’. The first caveat was that they had only dealt with three variables because they could then use graphical displays and avoid the mathematical exposition that would be required if more variables were used. They acknowledged that the inclusion of further variables could change the results. For example, the inclusion of more inputs and outputs would generally lead to a greater number of charities appearing efficient.

The second caveat concerned the selection of DMUs (charities) to be compared. They made the point that there is always a strong argument to compare like with like (DEA has better application to sets of homogeneous DMUs). They suggested further work making separate analyses for different charity sectors, such as charities for the blind or charities geared towards animal protection. This could shift the efficiency frontier making some efficiency scores higher.

Tofallis and Sargeant (2000) concluded that, notwithstanding their caveats, the results suggested that there could be justification for donor concerns about fundraising and administrative expenditures. They acknowledged that further work would be necessary to compare the operations of efficient charities and inefficient charities identified by their analyses. Finally, they suggested that such work would assist in improving operational stewardship of the voluntary sector (charities), and also in guiding donors in making choices to donate to organisations where the donations would have the greatest impact on a chosen category of cause.

A comprehensive search of literature published since Tofallis and Sargeant (2000) has failed to produce any evidence that their caveats have been addressed. It is important that their study is one of the few that has applied DEA to charities and that it emphasised the need for further work.

Basso and Funari (2004) used DEA to evaluate the technical efficiency of NFP Italian municipal museums. They created a relative efficiency measure for each museum, taking into account resources used by museums and the results of museum activities. They stated that DEA is able to overcome some of the difficulties found when applying other indicators of productivity in evaluating the technical efficiency of cultural institutions. The authors claimed that measurement of the performance of NFP organisations, such as schools, hospitals, universities and museums, was complicated by the presence of goals of different nature — some of which were difficult to measure. In particular, they said that the presence of a multiple output situation made it difficult to identify an evident performance indicator such as profit, and impeded the search for a satisfactory measure of performance or, at least, of efficiency. DEA searches for an efficiency measure and is able to overcome some of the restrictions of

other evaluation approaches, even if the problem of using a quantitative approach to the efficiency analysis of cultural organisations is not completely solved.

They concluded that their empirical analysis showed that DEA could be usefully applied (Basso and Funari 2004). They gave information on the relative efficiency of NFP cultural organisations that could assist museum management, public financial bankers and sponsors. The authors suggested that a possible direction for further research would be to consider some variants of the basic DEA model, in order to take into account other aspects that can influence the efficiency of museums (e.g. environmental factors such as different cities and different organisational structures).

The usefulness of the study by Basso and Funari (2004) in the TGIA context is that again it demonstrated the successful application of DEA in an NFP setting and justified it. Notably, DEA can be usefully applied and gives information to assist management, as the study of TGIA has the potential to do.

There are four conceptual factors related to donations, as Trussel and Parsons (2003) posited. They are the efficiency of the organisation in allocating resources to its programs, the financial stability of the organisation, the quantity of information available to donors, and the quality of the information. These authors used factor analysis with variables from previous studies to test this conceptual framework on a large sample of charitable organisations. They found that the variables align on four components that appear to represent the factors that they conceptualised. They also used these four components as predictor variables in an ordinary least squares (OLS) regression specification of direct contributions. The model was significant and explained over 40% of the variations in contributions.

A study by Tinkelman and Mankaney (2007) found evidence consistent with donors reducing contributions to organisations reporting higher administrative expense ratios when the ratios were presumably most relevant and reliable. The authors suggested that certain prior studies failed to find significant associations largely because their samples contained many organisations for which the administrative ratios were unreliable or not helpful for donor needs.

Model specification issues also affected prior studies but were less critical than sample composition. When the authors replicated prior studies on samples containing established, donation-dependent organisations with non-trivial amounts of fundraising and administrative expenses, they generally detected a significant negative association. Note that the administrative expense ratio is a proxy for an accounting measure of efficiency. Technical efficiency does not appear to have been considered (Tinkelman and Mankaney 2007).

Gordon, Knock and Neely (2009) examined whether the 0- to 4-star ratings provided by the Charity Navigator Website at 20 June 2007 (the largest charity evaluator in USA) had additional information content for donors and influenced donations. Gordon et al. (2009) stated that, given the existing literature, they knew that there was a relationship between price, fundraising expenditures and charitable donations. They used a random sample of 405 charities rated by Charity Navigator Website at 20 June 2007, and a regression analysis, and tested two research hypotheses:

- H_1: A positive (negative) change in rating by Charity Navigator Website at 20 June 2007 is associated with a positive (negative) percentage change in contributions to a NFP organisation.
- H_2: The level of current year contributions is a function of the current year change in Charity Navigator Website at 20 June 2007 rating and the prior year rating of the organisation.

The authors used financial data and ratings obtained from the Charity Navigator Website at 30 June 2007 to test the hypotheses. They employed a percentage change model in their analysis because of its econometric advantages: namely, that a change specification can provide a more theoretically correct model for interpreting the research question of interest; a change specification implicitly controls for size and thus mitigates the problem of heteroscedasticity; and a change specification controls for unobservable variables that remain constant over time and could influence the results — citing Landsman and Magliolo (1988).

They also used a levels specification with controls for size to provide sensitivity analysis and another window on the issue. A log-linear model was specified that was a variation on the model of Weisbrod and Dominguez (1986) which was intended to

parallel the levels model rather than replicate change models used in earlier research by Steinberg (1986) and Tinkelman (1999).

Gordon et al. (2009) concluded that research aimed at understanding the impact of the ratings issued was useful for determining whether organisations were making the market for donations more efficient. Their results suggested that rating changes do affect contributions. Positive rating changes were positively associated with an increase in contributions; organisations with declines in rating were associated with decreased contributions. These effects were in addition to what would be predicted using an efficiency ratio commonly computed from accounting data (not technical efficiency) and other control variables. The results suggested that rating changes do have an impact on donations. Positive rating changes were positively associated with an increase in donations and organisations with a decline in rating were associated with decreased donations. Both the level of contributions and the change in contributions varied with the size and direction of changes.

Marudas and Jacobs (2008) identified 12 studies to 2007 that examined the effects of an accounting measure of NFP organisational inefficiency on donations, a major end product of fundraising efforts. Eleven of these studies examined the effect of the reciprocal of a particular well-publicised measure of NFP organisational efficiency — the program spending ratio (PSR) — on donations to US NFP organisations (Posnett and Sandler 1989; Callen 1994; Khanna, Posnett and Sandler 1995; Tinkelman 1999; Khanna and Sandler 2000; Marudas and Jacobs 2004; Marudas 2004; Marudas and Jacobs 2006; Jacobs and Marudas 2006; Marudas and Jacobs 2007). The PSR is the percentage of expenses that is allocated to programs rather than to administrative or fundraising functions (Trussel 2003). The reciprocal of ‘program spending’ that is tested is called the ‘price of giving’, a measure of organisational inefficiency, and is defined as total expenses/program expenses.

The 11 studies tested models of donations to NFPs as a function of NFP characteristics. Some of these studies included a size control in their model, but some studies specified size as total assets and other studies specified size as total revenues. An additional study, Frumkin and Kim (2001), tested an alternative measure of inefficiency — ‘administrative inefficiency’, defined as administrative expenses/total expenses — and

specified size in another way, as program expense. No study examined the sensitivity of results, from a given model, to the different specifications of size. Furthermore, the latest data used in any of these prior studies were from 2001.

Of the papers that Marudas and Jacobs (2008) identified, the paper by Callen (1994) was the only one that considered the technical efficiency of charities using DEA in the context of voluntary income of charities. Callen (1994) also stated that previous empirical studies failed to include voluntary labour as one potential variable. In relation to the TGIA case study in which DEA is applied, including consideration of voluntary labour, the study by Callen (1994) would therefore appear to be the only one worthy of further consideration.

The purpose of the paper by Callen (1994) was to explain the cross-sectional variation in money donations to charities at an organisational level, part of which embraced the measurement of technical efficiency by DEA. Callen used DEA and regression analysis and tested the hypotheses that money donations were positively related to volunteering and the technical efficiency of the firm. The empirical results indicated that the more technically efficient the charity, the more money donations it was able to raise.

Callen (1994) built on and tested regression models for voluntary giving to charities, as developed by Weisbrod and Dominguez (1986). He estimated an economic model using data from a sample of 72 ‘health focus’ Canadian charities for the period 1986–1987. The results indicated that the model was adequate. Following consideration of this initial model, Callen (1994) turned to measuring the relative technical efficiency of the 72 charities using DEA under different assumptions of CRS and VRS, and substitutable and non-substitutable output technologies, so he could use technical efficiency scores as an independent variable in an expanded regression model. However, the TGIA case study does not take that approach because of a perceived endogeneity problem. Nor do any other studies subsequent to Callen (1994) appear to have taken that approach — which is not surprising given that such an approach suggests endogeneity.

More recently, Song and Yi (2010) examined how efficient NFP art organisations (museums, performing art organisations, and cultural and humanities organisations) are in raising funds from private giving. They used constructed data from US federal tax returns filed by art organisations for the 2004 fiscal year. These organisations had NFP status in the USA. The authors measured fundraising efficiency using a Bayesian estimation approach to estimate a stochastic frontier production (Cobb–Douglas) model. They found that fundraising efficiencies were generally quite low for art organisations in the USA when private giving was only considered as a fundraising output; however, when the effect of fundraising on ticket sales was considered, fundraising efficiencies improved substantially.

Song and Yi (2010) also provided evidence that government grants or subsidies had a negative impact on the fundraising efficiency of art organisations and therefore partially crowded out private giving. This is not relevant for TGIA because there is no government funding, but it may have relevance for other charities and NFP organisations operating in Australia.

Song and Yi (2010) defined fundraising as 'the act of generating revenue in the form of monetary private donations', and calculated fundraising efficiency at an individual organisation level using the stochastic frontier analysis (Song and Yi 2010, page 171). For the study of TGIA, the definition is wider, and includes other elements such as bequests and legacies, to have an all-embracing term for private and voluntary contributions called donations or voluntary income.

The authors acknowledged that the NFP or philanthropy sector plays an important role in the provision of important services in different fields in US society such as health, education, social services and art. They commented that, despite the rapid expansion of the NFP sector and its contribution to US society, detailed economic analyses of the efficiency of NFP organisations remained relatively limited (Song and Yi 2010). They claimed that their paper added to this important field by investigating the efficiencies of NFP art organisations in raising revenues through private giving, and by identifying the factors that could affect efficiency.

After detailed commentary on their results and analysis, Song and Yi (2010) concluded that private giving is an important part of the NFP art organisations' sources of revenue. They considered ticket sales as a part of fundraising outcome because fundraising activities and efforts had a positive impact on private giving and on ticket sales. Note that 'ticket sales' or similar sources of 'sales' revenue are not relevant in the study of TGIA/TGI, even though there are sales of merchandise items by TGIA/TGI. Although the use of DEA has prominence in this thesis, it was considered important to review the paper by Song and Yi (2010) in the context of the TGIA case study because it provided some insight and an indication of other research work being done in relation to NFP organisations having a fundraising motive like charities.

These are some key points from the above studies.

(i) Although some analysts used DEA, there was generally a tendency towards the use of regression analysis.

(ii) They all focused on various aspects of fundraising without consideration of service activities of charities and NFPs.

(iii) Technical and other types of efficiency were considered but productivity for service activities and fundraising activities was not.

(iv) The studies were at industry and/or cross-charity/NFP level (i.e. not at the branch level of any one particular entity).

These and other points provide useful background information in framing the approach used for the TGIA case study.

4.1.4 A comparison between charity branches and bank branches

(a) Background and previous studies

It is evident from the literature review to this point that previous studies involve cross-charity comparisons. There appears to be an absence of cross-branch studies of single charities using the methods applied in this study of TGIA branches. It is possible that there are parallels with studies of bank branches of single banks even though charities are generally NFP while banks are generally for-profit. This possibility is explored below using a sample of studies of branches of single banks.

Vassiloglou and Giokas (1990) presented results of a systematic application of DEA at a single bank, the Commercial Bank of Greece, in assessing the relative efficiency of bank branches. The study was performed for a set of 20 branches from the Athens area in Greece based on the bank's 1987 budget. The main contribution from this study lies in the way in which the findings from DEA for the branches were used by bank management to follow up on the study. Vassiloglou and Giokas (1990) reported that once the first conclusions had been formulated, the study was forwarded to top bank management for examination and comments. It was also discussed extensively with bank managerial staff responsible for branch operations. The authors stated that the discussion focused mainly on the following three themes:

(a) The acceptability of the evaluation of specific branches;

(b) The possibility for improvement of the formulation of the model, in view of the experience gained (e.g. regarding input–output specification, product classification); and

(c) the overall benefits of the application for the bank.

The authors reported that acceptability of the branch evaluations was examined by responsible personnel in view of their knowledge of the branch network. In general, the assessments appeared to correspond with the evaluations they had arrived at on the basis of information already available to them. When unexpected negative branch evaluations were encountered, the responsible personnel further explored those situations.

Improvement in model formulation needs to be examined in light of the limitations of DEA. As part of the overall benefits of the application, the exchange of knowledge that occurred during the follow-up process was particularly important. Apart from the immediate results of the application, the project offered an opportunity for communication with middle management at a number of the bank's divisions. These discussions were extremely valuable, allowing some staff to become familiar with a variety of operational issues of the bank, while others had the opportunity to experience certain aspects of the application of a quantitative technique to their area of work.

The follow-up process in particular, covered by Vassiloglou and Giokas (1990) in their study of bank branches of a single bank, is interesting, and a similar process could be applied after this study of TGIA branches. It is hoped and anticipated that TGIA management will be receptive to discussion of the results and their implications, with a view possibly to enhancing performance in the future.

Athanassopoulos (1998) proposed models for assessing the efficiency in large networks of bank branches. He distinguished bank branch efficiency that related to market or cost components, suitably modified to capture different tiers of bank management, and sought to investigate issues related to the assessment of performance of bank branches. The methodology included the use of multivariate analysis to ensure the homogeneity of the branches assessed, and then DEA for assessing efficiency. Athanassopoulos applied DEA to a sample of 580 branches of a single commercial bank in the UK. The results obtained reinforced previous claims regarding the presence of high technical inefficiencies and economies or diseconomies of scale at the branch level from a production and cost point of view.

Athanassopoulos (1998) put forward market efficiency as a new dimension of bank branch efficiency, which he claimed had been systematically neglected by the efficiency assessment literature in banking. He proposed a framework where market and cost efficiency were recognised as two complementary components of efficiency. He suggested non-parametric deterministic frontier analysis models for assessing site-specific and aggregate market and cost efficiency of bank branches, and applied this framework on a large scale by grouping the bank branches into clusters of homogeneous operating profiles. The results he obtained showed a site-specific and aggregate average market efficiency of 90% and 85% respectively, and demonstrated that there was scope for improving sales performance throughout the bank branch network. Considerable inefficiencies were also found on the site-specific (88%) and aggregate (82%) cost behaviour of branches.

The assessment also concentrated on the presence of economies of scale, and Athanassopoulos also compared the cluster profiles of bank branches for their market and cost efficiency. This assessment indicated diverse prospects for competitive advantage across the different clusters. The definition of market efficiency as a key

component of bank branch operations, along with the traditional definition of cost efficiency, offered an improved framework for assessing the performance of banking institutions. Athanassopoulos (1998) suggested that future research should touch upon the effects of product mix and economies of scope on the assessment of market and cost efficiency of bank branches. He also proposed that another direction could be the incorporation and assessment of service quality as a performance indicator in the operations of bank branches.

At least one of Athanassopoulos' (1998) suggestions for future research (product mix) in his study of bank branches of a single bank gives meaningful insight and is a parallel to be considered after the study of TGIA branches. The effects of product mix have relevance to the study of TGIA branches. In this study, only total Bible distribution at various levels to all outlets has been considered, but in practice the distribution team works with different types of Bibles used and targets different outlets. Results of the TGIA study may change after refining the study and changing the product mix in this area; and there may be a similar effect on TGIA's fundraising of donations, where donations are of different types and come from different sources.

Camanho and Dyson (1999) described an application of DEA to the performance assessment of a single Portuguese bank's branches. The analysis showed how DEA could complement the profitability measure used at the bank. The use of an efficiency–profitability matrix enabled the characterisation of the branches' performance profile. Consistent with the bank's development objectives, the analysis focused on the relation between branch size and performance. Two alternative target-setting strategies were explored. One eliminated pure technical inefficiencies by focusing on the selection of appropriate benchmarks. The other attained the branches' most productive scale size through the elimination of scale inefficiencies, with minimal changes to branch size.

The report was part of an on-going study of the efficiency of branches from a single Portuguese bank. The use of the DEA efficiency measure to complement the profitability measure used at the bank provided important insights on how branches' performance could be improved. Although a profitability measure is not relevant to the study of TGIA because it is NFP, the improvement of TGIA branch performance is

relevant and important, so the insights from Camanho and Dyson (1999) can be considered.

Camanho and Dyson (2005) extended the work in their 1999 paper reviewed above. Their 2005 paper developed a framework for performance appraisal in the context of a bank branch network. It advocated a DEA model that used a cost-minimisation perspective. Their paper addressed two tasks: first, the development of a DEA model that could identify both input and output inefficiencies with a cost-minimisation perspective. The second task was the joint use of the production and value–added approaches for a comprehensive assessment of bank branch efficiency and its managerial implications. An important implication of the analysis in Camanho and Dyson (2005) is that there are a number of ways in which banks can use branch measures of efficiency, as a complement to their own performance measurement system, to make their branch networks more efficient.

This paper was drawn from the use of DEA in helping a Portuguese bank to manage the performance of its branches. The bank wanted to set targets for the branches on variables such as growth in number of clients and growth in funds deposited. These variables can take positive and negative values but, apart from some exceptions, traditional DEA models had up to then been restricted to non-negative data. There are parallels between that situation and the study of TGIA branches presented in this thesis, because it is anticipated that the results and evaluation of the TGIA analyses will also be useful in managing TGIA branch performance.

Portela, Thanassoulis and Simpson (2004) reported on the development of a model to handle unrestricted data in a DEA framework and illustrated the use of that model on data from the bank concerned. They claimed that in the presence of negative data, traditional radial models for efficiency assessment could not be used without transforming the data, because they moved negative inputs or outputs in the wrong direction. The standard additive model was the main efficiency assessment tool that had been used in these cases, because of its translation–invariant properties (and units invariant in some cases). However, in their paper Portela et al. overcame two main disadvantages of the additive model:

- It tends to project units on the furthest points of the frontier, therefore implying unnecessary efforts by production units.
- It does not provide a final efficiency measure by which comparisons and rankings can be made.

The authors developed a model based on the directional distance function approach, where the direction was the range of possible improvement (defined as maximum output minus observed output, or observed input minus minimum input). Portela et al. called this the range directional model (RDM). The RDM was units and translation invariant, which made it suitable to be used in the presence of negative data. In addition, the RDM resulted in an efficiency measure that was very similar to those used in radial models, except that the point with reference to which efficiency is measured was no longer the origin but an ideal point (having maximum outputs and minimum inputs). They claimed that such a measure represented an interesting development in the literature because there was until then no radial or non-radial efficiency measure, to the authors' knowledge, that could be applied directly to negative data.

Portela et al. (2004) extended their approach by considering a variant of the RDM, where the directional vector was the inverse of the range of possible improvement. The resulting inverse range directional model (IRDM) had the advantage of prioritising improvement of the factors on which the unit performed best, and therefore it tended to yield closer targets to the assessed unit than the RDM model or the additive model. The RDM and IRDM were applied to a sample of Portuguese bank branches. The advantage of using both specifications was that bank branches could choose from different types of targets (one prioritising improvements on the factors on which the unit performs worst, and the other prioritising improvement of the factors on which the unit performs best), both leading to the production frontier.

No specific negative data were apparent for TGIA, but there was technical regress in some cases for TGIA because some TFP* scores were lower in a current year than in previous years.

Yang (2009) examined the performance of 758 branches of one big Canadian bank nationwide using DEA from several perspectives. The DEA models used in the paper considered the systematic differences among the various geographical areas. Five alternatives to express outputs were presented so as to provide complementary information to the bank management, and the cause of inefficiency when assessing bank branches was investigated further. A correlation analysis of different models was provided and potential management uses of DEA results were presented.

Among other things, Yang (2009) concluded that although all the DEA models in the study identified plenty of potential to improve the branch performance, the saving in practice would almost certainly be substantially less. Especially when the output-oriented DEA models were applied, the bank management must consider the external environment and the customer base of the inefficient branches when they set up the targets for them. Throughout the study, special emphasis was placed on how different output measures affected the efficiency rating so as to provide more guidance to top management on what to manage and how to accomplish the changes. A statistical test was conducted to test the correlation between different DEA models. Finally, Yang recommended how management could use the DEA results. The potential guidance to management is worthy of note in relation to the TGIA study.

(b) Some similarities and differences between banks and charities

(i) Mode of operation

Banks are usually for-profit. Charities differ and generally are NFP. Banks tend to focus mainly on their profit motive and satisfy shareholders. Charities tend to focus mainly on providing a better service and raising more donations.

(ii) Method of analysis

In the context of DEA, Tobit regression analysis and MFA as considered in this thesis, it could reasonably be expected that the method of analysis would generally be the same for bank and charity branches. These methods are all justified in their application across numerous sectors, industries, countries and other levels as demonstrated in earlier chapters.

(iii) Data requirements and output or input variables

Data requirements and output or input variables for banks, when assessing productivity and efficiency using different methods of analysis, will reflect profit and/or cost–minimisation motives. Data requirements and output or input variables for charities or NFPs will reflect motives of service and maximising fundraising. By the very nature of NFP status, charities/NFPs are not generally motivated by a profit-making objective. The general absence of pricing and cost data for charities/NFPs will also generally preclude consideration of any cost-minimisation impact on the productivity and efficiency of charities/NFPs.

The similarities and differences between banks and charities/NFPs addressed in this section appear to hold true for TGIA and TGI. The main reason for including the section on bank branches was for comparison, in the apparent absence of cross-branch studies of single charities using the methods applied in this study of TGIA branches. Possible parallels with studies of branches of single banks were sought. The author of this thesis believes the comparison has been worthwhile, particularly in the useful comments by some researchers about the potential for the results to be of guidance to management. It is hoped that the current study of TGIA will also be of guidance to management. In saying this, it is acknowledged that a key difference is the control a manager has over the effort put in by labour inputs paid for by remuneration and incentives in the banking industry, compared to charities like TGIA/TGI which rely on unpaid voluntary labour. Low levels of technical efficiency in charities, as discussed elsewhere in this thesis, may be partly explained by the limited control that managers have over this unpaid volunteer labour. In the context of TGIA/TGI, sustained positive encouragement to work and pray harder is continuous. Other than that, it would appear that little more can be done to induce volunteer workers and branches to perform better.

4.2 Summary and conclusions

In this chapter the literature relevant to the charitable and NFP sector has been examined and reviewed. The interested reader is also directed to the following additional references: Heijden (2013); Golden, Brockett, Betak, Smith and Cooper (2012); Berber, Brockett, Cooper, Golden and Parker (2011); Connolly and Hyndman (2004); Lee (2003); Hager and Rooney (2001); Paton (1999); Kaehler and Sargeant (1998); Luksetish and Hugs (1997); Zaleski and Zech (1977). Full citations are included in the reference list. They are not annotated because they do not contain material affecting decisions on model building in this study, beyond that in the references that have been discussed in the literature review. In the light of the literature reviewed so far in this thesis it seems obvious that more work is needed in this topic area and on the target sector. In the next chapter the empirical models, data requirements and data sources for the TGIA study are addressed.

CHAPTER 5: EMPIRICAL MODELS, DATA REQUIREMENTS AND DATA SOURCES

In this chapter the analysis and empirical models that were estimated for TGIA are summarised. Descriptive statistics for the variables used are presented and discussed in order to assist in providing a profile of TGIA. The different variables used in the empirical models are detailed and discussed. The way in which the data for each variable were compiled is presented and measurement issues are addressed. There is also discussion of how the data were summarised, how the models were estimated and which software packages were used.

5.1 Segmentation into state groups

In the study data envelopment analysis (DEA) and Tobit regression analysis (TRA) were used at both the national (all Australia) and the state region levels.

(a) Background

The national level or whole of Australia is here defined as a meta-frontier for BDIST and DON, enveloping a number of defined TGIA groups or subsets of the Australia meta-frontier. DEA and TRA were applied at the meta and defined group levels. Group status could be assigned to each TGIA branch on the basis of any predetermined characteristic that distinguished a subset of TGIA branches from another subset (e.g. regional location). The DEA productivity and efficiency scores for each branch at the group level could then be compared with the corresponding DEA scores for BDIST and DON for each TGIA branch at the Australia meta-frontier level. Meta-frontier ratios for BDIST and DON could be calculated and analysed in terms of magnitude, and attempts could be made to explain the difference in TGIA branch scores at the meta-frontier and group level for BDIST and DON (see later in this chapter and Chapter 7 below).

(b) State groups

There are five state groups of TGIA branches, and data are readily available for them for BDIST and DON. At the time of writing, there were no other groupings for which data could be readily obtained, although less comprehensive data were available at area level within state regions. The five groups were: Northern state (Queensland and Northern Territory), Eastern state (New South Wales and the Australian Capital Territory), Southern state (Victoria and Tasmania), Central state (South Australia) and Western state (Western Australia). At the time of writing, there was no official representation of TGIA in any other Australian region such as the islands surrounding Australia or the Australian Antarctic Territory.

The state groups/regions do not have equal numbers of observations because some of the five TGIA state regions/groups have more or fewer branches than others. However, a balanced panel dataset for meta and each state region/group was always used in this TGIA case study because time series data are involved. As mentioned previously, DEA is ideally suited to applications where the DMUs (TGIA branches) have a homogeneous set of outputs and inputs and generally carry out the same activities by the same methods. Such is the case for TGIA branches and at the meta-frontier and group levels. Therefore, heterogeneity was not considered to be of concern in this part of the TGIA case study.

5.2 Empirical models and variables

In this section, the assessment of the performance of TGIA is described in relation to Bible distribution (BDIST) and fundraising of private donations (DON) in Australia from 2008 to 2013. The data envelopment analysis (DEA) models are presented first, followed by the Tobit regression analysis (TRA) models. A DEA model with a single output variable and two input variables was used in all cases. For the BDIST Tobit regression, a model with a dependent variable and five independent variables was used. For the DON Tobit regression a model with a dependent variable and six independent variables was used.

5.2.1 Bible distribution (BDIST)

(a) BDIST DEA (first stage)

(i) DEA model for BDIST

A DEA VRS linear programming model for BDIST with a single output variable and two input variables was used for each TGIA branch. The general format of the model was as shown in Equation 5.1 below.

$$\text{Maximise}_{\phi,\lambda}\ \phi \qquad \text{(Equation 5.1)}$$

$$\text{Subject to}\quad -\phi\mathbf{q_i} + \mathbf{Q\lambda} \geq \mathbf{0}$$

$$\mathbf{x_i} - \mathbf{X\lambda} \geq \mathbf{0}$$

$$\mathbf{I1'\lambda} = 1$$

$$\boldsymbol{\lambda} \geq \mathbf{0}\ ,$$

where $1 \leq \phi < \infty$, ϕ-1 is the proportional increase in outputs that could be achieved by the I th DMU, with input quantities held constant, and **I1** is an I × 1 vector of ones to account for VRS. The constraint $\mathbf{I1'\lambda} = 1$ ensured that an inefficient branch was only benchmarked against branches of similar size. There were data available on $N = 2$ inputs and $M = 1$ output for each of $I = 121$ TGIA branches. For the i-th TGIA branch ($i = 1, \ldots, 121$), N and M were represented by the column vectors $\mathbf{x_i}$ and $\mathbf{q_i}$ respectively (M, N, I, i were all integers ≥ 1). Also, the $N \times I$ input matrix, **X**, and the $N \times I$ output matrix, **Q**, represented the data for all I TGIA branches. Further details of this model and DEA concepts applied to TGIA are in Appendix 2.

(ii)DEA output variable for BDIST

The single output variable BDIST_{Eit} was used for each TGIA branch representing the various measures of productivity and efficiency from DPIN ('$_E$') for the i-th branch in year t. For TGIA, 'production' is Bible distribution (BDIST) and fundraising of private donations (DON). If BDIST is defined as the set of all Bibles distributed in Australia by TGIA, it is possible to break the variable into subsets of different types of Bibles distributed. The same applies to DON, where different types of donations could be viewed as subsets of the set DON. This study focused on the sets BDIST and DON only, leaving the analysis of the respective subsets for possible further research. An

implicit assumption, which appears reasonable given recent trends in Bible distribution by TGIA across Australia, was that there were always sufficient Bibles to distribute at any level of demand (output) and labour (input — see next section).

From the discussion of TGIA activities in previous chapters, it is apparent that the activities of TGIA are characteristic of charities generally, in that any charity will seek to do two things: to provide a service (service activities), and to raise funds (fundraising activities) to provide that service. For TGIA, these two activities or outputs are reflected in BDIST and DON. Indeed, promotional work at TGIA is directed towards maximising BDIST and DON as the primary physical output objectives. The choice of BDIST and DON as outputs would therefore appear justified.

(iii) DEA input variables for BDIST

Two traditional input variables were included in the Bible distribution DEA model:

1. GID_{it} = number of male members of each branch *i* in year *t* (volunteer Gideon labour); and
2. AUX_{it} = number of female members of each branch *i* in year *t* (volunteer Auxiliary labour). As noted previously, the organisation is supported by an Auxiliary of the wives (female members) of Gideon members.

GID and AUX were justified because volunteer labour is exclusively used for Bible distribution. Separate data are available for GID and AUX and TGIA/TGI is always interested in how each is performing in their own right. It was therefore considered prudent to have GID and AUX kept as separate inputs, and there appeared to be no harm in so doing. Indeed it would appear to facilitate better analysis of results. There are no data available for other traditional inputs such as some form of capital (e.g. vehicle transport for Bibles) and, as stated previously, there is no shortage of Bibles available for distribution.

(b) Factors affecting performance — Tobit regression analysis (TRA) for BDIST (second stage)

Based on TRA being the preferred method in previous studies discussed earlier (e.g. Fizel and Nunnikhoven 1992), this study used TRA for the calculation of the coefficients of all variables in Equation 5.2 (BDIST) and Equation 5.3 (DON) below. Discussion on the format of the models, the various coefficients and other aspects below is applicable to all BDIST and DON meta and group analysis.

The general BDIST TRA empirical model for both the meta and group cases for each productivity and efficiency measure from DPIN was:

$$\text{BDIST}_{Eit} = \beta_0 + \beta_1\text{GIDPM}_{it} + \beta_2\text{AUXPM}_{it} + \beta_3\text{BAGE}_{it} + \beta_4\text{RATAG}_{it-1} + \beta_5\text{URB}_{it} + \varepsilon, \qquad \text{(Equation 5.2)}$$

where $\varepsilon \sim N(0, \sigma^2)$ was a random error term.

The independent variables on the right-hand side (RHS) of Equation 5.2 are now described.

(i) TRA internal variables for BDIST

The BDIST TRA model included four internal variables:

1. GIDPM_{it} = number of Gideon prayer meetings for each branch *i* in year *t* ;
2. AUXPM_{it} = number of Auxiliary prayer meetings for each branch *i* in year *t* ;
3. BAGE_{it} = branch age (number of years each branch *i* had been operating in year *t*); and
4. RATAG_{it-1} = ratio of AUX_{it-1} to GID_{it-1}.

The justification for including GIDPM and AUXPM is grounded in the Christian spiritual belief that prayer could lead to positive outcomes generally. There have been studies on the benefit of prayer, for example, in the health sphere. Jantos and Kiat (2007) explored four possible mechanisms by which prayer may lead to improved health. They stated that 'Many people use prayer, and some studies have shown a positive association between prayer and improved health outcomes' (Jantos and Kiat

2007, page 51). Another common belief among Christians is related to the notion of ‘God room’ (Graham 1995, pages 133–142); that is, allowing for a ‘God factor’ in things they put their hands to and thereby, for them, explaining outcomes that cannot be explained otherwise. Such unexplained phenomena may, for example, be labelled simply as an unknown factor by those without such beliefs. GIDPM and AUXPM were included to see if the number of TGIA prayer meetings had any statistical significance.

The inclusion of BAGE as a variable was justified because some studies claim branch age to be a proxy for the goodwill, reputation and good standing of an organisation. For example, Weisbrod and Dominguez (1986) argued that the institution’s age since founding could serve as a proxy for its reputation and, hence, quality of services, in the absence of more direct information about product or service quality. One could hardly deny that both TGIA (established in 1956) and TGI (established in 1899) are beyond reproach, and have good standing and an excellent reputation.

At the TGIA branch level, it could be argued that $BAGE_{it}$ for the *i*-th branch is reflective of the good standing and excellent reputation of the individual branch as well as the overall organisation. This may or may not be true, so BAGE was included in line with previous studies of charities attempting to explain donation levels in particular (e.g. Weisbrod and Dominguez 1986; Callen 1994; Okten and Weisbrod 2000). In this study, BAGE was included in both the BDIST and DON models so that its significance could be examined.

RATAG was included because some people at TGIA make the empirically unsubstantiated observation that a branch will perform better if its ratio of Auxiliary members to Gideon members is higher. The inclusion of RATAG in both the BDIST and DON models facilitated the testing of this proposition. The possibility or suggestion of endogeneity in the case of RATAG was addressed by lagging this variable by one year ($t - 1$).

(ii)TRA environmental/external variables (EV) for BDIST

Although any number of EVs might be speculated, the general absence of readily available data precluded the inclusion of any EVs in the various models. However, data had been constructed for one EV, namely a categorisation of TGIA branches into urban and regional. Among previous studies, Fizel and Nunnikhoven (1993), for example, used a dummy variable (DV) for urban/rural (URB = 1) in a study of technical efficiency from DEA on for-profit and non-profit hospitals, and found its coefficient to be negative and insignificant in all cases.

Following the approach adopted by Fizel and Nunnikhoven (1993), this study introduced an urban/regional DV (URB) in the TGIA TRA models to capture at least some of the effect of concealed environmental factors, e.g. socio-economic conditions and the quality of volunteer labour, where

$$\text{URB}_{it} = 1, \text{ for urban; } \text{URB}_{it} = 0, \text{ for non-urban for the } i\text{-th branch at time } t\,.$$

The following should be read in conjunction with the description and justification of the variables in Equation 5.2.

1. The subscript E_{it} represented the particular measure of efficiency or productivity for branch i in year t .
2. β_1 and β_2 were predicted to be positive and statistically significant because, from a Christian belief perspective, it appeared reasonable that a unit increase in the number of prayer meetings would have a positive effect on productivity and efficiency.
3. For β_3 no prediction was made because it was not known whether its effect would be positive or negative.
4. β_4 was predicted to be positive and statistically significant because physical observation by experienced people at TGIA had suggested that an increase in the ratio RATAG had a positive effect on productivity and efficiency. RATAG was lagged by one year to allow for the possibility of endogeneity for that variable.
5. For β_5, no prediction was made because it was not known whether its effect would be positive or negative.

The results of applying DEA and TRA to TGIA data for BDIST are presented in Chapter 6 below.

(c) Meta-frontier approach/analysis (MFA) for BDIST

The concept of MFA was introduced in Chapter 3. The study of TGIA provided an ideal opportunity to apply MFA because TGIA (branch, state, national) and indeed TGI (country, region, global) also are ideally structured and have data availability at various levels within that structure. It was considered that the results and insights gained from applying MFA had the potential to enhance performance management at TGIA/TGI. In hindsight the outcomes of its application of MFA supported the conduct of the analysis. Use of MFA in the study also potentially adds to the literature in the MFA topic area, particularly in relation to TFP as reported by O'Donnell et al. (2011).

The MFA model for both BDIST and DON presented for TGIA embraced the meta (national), state group and branch levels at TGIA. Given that DMUs are mostly within 'regions' (e.g. TGIA branches within five states of Australia), it was possible to identify a 'regional frontier' using DEA on the data for DMUs from the given region. Thus, DEA was used to construct **g** regional frontiers. The meta-frontier was then constructed by using DEA to analyse the dataset obtained by pooling all the observations for DMUs from all the regions; for example, TGIA branches for all Australia (Battese, Rao and O'Donnell 2004; O'Donnell, Rao and Battese 2008). This application of MFA used data and results for TGIA from the earlier DEA work presented earlier in the thesis. Chapter 7 explores in detail an application of the MFA to TGIA.

(i) MFA model for BDIST

For TGIA, if region g = 1 ,..., 5 consists of data on L_g branches over T = 6 time periods, the LP problem that was solved for the i-th branch in an output-orientated DEA model for panel data was:

Maximise $\varphi_{it}, \lambda_{it}$ φit (Equation 5.3)

Subject to $-\boldsymbol{\varphi}_{it}\, \mathbf{q}_{it} + \mathbf{Q}_{igt}\, \boldsymbol{\lambda}_{it} \geq \mathbf{0}$

$\mathbf{x}_{it} - \mathbf{X}_{igt}\, \boldsymbol{\lambda}_{it} \geq \mathbf{0}$

$\mathbf{I1'}\boldsymbol{\lambda}_{\mathbf{it}} = 1$

$\lambda_{igt} \geq 0$

$t = 1, 2, \ldots, 6$

where

q_{it} was the $M \times 1$ vector of output quantities for the *i*-th branch over time period t;

x_{it} was the $N \times 1$ vector of input quantities for the *i*-th branch over time period t;

Q_{igt} was the $M \times L_g$ matrix of output quantities for all L_g branches over time period t;

X_{igt} was the $N \times L_g$ matrix of input quantities for all L_g branches over time period t;

λ_{igt} was an $L_g \times 1$ vector of weights; and

φ_{igt} was a scalar.

φ_{igt} takes a value greater than or equal to 1, and $\varphi_{igt} - 1$ was the proportional increase in outputs that could be achieved by the *i*-th branch in period t with input quantities held constant. Note also that $1 / \varphi_{igt}$ could define a total factor productivity (TFP) score or output technical efficiency (OTE) score which varied between 0 and 1.

The above LP problem (Equation 5.3) was solved L_g times; once for each branch in region *g*. Each LP produced φ_{igt} and λ_{igt} vectors. The φ_{igt} -vector provided information on the technical efficiency score for the *i*-th branch for period t, and the λ_{igt}-vector provided information on the peers of the (inefficient) *i*-th branch for time period t. The peers of the *i*-th branch were those efficient branches in the region that defined the facet of the frontier against which the (inefficient) *i*-th branch was projected.

The meta-frontier was constructed using a DEA model based on the pooled data for all branches in all regions over the time period T. Since there was a total of $L = \Sigma_g L_g$ = 121 TGIA branches, the above LP model (Equation 5.3) was re-run with the input and output matrices with data for all TGIA branches for all periods $t \in$ T:

Maximise φ_{it}^*, (Equation 5.4)

$$\varphi^*, \lambda^* \; \varphi_{it}^*, \lambda_{it}^*$$

such that $\varphi_{it}^* q_{it} + Q_{it}^* \lambda_{it}^* \geq 0$,

$x_{it} - X_{it}^* \lambda_{it}^* \geq 0$,

$\lambda_{it}^* \geq 0$,

where

q_{it} is the M×1 vector of output quantities for the i-th branch over time period T;

x_{it} is the N×1 vector of input quantities for the i-th branch over time period T;

Q_{it}* is the M×L matrix of output quantities for all the L branches over time period T;

X_{it}* is the N×L matrix of input quantities for all the L branches over time period T;

λ_{it}* is the L×1 vector of weights; and φ_{it}* is a scalar.

The optimum solution of the LP problem above (Equation 5.4) provides a total factor productivity (TFP) score or output technical efficiency (OTE) score for a given branch relative to the meta-frontier identified using data from all branches in all regions over time T, i.e. for TGIA in all five states/regions of Australia. Once the regional and meta-frontier measures are calculated, technology gap ratios (TGR) or now more commonly called meta-technology ratios (MTR), can be calculated for each TGIA branch. The MTR is the ratio of the TFP score (or OTE score) at the meta-frontier level to the corresponding score at group level. The software used to calculate the DEA estimates for the group and meta-frontier was DPIN. The MTR were calculated by Microsoft Excel. The same general model in Equations 5.3 and 5.4 is also applicable to DON. Further details of MFA concepts and the general model are given in Appendix 3.

(ii)Variables and results for BDIST MFA

The same output variable (BDIST) and input variables (GID and AUX) at the respective meta and state levels described earlier in this chapter were used for the meta-frontier analysis. The results of applying meta-frontier analysis to TGIA data for BDIST are presented in Chapter 7 below.

5.2.2 Fundraising of private donations (DON)

(a) DON DEA (first stage)

(i) DEA model for DON

A DEA VRS linear programming model was also used for DON with a single output variable and two input variables for each TGIA branch. In general format, the model was identical to that used for BDIST and specified in Equation 5.1 above.

(ii) DEA output variable for DON

The single output variable DON_{Eit} was used for each TGIA branch representing the various measures from DPIN ('$_E$') for the *i*-th branch in year *t* . The justification for using DON was covered previously.

(iii) DEA input variables for DON

The traditional input variables GID and AUX were justified in the DON model for the same reasons as in the BDIST model, covered above. Predominantly volunteer labour is used for seeking and producing donations. There are no other traditional inputs and there is no shortage of donations received for the purchase of Bibles for distribution.

(b) Factors affecting performance — Tobit regression analysis (TRA) for DON (second stage)

The analysis for DON was carried out in a similar way to that described above for BDIST. The general DON TRA empirical model considered for both the meta and group cases for each productivity and efficiency measure from DPIN was:

$$DON_{Eit} = \beta_0 + \beta_1 GIDPM_{it} + \beta_2 AUXPM_{it} + \beta_3 BAGE_{it} + \beta_4 RATAG_{it-1} + \beta_5 CPVIS_{it} + \beta_6 URB_{it} + \kappa \qquad \text{(Equation 5.5)}$$

where $\kappa \sim N(0, \rho^2)$ is a random error term.

The independent variables on the RHS of Equation 5.5 were as follows.

(i) TRA internal variables for DON

The inclusion of the four internal variables GIDPM, AUXPM, BAGE and RATAG was justified above for the BDIST models. The same justification and any related discussion for these variables for the BDIST TRA models applies to the DON TRA models.

An additional internal variable, number of church presentation visits by TGIA (CPVIS) was added for the DON TRA models, where $CPVIS_{it}$ is number of church presentation visits for each branch i in year t .

The justification for including this variable was that an integral part of branch activities for TGIA, and indeed globally across TGI, is the relationship between the organisation and Christian churches. Such church relationships are an important aspect of the organisation's promotional activities; they lead to the recruitment of volunteer members and the generation of donations from the churches for the purchase of Bibles for distribution.

(ii)TRA environmental or external variables (EV) for DON

The dummy environmental variable URB was also included in the DON TRA models. The same justification and any related discussion above for the URB variable for the BDIST TRA models applies to the DON TRA models.

The following should also be read in conjunction with the description and justification of the variables in Equation 5.2 above.

1. The subscript E_{it} represented the particular measure of efficiency or productivity for branch i in year t.
2. β_1 and β_2 were predicted to be positive and statistically significant, for the same reasons given for Equation 5.2 above.
3. For β_3, no prediction was made because it was not known which way it was likely to go.
4. β_4 was predicted to be positive and statistically significant for the same reason given for Equation 5.2 above.
5. β_5 was predicted to be positive and statistically significant because it appeared reasonable that a unit increase in CPVIS had a positive effect on DON.
6. For β_6, no prediction was made because it was not known which way it was likely to go.

The results of the application of DEA and TRA to TGIA data for DON are also presented in Chapter 6 below.

(c) Meta-frontier analysis (MFA) for DON

(i) MFA model for DON

In general format the model was identical to those used for BDIST and specified in Equations 5.3 and 5.4 above.

(ii)Variables and results for DON MFA

The same output variable (DON) and input variables (GID and AUX) at the respective meta and state levels described earlier in this chapter were also used for the meta-frontier analysis. The results of the application of MFA to TGIA data for DON are also presented in Chapter 7 below.

5.3 Data requirements

Now that the different variables used in the empirical models for TGIA have been described, the data requirements can be identified. The availability of data for any variable is an important consideration before even selecting the variables in the first place. It was found that all data were available for all selected variables at all levels for each year for the 121 TGIA branches studied. The data were made available by TGIA for the purpose of the study.

It was necessary to ensure that the data required for the output variables and input variables in the DEA models for BDIST and DON could be obtained in a format conducive to construction for the purposes of the study. Fortunately this was the case and the Microsoft Excel 2003 .xls format by which the data had been compiled by TGIA was most beneficial in facilitating data construction for the purpose of the study.

Similar comments on data requirements apply for GIDPM, AUXPM and CPVIS in the TRA models and for RATAG in the TRA models. Obtaining the required data for BAGE and URB in the TRA models was more challenging but was accomplished as explained in the next section, in which the sources of data and the compilation and construction methods are also described.

5.4 Data sources, compilation and construction

5.4.1 Introduction

The research was carried out by first constructing from TGIA databases and other sources a set of balanced panel data on input, output and other variables used in the analysis. A balanced panel dataset ensured compatibility with software applied in the analysis.

Cross-sectional, time series and panel data were made available for the purposes of the research in this thesis, and ethical issues were addressed. The structure of the organisation and the availability and other aspects of the data suited the research to which this thesis relates. Dyson and Shale (2010) used DEA to examine the technical efficiency of four entities in the UK, two of which were non-profit, and commented that 'there was no shortage of data so that the issues discussed are as far as possible not driven by lack of information' (page 26). Such a comment applies equally to this case study of TGIA.

TGIA's financial year starts on 1 June each year and runs to 31 May in the following year. All year-to-year data relate to annual figures to 31 May in a particular year. Consistent with other studies where DEA and other productivity and efficiency analysis techniques are used, only the TGIA branches with all data for all variables for all years were included in the datasets analysed. The outcome of this restriction was that out of a possible 133 branches at 31 May 2013, 121 branches (approximately 90%) were found to meet the criteria. Where appropriate, 0 values were replaced by 0.000001 to enable the software to work. It was considered that 0.000001 was too small to have any relevant impact on the model results. Any gaps in data were addressed by excluding any TGIA branch that did not have all data for all years (e.g. Taylor and Harris 2004, page 73).

The main data source was the Australian data tables of TGIA and some international data tables of TGI that include Australian data. The detailed data compilation was carried out for BDIST and DON respectively as follows:

(a) Raw data were sourced for each year 2008–2013 from TGIA databases. Some of these databases were in Microsoft Excel 2003 .xls format while others were in Adobe Portable Document Format (.pdf).

(b) Panel data spreadsheets were compiled or constructed from raw data for the national/meta level and each of the five state regions/groups: Northern, Eastern, Southern, Central and Western (Microsoft Excel 2003.xls format).

Relevant data measurement issues were addressed along the lines set out by Coelli et al. (2005, pages 133–160). This was done for output and input variables in the TGIA BDIST and DON models, and for internal variables and EVs that were examined in the second-stage TRA models.

The main attributes of the TGIA data are:

(a) Volume and sufficiency — there is no shortage of data; the analysis and issues addressed are not being driven by lack of information.

(b) Availability — the data have been made available in Australia, and internationally (over 190 countries).

(c) Richness — the data are detailed and complete enough to provide a full and revealing picture of what is going on.

(d) Integrity — the data are complete, consistent, certified and reconciled (e.g. peer and hierarchical review); they are subject to an annual financial audit and all characteristics are correct.

(e) Reliability and robustness — data reflect what drives them; they are positively and properly documented.

(f) Adaptability — the data record and account for all variables; they are understandable and have utility and contain a record of systematic review, and methods are available for adapting them to suitable formats for construction of datasets that facilitate the analysis by the software used in this research project.

5.4.2 Data sources, measurement issues and possible bias

The source of primary data for BDIST, DON, GID, AUX, GIDPM, AUXPM and CPVIS was a monthly ‘year to date’ report at 31 May for the years 2008–2013 inclusive. The data for CPVIS are relevant to the DON models but not to the BDIST models. Given the integrity of the data in these reports, as previously discussed,

generally there would appear to be no adverse measurement issues or material sources of bias.

The source of the data for BAGE is not so straightforward. Initially it was considered that it would not be possible to have BAGE because of lack of data on the dates of establishment of TGIA branches. Subsequently, however, a particular sequence of research steps helped determine dates of establishment of all branches, albeit not with complete certainty. Obviously this is a possible source of bias. The date of establishment of each branch has been standardised and is now included in the official TGIA database of branch demographics on the basis of the financial year ended 31 May in which establishment appears to have occurred. In most cases an exact date–month–year could not be established. The following steps were taken.

(a) Perusal of a book on the history of TGIA (Fisher 1992). This yielded only a few results but provided a useful starting point.

(b) Examination of a very old TGIA handwritten archived financial general ledger with branch by branch folios provided dates in each folio and the assumption was made that the first date recorded must be in the financial year in which the branch first operated.

(c) Examination of the current TGIA database of demographics by branch established the longest-serving Gideon in the branch. The assumption was then made that, assuming low mobility between branches, a particular branch was generally as old as the date of joining of the longest-serving Gideon.

(d) The above three steps gave a first approximation of the dates of establishment of the various branches.

(e) There was a limited peer review at TGIA of the dates referred to above by long-serving Gideons, to give more credibility to the dates recorded in the TGIA database.

The dates arrived at after taking the above steps were used in constructing BAGE for the analysis in this thesis.

The data for the dummy environmental variable URB for each branch for each year came from consultation with experts at TGIA on branch boundaries and branch

establishment. This is acknowledged as a subjective process and the study has included due caution about possible bias and uncertainty.

5.5 Profiling of TGIA and descriptive statistics of the variables

The descriptive statistics below provide further information on TGIA's profile. Table 5.1 presents the descriptive statistics for the variables used in the empirical application of DEA and TRA to TGIA BDIST and DON. The sources of raw data for each, and the way in which panel data were constructed for them, are covered in the sections below. The descriptive statistics provide a profile of the range for each variable together with its mean and standard deviation over the 6-year period, by meta and state level.

Table 5.1 — Descriptive statistics for variables for 6-year period 2008–2013

Level	Output		Input		Internal Variables				
	BDIST	**DON**	**GID**	**AUX**	**GIDPM**	**AUXPM**	**BAGE**	**RATAG**	**CPVIS**
Meta									
Mean	2454	18920	18	10	34	16	38	0.568	11
Std Dev	1764	15295	7	5	18	11	9	0.185	10
Min	60	1010	3	0	0	0	1	0.091	0
Max	13305	136146	45	27	102	68	57	1.250	67
Northern									
Mean	2929	24503	20	12	40	18	39	0.597	14
Std Dev	1688	20679	6	5	20	11	7	0.143	11
Min	245	1010	7	5	0	0	22	0.226	0
Max	8620	136146	35	27	102	56	54	1.143	55
Eastern									
Mean	3153	16548	17	9	33	14	40	0.492	12
Std Dev	1962	10420	6	4	17	12	9	0.187	11
Min	300	2509	6	0	0	0	1	0.100	0
Max	13305	44901	38	20	74	53	57	1.091	67
Southern									
Mean	1552	18679	17	10	32	16	37	0.628	10
Std Dev	966	16426	9	6	17	11	11	0.164	8
Min	60	1546	3	1	0	0	1	0.167	0
Max	6120	107130	45	27	75	68	54	1.000	38
Central									
Mean	1723	14963	15	9	34	13	34	0.620	13
Std Dev	1498	8298	6	3	18	7	7	0.200	10
Min	150	1455	3	2	0	0	15	0.313	0
Max	6957	35740	37	18	80	24	50	1.250	44
Western									
Mean	2491	16779	15	7	28	18	33	0.481	7
Std Dev	1981	8949	6	3	16	15	6	0.217	8
Min	120	3858	5	2	0	0	20	0.091	0
Max	7820	48578	28	14	65	60	44	0.875	38

The external variable URB is not included in Table 5.1 because it is a dummy variable that can only take the value 1 for urban and 0 for non-urban. Table 5.2 presents information on URB at meta and state levels for the categorisation of urban or non-urban for the purposes of this empirical application to TGIA.

Table 5.2 – Percentage of TGIA branches categorised as urban and non-urban

Level	Total branches	Urban (number)	Urban (%)	Non-urban (number)	Non-urban (%)
Meta	121	40	33	81	67
Northern	30	7	23	23	77
Eastern	35	16	46	19	54
Southern	32	7	22	25	78
Central	14	6	43	8	57
Western	10	4	40	6	60

The figures at the meta level in Table 5.2 mean that of the 121 branches examined, 40 (33%) were categorised as urban and 81 (67%) non-urban. A similar interpretation can be given to the figures at the respective state levels.

5.6 Estimation procedures

Panel data spreadsheets were compiled or constructed in Microsoft Excel 2003 .csv format by branch and/or mean for BDIST and DON at the meta and state group levels to facilitate DEA and TRA analysis. The raw data and spreadsheets described in Section 5.3 were used for this purpose.

All first-stage DEA models for BDIST and DON were estimated using the DPIN 3 computer software standard version to run DPIN (set to VRS) analysis, allowing technical regress for national and group levels, to obtain scores for measures of productivity and efficiency.

The DPIN software produces results or output in Microsoft Excel 2003.csv format; these were converted to .xls format, and tabulated. Panel data spreadsheets included both original data and DPIN results at national and group levels (Microsoft Excel 2003.xls format). From these spreadsheets, Microsoft Excel 2003.csv spreadsheets at national and group levels were constructed for each productivity and efficiency measure given by DPIN. The data for the variables for the Tobit regression analysis were also included in those spreadsheets.

The second-stage TRA models for BDIST and DON were estimated using the LIMDEP 9 computer software. Tobit fixed effects model (FEM) analysis using

LIMDEP was carried out for all the above, saving each as a LIMDEP.lim (text file) and a Microsoft Word 2003.doc file. A likelihood ratio test for Tobit FEM model significance using the LIMDEP procedure in the LIMDEP Version 9 Reference Guide (Section R11.6.3 on page R11–23) (Greene 2007) was carried out for all the above, saving each as a LIMDEP.lim (text file) and a Microsoft Word 2003.doc file.

5.7 Summary and conclusions

Based on the earlier chapters, in this chapter the analysis and empirical models that were estimated have been summarised. The variables used in the empirical models have been detailed and discussed. The way in which the data were compiled was presented and measurement issues were addressed. Also discussed in this chapter was how the data were summarised, how the models were estimated and the software used. The descriptive statistics of the variables included in the models were also presented.

In the study two general DEA models were considered separately, for BDIST and DON (Equation 5.1). A single output variable was considered for the DEA applications to obtain productivity and efficiency scores included in the second-stage TRA for BDIST and DON respectively. Two input variables, GID and AUX, were considered in each case for BDIST and DON respectively in obtaining the productivity and efficiency scores from DPIN. Two general TRA models were also considered separately, one for BDIST (Equation 5.2) and one for DON (Equation 5.5). There was necessarily an overlap of most inputs, and internal and environmental variables, for BDIST and DON. The only exception was that an additional internal variable, CPVIS, was added for DON. The possibility of endogeneity in relation to RATAG was addressed by considering a distributed lag of 1 year for that variable. Two general MFA models were also considered separately for BDIST and DON (Equations 5.3 and 5.4).

Constructed datasets were compiled from data made available for the purpose of the research and ethical issues were addressed. Only the TGIA branches with all data for all years were included in the analysis (121 branches). All data for TGIA used in the research were considered clean, rich, reliable and accurate because of the

organisation's peer and hierarchical reviews including annual financial audits as a legal requirement.

The following justified and empirically validated techniques and related software were used in the analysis:

(a) Microsoft Excel 97–2003 for datasets, analysis, descriptive statistics, tabulation of results and graphical presentation; and calculation of meta-technology ratios (MTR);

(b) DPIN 3.0 (standard version) with its underlying DEA calculations, to obtain various productivity and efficiency scores;

(c) DEAP 2.1 to obtain slacks, peers and targets; and

(d) LIMDEP 9 for TRA.

In concluding Chapter 5, it is noted that the availability of, and extensions to, relevant techniques are always expanding, and productivity and efficiency researchers should be on the lookout for such changes. Equally, bridging the gap between theory, research and practice in productivity and efficiency studies is an important consideration that is discussed by various researchers on the topic.

The results are presented and evaluated in two separate chapters. Results from the application of DEA and TRA are addressed in Chapter 6. In Chapter 7, the results from the application of MFA are addressed.

CHAPTER 6: PERFORMANCE OF TGIA

In this chapter the results from estimating the data envelopment analysis (DEA) and Tobit regression analysis (TRA) empirical models that were discussed in Chapter 5 are summarised, presented and evaluated. The descriptive statistics of the productivity and efficiency scores are also presented and discussed. Some of the results in tables for Bible distribution (BDIST) and fundraising of private donations (DON) in this chapter are included for completeness for the interested reader because the information was produced as a matter of course by the computer software used (DPIN 3 and LIMDEP 9). However, attention has focused on what are considered the most important results. More comprehensive tables and plots of the descriptive statistics are included in appendices. Commentary on the results in the context of the environment in which TGIA operates is included towards the end of the chapter.

6.1 Results of DEA calculations performed by DPIN

The DPIN software estimates the production technology (and associated measures of productivity and efficiency) using DEA linear programs (O'Donnell 2011, page 8). In this study DPIN was used as a tool to achieve two of the objectives of the research and to solve or understand the research questions underlying each objective, as follows.

(a) **Objective 1:** To measure the relative overall performance of TGIA branches' service activities of Bible distribution and fundraising of private donations in Australia for the period 2008–2013.

(i) What were the relative productivity levels of Bible distribution and fundraising of private donations achieved by TGIA branches in Australia during the period 2008–2013 inclusive?

(ii)Have these levels changed year by year from 2008 to 2013 inclusive?

(b) **Objective 2:** To examine measures of efficiency of TGIA branches for the period 2008–2013.

(i) What were the relative levels of measures of efficiency of Bible distribution and fundraising of private donations of TGIA branches in Australia during the period 2008–2013 inclusive?

(ii)Have these levels of measures of efficiency changed year by year from 2008 to 2013 inclusive?

Against this background, it is noted that in Tables 6.1A to 6.4 for BDIST and Tables 6.10A to 6.13 for DON the results all come from DPIN. The equations used to calculate the scores in Tables 6.1A and 6.10A are embodied in the DPIN computer program used for the analysis. They are quite complex and extensive. The interested reader is directed to the full details in O'Donnell (2011) (DPIN 3.0: A program for decomposing index numbers) that is cited fully in the reference list at the end of the thesis. The full words represented by the acronyms in Tables 6.1A and 6.10A are listed in the "LIST OF ACRONYMS, ABBREVIATIONS AND TERMINOLOGY" at the beginning of the thesis. These acronyms are also clearly defined in O'Donnell (2011), and some are defined at pages 72 and 73 of this thesis. The actual achievement of Objectives 1 and 2 and answering the related research questions more specifically is addressed in Chapter 8.

6.2 Bible distribution (BDIST)

6.2.1 BDIST productivity and efficiency scores

The results for BDIST reported in this section are presented in Tables 6.1A, 6.1B, 6.2, 6.3 and 6.4. Means at different levels (meta and state groups) are summarised for BDIST for the 6-year period 2008 to 2013. More comprehensive tables and plots presenting BDIST mean productivity and efficiency scores by level for each year are included in the appendices.

The calculated BDIST mean productivity and efficiency scores by level are presented in Table 6.1A. Discussion in this section focuses mainly on the results for TFP and OTE. It is considered that the results for those two measures are more likely to be of interest to users of the findings of the study, such as other researchers, charity management and governing bodies. Branch-level results for BDIST are also available where applicable but are not presented in the thesis or appendices because they are too voluminous.

Table 6.1A — BDIST mean productivity and efficiency scores by level for the 6-year period 2008–2013

Level	Meta	Northern	Eastern	Southern	Central	Western
TFP	0.064	0.170	0.106	0.104	0.114	0.289
TFPE	0.265	0.357	0.344	0.341	0.376	0.491
OTE	0.341	0.520	0.432	0.529	0.528	0.724
OSE	0.821	0.771	0.833	0.702	0.845	0.844
OME	1.000	1.000	1.000	1.000	1.000	1.000
ROSE	0.790	0.679	0.812	0.657	0.762	0.689
OSME	0.790	0.679	0.812	0.657	0.762	0.689
ITE	0.423	0.621	0.530	0.533	0.670	0.832
ISE	0.641	0.623	0.664	0.690	0.607	0.698
IME	0.948	0.924	0.982	0.928	0.870	0.902
RISE	0.646	0.595	0.660	0.697	0.620	0.625
ISME	0.618	0.550	0.646	0.646	0.542	0.568
RME	0.963	0.876	0.979	0.937	0.896	0.813

In Table 6.1B, BDIST maximum productivity achievable (TFP*) scores are presented by branches by level and year (these are actual and not means).

Table 6.1B — BDIST maximum productivity achievable (TFP*) by branches by year at meta and state/group level

Year	Meta	Northern	Eastern	Southern	Central	Western
2008	0.254	0.452	0.325	0.227	0.257	0.588
2009	0.183	0.401	0.239	0.389	0.320	0.648
2010	0.308	0.473	0.393	0.328	0.418	0.508
2011	0.203	0.505	0.255	0.349	0.228	0.613
2012	0.275	0.427	0.345	0.249	0.388	0.557
2013	0.269	0.625	0.338	0.342	0.267	0.624

Considering Table 6.1B first, the results suggest generally low TFP* scores for BDIST. Only the Western Group had scores above 0.5 (or 50%) for all years, and the Northern Group for 2010 and 2013. The 0.5 or 50% benchmark was suggested by Tofallis and Sargeant (2000) who were ‘disturbed’ by the distribution of efficiency scores because only 15% of the sample had efficiency scores above 50% (Tofallis and Sargeant 2000, page 6). This 50% figure was also applied elsewhere in this thesis when reporting results; scores less than or equal to 0.5 are regarded as low throughout. Technical

regress was identified in some cases with some BDIST TFP* scores declining over the study period.

The BDIST mean TFP scores by level reported in Table 6.1A are all low. This is reflected in the low mean TFPE scores. Mean OTE scores are low at the meta level, with improvement at group levels. The remaining mean efficiency scores for BDIST in Table 6.1A appear larger.

In Table 6.2, the BDIST efficient branches by year are listed for all measures of productivity and efficiency. These are the only branches that scored 1 for all measures of productivity and efficiency at a particular level in a particular year. There were only 17 of the 121 branches (14.0%) in the 6-year period that achieved this result at any level. Some branches achieved this in more than one year and some achieved it at both the meta and group levels for a particular year (see note and comments in Table 6.2) and this has been taken into account in arriving at the figure of 17.

Table 6.2 — BDIST summary of efficient branches by year for all measures of productivity and efficiency

Branch number	Year	TFP	Note
National/All Australia/Meta (M)			
M49	2008	0.254	GE
M38	2009	0.183	
M62	2010	0.308	GE
M60	2011	0.203	GE
M62	2012	0.275	GE
M49	2013	0.269	GE
Northern (N)			
N29	2008	0.452	
N29	2009	0.401	
N15	2010	0.473	
N28	2011	0.505	
N16	2012	0.427	
N15	2013	0.625	
Eastern (E)			
E19	2008	0.325	M
E22	2009	0.239	
E32	2010	0.393	M
E30	2011	0.255	M
E32	2012	0.345	M
E19	2013	0.338	M
Southern (S)			
S13	2008	0.227	
S20	2009	0.389	
S20	2010	0.328	
S23	2011	0.349	
S23	2012	0.249	
S23	2013	0.342	
Central (C)			
C13	2008	0.257	
C13	2009	0.320	
C13	2010	0.418	
C4	2011	0.228	
C13	2012	0.388	
C13	2013	0.267	
Western (W)			
W5	2008	0.588	
W10	2009	0.648	
W5	2010	0.508	
W5	2011	0.613	
W3	2012	0.557	
W10	2013	0.624	

Comment

The TFP was the best achievable based on the data at the time

Notes

1. GE = branch also efficient at Eastern Group level
2. M = branch also efficient at meta (all Australia) level

6.2.2 BDIST descriptive statistics of productivity and efficiency scores

Descriptive statistics are presented for all BDIST mean TFP and OTE at the meta and group levels for the 6-year period in Tables 6.3 to 6.4. The difference in variability suggested by high coefficients of variation (CV) reflected in those tables might be attributable to different or more prominent environmental factors affecting the performance of branches in a particular state and at the meta level. From Table 6.3 (BDIST mean TFP) it can be seen that mean (observed) TFP over the 6-year period was low at all levels. Even though the 6-year mean TFP for each state group was higher, it was still low in magnitude. The magnitude of the coefficient of variation (CV) indicates wide variation at all levels with Eastern and Western showing less variation than at other levels.

Table 6.3 — Descriptive statistics of BDIST mean TFP by level for 2008–2013

Level	Mean	Min	Max	Std Dev	CV %
Meta	0.064	0.003	0.308	0.044	69
Northern	0.170	0.012	0.625	0.119	70
Eastern	0.106	0.013	0.393	0.065	61
Southern	0.104	0.006	0.389	0.069	66
Central	0.114	0.016	0.418	0.082	72
Western	0.289	0.014	0.648	0.172	60

Note: CV is the coefficient of variation = (Std Dev/Mean x 100) %

From Table 6.4 (BDIST mean OTE) it can be seen that mean OTE over the 6-year period was larger, compared to TFP. The overall 6-year mean OTE at the meta level was 0.341 (34.1%). It suggests that output (BDIST) could have increased by 65.9% without any change in the available level of inputs (number of Gideon and Auxiliary members). Similar interpretations can be applied at each state or group level. The magnitude of the CV indicates wide variation at all levels, and particularly at the meta level, with Eastern, Southern and Western showing less variation than at other levels.

Table 6.4 — Descriptive statistics of BDIST mean OTE by level for 2008–2013

Level	Mean	Min	Max	Std Dev	CV %
Meta	0.341	0.019	1.000	0.234	69
Northern	0.520	0.039	1.000	0.296	57
Eastern	0.432	0.051	1.000	0.259	60
Southern	0.529	0.045	1.000	0.273	52
Central	0.528	0.054	1.000	0.334	63
Western	0.724	0.030	1.000	0.341	47

Tables displaying descriptive statistics for measures other than TFP and OTE for BDIST are available but are not included in this thesis. They are not included for TFPE because of the close relationship between TFP and TFPE. It was observed that mean efficiency scores for the remaining measures for BDIST (e.g. OSE) generally appear comparatively high at the meta and all-state-group levels. It was considered therefore that little would be lost by not including descriptive statistics for measures other than TFP and OTE.

6.2.3 BDIST overall performance (TFP and TFP*) and efficiency (OTE)

From an overall perspective, TFP and more particularly TFP* scores were generally low. When considering that Bibles are distributed and funds are raised through volunteering, however, low scores can be expected; this general comment is relevant in varying degree throughout this chapter for all aspects and results for BDIST and DON. One of the few previous studies of charities and/or NFP organisations, albeit at the cross–industry and/or cross–country level, also found low scores (Tofallis and Sargeant 2000). The principal explanation may lie in the voluntary labour that TGIA/TGI deals with — like numerous other charities and NFP organisations. Detail of voluntary labour, such as whether the labour is working full time for TGIA/TGI or other charities, is not generally available. Callen (1994) suggested that the number of volunteers was not a very important piece of information compared to the number of volunteer hours spent. The TGIA study used number of volunteers (GID and AUX) because those data were available, while data on hours worked by volunteers were not available. In this respect, caution is needed when considering all the results in this thesis.

During the 6-year period examined, only 17 of the 121 branches studied (14.0%) were 100% efficient for BDIST for all measures of efficiency at all levels in the whole period. This result is comparable to the results of previous studies of similar organisations. In a study of 327 UK charities using 1997 data, Tofallis and Sargeant (2000) found that only 13 (4%) of the charities examined were 100% efficient.

6.2.4 BDIST Slacks, Peers and Targets

For BDIST and DON, input and output slacks, and peers were identified and targets calculated for the 2013 year. At the time of undertaking this calculation the results gave the most recent indicator of branch slacks and peers together with achievable output levels at full efficiency (targets) for TGIA branches. The DEAP 2.1 computer program which was written to conduct DEA (Coelli 1996) was used for this purpose as it produces the required results as a matter of course whereas DPIN does not.

Results for slacks for BDIST are summarised in Table 6.5 below. Full details are included in the appendices. It can be seen from Table 6.5 that there is evidence of input slack at all levels for BDIST.

Table 6.5 — BDIST 2013 summary of slacks at meta and group levels

Level	*Mean BDIST output slacks at meta level*	*Mean GID input slacks at meta level*	*Mean AUX input slacks at meta level*	*Mean BDIST output slacks at group level*	*Mean GID input slacks at group level*	*Mean AUX input slacks at group level*
Meta	0	1	6	N/A	N/A	N/A
Northern	0	2	8	0	5	4
Eastern	0	1	4	0	1	6
Southern	0	2	6	0	4	0
Central	0	1	5	0	1	1
Western	0	1	3	0	1	3

For BDIST, at least one peer was evident for each branch with some branches having two or at most three peers at a maximum. The meta and each state group levels were examined for BDIST to establish peers for each branch within each level. Detailed results by branch, state and meta levels for BDIST are included in the appendices.

Results for targets for BDIST are summarised in Table 6.6 below. Full details are included in the appendices. It can be seen from Table 6.6 that the results suggest a much higher potential achievement at full efficiency for Bible distribution when branches are compared across the national or meta level rather than just within their state region.

Table 6.6 — BDIST 2013 summary of targets at meta and group levels

State group	Target at meta level	Target at group level
Northern	330461	228252
Eastern	323887	316662
Southern	265817	79917
Central	116908	45657
Western	78161	35183
Totals	**1115234**	**705671**

6.3 BDIST results from second-stage Tobit regression analysis (TRA)

The TRA (Tobit regression analysis) results for BDIST and DON came from the LIMDEP 9 computer program. In Table 6.7, the overall summary of TRA results is presented for the 6-year mean for TFP and OTE using BDIST dependent variables. In Tables 6.8 to 6.9, summaries of TRA results are presented for TFP and OTE by level respectively, used as the dependent variable, for the 6-year mean in each case. From these tables it can be seen that the model for BDIST in Equation 5.2 is statistically significant in all cases for TFP and OTE at the meta and all group levels. Overall model significance for the respective dependent variables for BDIST was tested using a likelihood ratio test obtained by running the LIMDEP software program (LIMDEP Version 9 Reference Guide, pages R11-R23).

Table 6.7 — BDIST overall summary of TRA results, 6-year mean

Level	Dependent variable (6-yr mean)	Tobit model overall significance	(Coefficient), Direction (+/-) and % significance of independent variable				
			GIDPM	AUXPM	RATAG	BAGE	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$	$\beta_1 = 0(+)$	$\beta_2 = 0(+)$	$\beta_3 = 0$	$\beta_4 = 0(+)$	$\beta_5 = 0$
Meta (i.e. national)	TFP	TS	(.000) –NS	(.000) –NS	(.000) –NS	(.000) –NS	(.030) +1
	OTE	TS	(.001) +NS	(-.002) –10	(-.013) –S	(-.001) –NS	(.150) +1
Northern	TFP	TS	(-.001) –5	(.001) +NS	(-.369) –1	(.000) +NS	(.052) +1
	OTE	TS	(-.002) –10	(.002) +NS	(-.389) –5	(-.000) –NS	(.116) +5
Eastern	TFP	TS	(.000) +NS	(-.002) –1	(-.001) –NS	(.001) +NS	(.054) +1
	OTE	TS	(.003) +1	(-.008) –1	(-.131) –NS	(.002) +NS	(.158) +1
Southern	TFP	TS	(-.001) –10	(-.000) –NS	(.067) +5	(-.002) –1	(.048) +1
	OTE	TS	(.000) +NS	(-.000) –NS	(.236) +10	(-.004) –5	(.185) +10
Central	TFP	TS	(.002) +1	(-.002) –5	(.056) +10	(.005) +1	(.085) +1
	OTE	TS	(.007) +1	(-.020) –1	(.278) +5	(.016) +1	(.380) +1
Western	TFP	TS	(-.001) –NS	(.007) +1	(-.100) –NS	(-.003) –NS	(.099) +10
	OTE	TS	(-.003) –NS	(.008) +10	(-.419) –NS	(.006) +NS	(.034) +NS

(See the explanatory notes below in relation to Tables 6.7 to 6.9.)

The following explanatory notes must be read in conjunction with Tables 6.7 to 6.9 for the BDIST TRA model results:

1. A '+' sign indicates a positive effect and a '–' sign indicates a negative effect on the dependent variable.
2. The 1% level of significance is indicated by '1' and can be interpreted as having 99% confidence in the given result (very high).
3. The 5% level of significance is indicated by '5' and can be interpreted as having 95% confidence in the given result (high).
4. The 10% level of significance of is indicated by '10' and can be interpreted as having 90% confidence in the given result (moderately high).
5. NS = not significant at the 1%, 5% or 10% levels.
6. TS = Tobit model is significant overall (H_0: all $\beta_i = 0$; H_1: at least one of the $\beta_i > 0$, for i =1, 2, 3, 4, 5) (Reject H_0 if P value < 0.1).
7. A positive sign in brackets '(+)' after a particular β_i in the column headings indicates that the coefficient was predicted to be positive and statistically significant. For the other coefficients, no prediction was made.

The following results were found for the five independent TRA variables.

6.3.1 BDIST TFP 6-year mean

At the meta level, the results in Table 6.8 suggest a negative but statistically insignificant effect of all independent variables except URB on BDIST TFP for the study period. This suggests that most variables had no effect on the efficacy of Bible distribution — a suggestion that needs investigation. URB had a positively significant effect at the 1% level, which means that there can be a 99% level of confidence (LOC) in this result for URB. No prediction had been made for URB; now this study has indicated that in future studies the effect of URB could be expected to be positive.

The results at the state group level suggest that URB had a positive effect at the 1% level for all groups except Western (90% LOC), providing further evidence to support a prediction of a positive effect for URB in future. The remaining group results vary in significance and direction. Notably, almost all variables were positively significant for the Central Group; the exception was AUXPM which was negatively significant.

Table 6.8 — BDIST summary of TRA results for TFP, 6-year mean

Level	TFP score (6-yr mean)	Tobit model overall significance	Direction (+/-) and % significance of independent variable				
			GIDPM	AUXPM	RATAG	BAGE	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$	$\beta_1 = 0(+)$	$\beta_2 = 0(+)$	$\beta_3 = 0$	$\beta_4 = 0(+)$	$\beta_5 = 0$
Meta	0.064	TS	–NS	–NS	–NS	–NS	+1
Northern	0.170	TS	–5	+NS	–1	+NS	+1
Eastern	0.106	TS	+NS	–1	–NS	+NS	+1
Southern	0.104	TS	–10	–NS	+5	–1	+1
Central	0.114	TS	+1	–5	+10	+1	+1
Western	0.289	TS	–NS	+1	–NS	–NS	+10

(See the explanatory notes above in relation to Tables 6.7 to 6.9.)

6.3.2 BDIST OTE 6-year mean

At the meta level for BDIST OTE, the results in Table 6.9 show a negative but statistically insignificant effect for RATAG; this was unpredicted. The variable BAGE was also negatively insignificant but no prediction had been made and this result therefore suggests that a prediction of no effect for BAGE on BDIST OTE in future may be appropriate. The result for AUXPM suggests negative significance at the 10% level. An insignificant coefficient was observed for GIDPM. Positive significance for URB at the 1% level was observed; there had been no prediction. This observation suggests a positive effect can be predicted for URB on BDIST OTE in future.

The results at the state group level suggest that URB had a positive effect at either of the 1% (99% LOC), 5% (95% LOC) or 10% (90% LOC) levels for most state groups with Western being the only one being positive but insignificant. The remaining group results suggest varying significance, insignificance and direction. Notably all variables were positively significant for the Central Group except for AUXPM for which the result was negative significant and unpredicted.

Table 6.9 — BDIST summary of TRA results for OTE, 6-year mean

Level	OTE score (6-yr mean)	Tobit model overall significance	Direction (+/-) and % significance of independent variable				
			GIDPM	AUXPM	RATAG	BAGE	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$	$\beta_1 = 0(+)$	$\beta_2 = 0(+)$	$\beta_3 = 0$	$\beta_4 = 0(+)$	$\beta_5 = 0$
Meta	0.341	TS	+NS	–10	–NS	–NS	+1
Northern	0.520	TS	–10	+NS	–5	–NS	+5
Eastern	0.432	TS	+1	–1	–NS	+NS	+1
Southern	0.529	TS	+NS	–NS	+10	–5	+10
Central	0.528	TS	+1	–1	+5	+1	+1
Western	0.724	TS	–NS	+10	–NS	+NS	+NS

(See the explanatory notes above in relation to Tables 6.7 to 6.9).

6.3.3 BDIST — other measures of efficiency, 6-year mean

Calculations were made to get TRA results for measures other than TFP and OTE for BDIST. These results are available but not included in this thesis for the same reason given for the BDIST DEA results in 6.2.2 above. It was noted however that the TRA results for Central for OSE suggested insignificance for all independent variables albeit with some positive and others negative. This was consistent with the result of the likelihood ratio test for Central that suggested one of the four instances only of insignificance for the overall Tobit model being examined for BDIST in this study.

6.3.4 General discussion of BDIST factors affecting performance (TRA for TFP and OTE)

Examination of the results of factors affecting BDIST TFP and OTE found a mixture of predicted and unpredicted results. The results showed that the estimated model was, overall, significant for BDIST TFP and OTE at the meta and all group levels, based on the likelihood ratio tests conducted. Further hypothesis testing of the independent variables in the model suggested an unpredicted negative effect on the efficacy of Bible distribution (BDIST TFP) by all variables except for URB, which had an unpredicted positive effect.

The positive effect of URB on BDIST OTE is noted. The unpredicted negatively significant effect of AUXPM on OTE, and on TFP, stands out. Many of these results need further investigation and may need to be addressed as appropriate by TGIA/TGI.

From the above discussion, the negative effect of AUXPM would appear to be most notable generally as a theme for further research, given its unpredicted effect. Another possible research theme is the value of TRA as a method for elucidating unpredicted directions and significances of factors affecting BDIST BAGE and URB. For future studies of TGIA/TGI, these factors could be predicted as likely to have positive and significant effects on TFP and OTE. The results of applying the TRA method in this study suggest that few of the independent variables used here have positive effects on TFP and OTE, and that TGIA/TGI need to investigate further.

6.4 Fundraising of private donations (DON)

6.4.1 DON productivity and efficiency scores

The results for DON reported in this section are presented in Tables 6.10A, 6.10B, 6.11, 6.12 and 6.13 where the means at different levels (meta and state groups) for DON for the period 2008 to 2013 are summarised. More comprehensive tables, figures and plots presenting DON mean productivity and efficiency scores by level for each year are included in the appendices. Mean TFP scores by level, as recorded in Table 6.10A, are all low. This is reflected in the low mean TFPE scores. Mean OTE scores are low at the meta level, with improvement at group levels. The remaining mean efficiency scores for DON in Table 6.10A appear higher.

Table 6.10A — DON mean productivity and efficiency scores by level for the 6-year period 2008–2013

Level	Meta	Northern	Eastern	Southern	Central	Western
TFP	0.044	0.088	0.232	0.093	0.213	0.300
TFPE	0.203	0.238	0.445	0.326	0.526	0.619
OTE	0.302	0.387	0.584	0.482	0.744	0.843
OSE	0.831	0.768	0.851	0.773	0.818	0.826
OME	1.000	1.000	1.000	1.000	1.000	1.000
ROSE	0.730	0.684	0.786	0.718	0.731	0.739
OSME	0.730	0.684	0.786	0.718	0.731	0.739
ITE	0.441	0.629	0.673	0.562	0.787	0.877
ISE	0.549	0.433	0.711	0.637	0.751	0.793
IME	0.896	0.927	0.969	0.953	0.923	0.938
RISE	0.528	0.410	0.681	0.618	0.734	0.754
ISME	0.482	0.382	0.658	0.588	0.681	0.713
RME	0.888	0.886	0.929	0.935	0.896	0.888

Actual maximum productivity achievable (TFP*) by branches by level and year is presented in Table 6.10B. The results suggest generally low TFP* scores, particularly at the meta level. None of the groups had scores above 0.5 for all years; however, with the exception of Southern, each group had a score of above 0.5 for one or more years during the 6-year period. Technical regress was identified in some cases with some DON TFP* scores.

Table 6.10B — DON maximum productivity achievable (TFP*) by branches by year at meta and state/group level

Year	Meta	Northern	Eastern	Southern	Central	Western
2008	0.183	0.304	0.474	0.250	0.300	0.492
2009	0.219	0.383	0.518	0.338	0.314	0.664
2010	0.189	0.261	0.507	0.382	0.524	0.485
2011	0.259	0.509	0.568	0.226	0.519	0.481
2012	0.201	0.371	0.597	0.242	0.534	0.475
2013	0.264	0.523	0.478	0.341	0.326	0.362

The efficient branches by year for all measures of productivity and efficiency are listed in Table 6.11. Only 15 of the 121 branches (12.4%) in the 6-year period achieved this result at any level. Some branches achieved it in more than one year and some achieved it at both the meta and group levels in a particular year; this has been taken into account in arriving at the Figure 15.

Table 6.11 — DON summary of efficient branches by year for all measures of productivity and efficiency

Branch	Year	TFP	Notes[1]
National/All Australia/Meta (M)			
M17	2008	0.183	GN
M17	2009	0.219	GN
M85	2010	0.189	GS
M17	2011	0.259	GN
M17	2012	0.201	GN
M17	2013	0.264	GN
Northern (N)			
N17	2008	0.304	M
N17	2009	0.383	M
N17	2010	0.261	
N17	2011	0.509	M
N17	2012	0.371	M
N17	2013	0.523	M
Eastern (E)			
E25	2008	0.474	
E1	2009	0.518	
E1	2010	0.507	
E1	2011	0.568	
E1	2012	0.597	
E1	2013	0.478	
Southern (S)			
S3	2008	0.250	
S3	2009	0.338	
S20	2010	0.382	M
S15	2011	0.226	
S31	2012	0.242	
S3	2013	0.341	
Central (C)			
C14	2008	0.300	
C3	2009	0.314	
C1	2010	0.524	
C1	2011	0.519	
C1	2012	0.534	
C13	2013	0.326	
Western (W)			
W3	2008	0.492	
W9	2009	0.664	
W4	2010	0.485	
W10	2011	0.481	
W9	2012	0.475	
W9	2013	0.362	

Comment

The TFP was the best achievable based on the data at the time

Notes

1. GN=branch also efficient at Northern Group level
2. GS=branch also efficient at Southern Group level
3. M=branch also efficient at meta all Australia level

6.4.2 DON descriptive statistics of productivity and efficiency scores

In Tables 6.12 and 6.13 below, descriptive statistics are presented for all DON mean TFP and OTE at the meta and group levels for the 6-year period. The difference in variability suggested by high coefficients of variation (CV) reflected in those tables might again be attributable to different or more prominent environmental factors affecting the performance of branches in a particular State and at the meta level. From Table 6.12 (DON mean TFP) it can be seen that mean observed TFP over the 6-year period was low at all levels. Even though the 6-year mean TFP for each state group was higher, it was still low in magnitude. The magnitude of the CV indicates wide variation at all levels, and very particularly for Northern, with Eastern, Central and Western showing much less variation than at other levels.

Table 6.12 — Descriptive statistics of DON mean TFP by level for 2008–2013

Level	Mean	Min	Max	Std Dev	CV %
Meta	0.044	0.005	0.264	0.028	64
Northern	0.088	0.007	0.523	0.070	80
Eastern	0.232	0.057	0.597	0.112	48
Southern	0.093	0.018	0.382	0.061	66
Central	0.213	0.046	0.534	0.098	46
Western	0.300	0.079	0.664	0.125	42

From Table 6.13 it can be seen that mean OTE over the 6-year period was more encouraging in terms of magnitude. The overall 6-year mean OTE at the meta level was 0.302 (30.2%), suggesting that the output of DON could have increased by 69.8% without any change in the available level of inputs (number of Gideon and Auxiliary members). Similar interpretations can be applied for each state group level. The magnitude of the CV indicates wide variation at all levels, and very particularly for Northern, with Eastern, Central and Western showing much less variation than at other levels.

Table 6.13 — Descriptive statistics of DON mean OTE by level for 2008–2013

Level	Mean	Min	Max	Std Dev	CV %
Meta	0.302	0.022	1.000	0.213	71
Northern	0.387	0.044	1.000	0.290	75
Eastern	0.584	0.132	1.000	0.277	47
Southern	0.482	0.075	1.000	0.296	61
Central	0.744	0.273	1.000	0.226	30
Western	0.843	0.272	1.000	0.236	28

Tables displaying descriptive statistics for measures other than TFP and OTE for DON are available but are not included in this thesis. They are not included for TFPE because of the close relationship between TFP and TFPE. It was observed that mean efficiency scores for the remaining measures for DON (OSE etc.) generally appear comparatively high at the meta and all state group levels. It was considered therefore that little would be lost by not including descriptive statistics for measures other than TFP and OTE.

6.4.3 DON overall performance (TFP and TFP*) and efficiency (OTE)

It is recommended that the discussion on BDIST in Section 6.2.3 above be read in conjunction with this section. Some of that discussion applies equally to DON.

Some results for DON from this study could cause management concern, as is the case for BDIST above. Overall, DON TFP and TFP* scores were generally low, similar to BDIST, and there were unexpected very low scores for TFP*.

During the 6-year period examined, only 15 of the 121 branches studied (12.4%) were 100% efficient for DON for all measures of efficiency at all levels in the whole period. This result again did not surprise given the results reported by Tofallis and Sargeant (2000), discussed in 6.2.3 above for BDIST.

6.4.4 DON slacks, peers and targets

Results for slacks for DON are summarised in Tables 6.14 below. Full details are included in the appendices. It can be seen from Table 6.14 that there is evidence of input slack at all levels for DON.

Table 6.14 — DON 2013 summary of slacks at meta and group levels

Level	Mean DON output slacks at meta level	Mean GID input slacks at meta level	Mean AUX input slacks at meta level	Mean DON output slacks at group level	Mean GID input slacks at group level	Mean AUX input slacks at group level
Meta	0	2	2	N/A	N/A	N/A
Northern	0	3	3	0	4	3
Eastern	0	2	1	0	0	1
Southern	0	2	2	0	2	0
Central	0	1	1	0	3	2
Western	0	2	1	0	2	1

For DON, at least one peer was evident for each branch with some branches having two or at most three peers at a maximum. The meta and each state group level were examined for DON to establish peers for each branch within each level. Detailed results by branch, state and meta levels for DON are included in the appendices.

Results for targets for DON are summarised in Table 6.15 below. Full details are included in the appendices. It can be seen from Table 6.15 that the results suggest a much higher potential achievement at full efficiency for Bible distribution when branches are compared across the national or meta level rather than just within their state region.

Table 6.15 — DON 2013 summary of targets at meta and group levels

State group	Target at meta level	Target at group level
Northern	3262825	2928281
Eastern	2920351	881183
Southern	2709708	1618845
Central	1200838	247110
Western	657417	155787
Totals	**10751139**	**5831206**

6.5 DON results from second-stage Tobit regression analysis (TRA)

An overall summary of TRA (Tobit regression analysis) results for the 6-year mean for TFP and OTE are presented in Table 6.16. In Tables 6.17 to 6.18, summaries of TRA results are presented by level using the 6-year means of TFP and OTE, respectively, as the dependent variable. From these tables it can be seen that the model for DON in Equation 5.5 in Chapter 5 above is significant in all cases for TFP and OTE at the meta and all group levels. Overall model significance for the respective dependent variables for DON was tested using a likelihood ratio test obtained from the output of the LIMDEP software program (LIMDEP Version 9 Reference Guide, pages R11-R23).

Table 6.16 — DON overall summary of TRA results, 6-year mean

Level	Dependent variable (6-yr mean)	Tobit model overall significance	(Coefficient), Direction (+/-) and % significance of independent variable					
			GIDPM	AUXPM	RATAG	BAGE	CPVIS	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$	β_1=0(+)	β_2=0(+)	β_3=0	β_4=0(+)	β_5=0(+)	β_6=0
Meta (i.e. National)	TFP	TS	(.000) +1	(-.000) –5	(.009) +NS	(-.000) –5	(.001) +1	(-.000) –NS
	OTE	TS	(.002) +1	(-.004) –1	(-.115) –5	(-.003) –1	(.006) +1	(-.008) –NS
Northern	TFP	TS	(.001) +1	(-.001) –10	(-.009) –NS	(-.004) –1	(.001) +5	(-.002) –NS
	OTE	TS	(.002) +10	(-.005) –5	(.107) +NS	(-.013) –1	(.002) +NS	(-.023) –NS
Eastern	TFP	TS	(.003) +1	(-.002) –1	(-.008) –NS	(.003) +1	(.003) +1	(.024) +NS
	OTE	TS	(.007) +1	(-.009) –1	(-.287) –1	(.004) +5	(.008) +1	(.029) +NS
Southern	TFP	TS	(.001) +1	(-.001) –5	(-.037) –NS	(-.000) –NS	(.002) +1	(.006) +NS
	OTE	TS	(.005) +1	(-.004) –10	(-.187) –NS	(-.002) –NS	(.013) +1	(.040) +NS
Central	TFP	TS	(-.000) –NS	(.003) +NS	(-.052) –NS	(.002) +NS	(.003) +1	(.024) +NS
	OTE	TS	(.001) +NS	(-.009) –10	(.131) +NS	(.007) +5	(.002) +NS	(.115) +5
Western	TFP	TS	(-.002) –NS	(.005) +1	(-.015) –NS	(-.002) –NS	(.007) +1	(-.091) –5
	OTE	TS	(-.002) –NS	(.006) +5	(-.298) –NS	(.006) +NS	(.010) +5	(-.310) –1

(See the explanatory notes below in relation to Tables 6.16 to 6.18.)

The following explanatory notes must be read in conjunction with Tables 6.16–6.18 for the DON TRA model results:

1. A '+' sign indicates a positive influence and a '–' sign indicates a negative influence on the dependent variable.
2. The level of significance of 1% is indicated by '1' and can be interpreted as having 99% confidence in the given result (very high).
3. The level of significance of 5% is indicated by '5' and can be interpreted as having 95% confidence in the given result (high).
4. The level of significance of 10% is indicated by '10' and can be interpreted as having 90% confidence in the given result (moderately high).
5. NS = not significant at the 1%, 5% or 10% levels.
6. TS = Tobit model is significant overall (H_0: all $\beta_i = 0$; H_1: at least one of the $\beta_i > 0$, for $i = 1, 2, 3, 4, 5, 6$) (Reject H_0 if P value < 0.1).
7. A positive sign in brackets '(+)' after a particular β_i in the column headings indicates that that coefficient was predicted to be positive and statistically significant. For the other coefficients, no prediction was made.

The following results were found for the six independent TRA variables.

6.5.1 DON TFP 6-year mean

At the meta level for the model with TFP as the dependent variable, it can be seen in Table 6.17 that the estimated coefficients for both GIDPM and CPVIS are positive and statistically significant at the 1% level (99% LOC). This means that GIDPM and CPVIS had a predicted positive effect on the efficacy of fundraising of private donations. A negative statistically significant effect is suggested for AUXPM and BAGE at the 5% level (95% LOC) while the coefficients of RATAG and URB were positive and negative, respectively, but insignificant. This means that AUXPM had an unpredicted negative effect on the efficacy of fundraising of private donations. No predictions were made for BAGE so at least now there is some evidence to support a prediction of negative effect in future for this variable.

The result that stands out at the state group level is that CPVIS has a positive effect on TFP at the 1% level for all groups except Northern (at the 5% level). The remaining group results suggest varying significance and direction. Notably, the coefficients for

RATAG were insignificant for all state group levels and at the meta level, which was unpredicted. Except for Central (insignificant) and Western (positively significant at 1% level), the results suggest an unpredicted negative effect on TFP by AUXPM, at varying levels of significance for the other state groups. URB for the state groups was generally insignificant except for Central, for which the coefficient is negative at 5% level of significance.

Table 6.17 — DON summary of TRA results for TFP, 6-year mean

Level	TFP Score (6-yr mean)	Tobit model overall significance	Direction (+/-) and % significance of independent variable					
			GIDPM	AUXPM	RATAG	BAGE	CPVIS	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$	β_1=0(+)	β_2=0(+)	β_3=0	β_4=0(+)	β_5=0(+)	β_6=0
Meta	0.044	TS	+1	–5	+NS	–5	+1	–NS
Northern	0.088	TS	+1	–10	–NS	–1	+5	–NS
Eastern	0.232	TS	+1	–1	–NS	+1	+1	+NS
Southern	0.093	TS	+1	–5	–NS	–NS	+1	+NS
Central	0.213	TS	–NS	+NS	–NS	+NS	+1	+NS
Western	0.300	TS	–NS	+1	–NS	–NS	+1	–5

(See the explanatory notes above in relation to Tables 6.16 to 6.18.)

6.5.2 DON OTE 6-year mean

At the meta level for OTE, the coefficients reported in Table 6.18 show a statistically insignificant effect for URB (not predicted), a negative significance at the 1% level for AUXPM (unpredicted) and BAGE (not predicted) and 5% level for RATAG (unpredicted). There was a predicted positive significance at the 1% level for GIDPM and CPVIS coefficients.

The results at the state group level suggested that AUXPM had an unpredicted negative effect at one of the 1%, 5% or 10% levels for most state groups, with Western being the only one with a predicted positive significance at the 5% level. GIDPM was also positively significant as predicted at the 1% level for Northern, Eastern and Southern while for Central and Western there was insignificance. The remaining group results suggest varying significance and direction.

Table 6.18 — DON summary of TRA results for OTE, 6-year mean

Level	OTE score (6-yr mean)	Tobit model overall significance	Direction (+/-) and % significance of independent variable					
			GIDPM	AUXPM	RATAG	BAGE	CPVIS	URB
Null hypothesis		$\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$	$\beta_1=0(+)$	$\beta_2=0(+)$	$\beta_3=0$	$\beta_4=0(+)$	$\beta_5=0(+)$	$\beta_6=0$
Meta	0.302	TS	+1	–1	–5	–1	+1	–NS
Northern	0.387	TS	+10	–5	+NS	–1	+NS	–NS
Eastern	0.584	TS	+1	–1	–1	+5	+1	+NS
Southern	0.482	TS	+1	–10	–NS	–NS	+1	+NS
Central	0.744	TS	+NS	–10	+NS	+5	+NS	+5
Western	0.843	TS	–NS	+5	–NS	+NS	+5	–1

(See the explanatory notes above in relation to Tables 6.16 to 6.18.)

6.5.3 DON - Other Measures of Efficiency, 6-Year Mean

Calculations were made to get results for measures other than TFP and OTE for DON TRA models. These results are available but not included in this thesis for the same reason given for the DON DEA results in Section 6.2.2 above. It was noted, however, that the TRA results for Western for OSE, ROSE and OSME suggest insignificance for all independent variables. This result was consistent with the result of the likelihood ratio test for OSE, ROSE and OSME for Western that suggested three of the four instances only of insignificance for the overall Tobit model being examined for DON in this study.

6.5.4 General discussion of factors affecting DON performance (TRA for TFP, and OTE)

There is again a mixture of predicted and unpredicted results evident when the results from TRA model estimates of factors affecting DON TFP and OTE. The estimated model was overall significant for DON TFP and OTE at the meta and all group levels, based on the likelihood ratio tests conducted. Further hypothesis testing of the independent variables in the model suggests more intuitive results for DON than for BDIST, with a predicted positive effect on the efficacy of fundraising of private donations (DON TFP) by GIDPM and CPVIS. It is notable that the results for AUXPM

suggest an unpredicted negative effect for that variable on the efficacy of fundraising of private donations (DON TFP). The unpredicted negatively significant effect of AUXPM on DON OTE is noted. Many of these results need further investigation and addressing as appropriate by TGIA/TGI.

From the above discussion, the negative effect of AUXPM would appear again to be most notable generally as a theme for further research, given its unpredicted effect. The presence of unpredicted results of the TRA suggests the absence of a theme of positive effect of some variables on TFP and OTE as was predicted for most variables. As in the case of BDIST, this also suggests a need for further investigation by TGIA/TGI.

6.6 Commentary on the results

In framing commentary on the results from this study for TGIA, it is important to remember the environment in which TGIA and other charities operate in Australia, discussed in Chapters 1 and 2. The results from DEA for TGIA generally showed low productivity and efficiency scores at all levels of operation for both BDIST and DON. The magnitude of the coefficient of variation (CV) at all levels, for both BDIST and DON, testifies to the wide spread of output and input at all levels from branch to state to meta for TGIA. This spread can easily be detected in a visual inspection of the raw data and so the magnitude of the CV was somewhat expected. The results from the TRA for TGIA for both BDIST and DON have thrown some light on influential factors affecting TFP and OTE. However, further research is suggested, to uncover other influential factors. All of this suggests prudential investigation by TGIA.

In terms of the Bible distribution (BDIST) activities in which it engages, TGIA appears unique. The results for BDIST from this study may be partly explained by the existence of legal and regulatory restrictions, together with a growing reluctance by those in authority outside TGIA to permit distribution of Bibles to traditional outlets. This suggestion has not been explored within the scope of this study and may prove to be elusive, for example if there is lack of data. For DON, the explanation of the results could also come from the increasing forces of competition for donations and other economic pressures — including higher administrative and compliance costs — across the whole spectrum of the not-for-profit and charitable sector in Australia (e.g.

Robertson 2014). This suggestion was not explored within the scope of this study because of lack of data.

It would therefore appear incumbent on the governing body of TGIA, in the short term, to formulate and adopt appropriate risk management and other policies as a matter of fiduciary responsibility and good governance to ensure the continuing viability of TGIA in the long term. This is essential in the environment of continuous risk and uncertainty that has come to be part of normal life. It is acknowledged that TGIA management might already have recognised, acted on or be working to solve some or all of these findings.

6.7 Summary and conclusions

In this chapter the results from the DEA, TRA and empirical models that were estimated and discussed in Chapter 5 have been summarised, presented and evaluated. The descriptive statistics of the productivity and efficiency scores have also been presented and discussed. More comprehensive descriptive statistics and plots are included in the appendices. Attention was paid in this chapter to what are considered the most important results. Commentary has been given on the results in the context of the environment in which TGIA operates. The coverage of MFA and MTRs in Chapter 7 that follows gives more commentary on comparisons made between different levels of operation in TGIA.

CHAPTER 7: PRODUCTIVITY DIFFERENCES BY STATE GROUP

In this chapter an application of the meta-frontier approach (MFA) in the TGIA context is explored. The main purpose of the chapter is to find productivity differences that could be attributed to differences in the grouping that has been specified earlier in the thesis. Data and results from the earlier work in the thesis are used in this application, which extends previous research work and adds to the literature in the MFA topic area. The concepts of MFA, a review of related literature and possible reasons for technology gaps at different levels of TGIA were addressed in Chapter 3. The empirical models estimated in this chapter were set out in Chapter 5 for Bible distribution (BDIST) and fundraising of private donations (DON) (Equations 5.3 and 5.4).

7.1 The empirical application to TGIA

In the context of TGIA in this thesis, MFA has been applied to the output technical efficiency (OTE) situation. The extension to total factor productivity (TFP) as in O'Donnell et al. (2011) has also been applied.

7.1.1 Introduction

Panel datasets for BDIST and DON were constructed from results obtained in the earlier stages of this study to facilitate the calculation of MTRs, which were calculated using Microsoft Excel 2003 .xls format. The same meta-frontier and five state regions/groups as in previous chapters were used for MFA. The MTR results were presented, examined and interpreted. Possible explanations for the existence of gaps between the results from the meta and group levels were addressed.

The MTRs displayed in Tables 7.1 to 7.14 are those for ratios of means at the meta and group levels. For this reason they reflect immaterial rounding differences that have arisen during the process. This has resulted in the ratio of the meta to state group figure not always being exactly the same as the MTR figure shown in the tables.

7.1.2 Extension to MFA for BDIST

(a) Results for BDIST

In Tables 7.1 to 7.7 the BDIST summary of mean meta-technology ratio (MTR) by level and year at the meta-frontier and all state group levels used to obtain estimates of total factor productivity (TFP) and output technical efficiency (OTE) are presented.

(i) Meta-frontier

Table 7.1 provides an overall summary of BDIST mean MTR by level and year.

Table 7.1 — BDIST summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Northern Mean 2008	0.067	0.170	0.412	0.359	0.507	0.735
Eastern Mean 2008	0.082	0.106	0.771	0.422	0.422	1.000
Southern Mean 2008	0.043	0.097	0.439	0.246	0.581	0.413
Central Mean 2008	0.041	0.099	0.413	0.222	0.587	0.389
Western Mean 2008	0.082	0.327	0.253	0.444	0.759	0.582
Meta Mean 2008	**0.063**	**0.160**	**0.458**	**0.338**	**0.571**	**0.624**
Northern Mean 2009	0.063	0.159	0.411	0.383	0.551	0.729
Eastern Mean 2009	0.077	0.100	0.770	0.458	0.477	0.975
Southern Mean 2009	0.045	0.103	0.439	0.277	0.494	0.549
Central Mean 2009	0.049	0.118	0.415	0.278	0.576	0.546
Western Mean 2009	0.084	0.340	0.251	0.504	0.735	0.697
Meta Mean 2009	**0.064**	**0.164**	**0.457**	**0.380**	**0.567**	**0.699**
Northern Mean 2010	0.068	0.175	0.412	0.333	0.528	0.670
Eastern Mean 2010	0.084	0.109	0.771	0.414	0.414	1.000
Southern Mean 2010	0.047	0.107	0.438	0.249	0.525	0.433
Central Mean 2010	0.052	0.126	0.413	0.229	0.435	0.558
Western Mean 2010	0.069	0.270	0.258	0.340	0.690	0.483
Meta Mean 2010	**0.064**	**0.157**	**0.458**	**0.313**	**0.518**	**0.629**
Northern Mean 2011	0.069	0.174	0.408	0.403	0.500	0.812
Eastern Mean 2011	0.082	0.106	0.771	0.480	0.480	0.999
Southern Mean 2011	0.050	0.114	0.438	0.326	0.457	0.695
Central Mean 2011	0.042	0.103	0.414	0.233	0.558	0.427
Western Mean 2011	0.066	0.262	0.253	0.389	0.754	0.531
Meta Mean 2011	**0.062**	**0.152**	**0.457**	**0.366**	**0.550**	**0.693**
Northern Mean 2012	0.061	0.155	0.405	0.345	0.596	0.597
Eastern Mean 2012	0.085	0.110	0.772	0.448	0.448	1.000
Southern Mean 2012	0.043	0.099	0.438	0.223	0.520	0.451
Central Mean 2012	0.052	0.127	0.414	0.322	0.431	0.722
Western Mean 2012	0.065	0.249	0.258	0.311	0.726	0.437
Meta Mean 2012	**0.061**	**0.148**	**0.457**	**0.330**	**0.544**	**0.641**
Northern Mean 2013	0.072	0.185	0.414	0.307	0.436	0.708
Eastern Mean 2013	0.079	0.102	0.772	0.342	0.352	0.968
Southern Mean 2013	0.046	0.104	0.438	0.219	0.599	0.350
Central Mean 2013	0.047	0.113	0.417	0.248	0.578	0.428
Western Mean 2013	0.073	0.289	0.259	0.328	0.680	0.492
Meta Mean 2013	**0.063**	**0.159**	**0.460**	**0.289**	**0.529**	**0.589**

The results in Table 7.2 show a mean TFP MTR of 0.458 (45.8%) for the 6-year period. That is, on average a state group with its group technology achieved only 45.8% of the TFP that it could have achieved if it had used the meta-technology. It suggests the existence of a technology gap of 54.2% between a group frontier and the meta-frontier. On a year-by-year basis there was almost negligible change in this MTR. The MTR used to estimate OTE of 0.646 (64.6%) indicates a gap of 35.4%. This is interpreted as showing that on average the state group with its own technology was only 64.6% as output technically efficient as it could have been if it had used the meta-technology. Again, there was little fluctuation in MTRs across the study period.

Table 7.2 — BDIST Meta summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Meta Mean 2008	0.063	0.160	0.458	0.338	0.571	0.624
Meta Mean 2009	0.064	0.164	0.457	0.380	0.567	0.699
Meta Mean 2010	0.064	0.157	0.458	0.313	0.518	0.629
Meta Mean 2011	0.062	0.152	0.457	0.366	0.550	0.693
Meta Mean 2012	0.061	0.148	0.457	0.330	0.544	0.641
Meta Mean 2013	0.063	0.159	0.460	0.289	0.529	0.589
6-Year Mean	**0.063**	**0.157**	**0.458**	**0.336**	**0.547**	**0.646**

(ii) Northern state group

The results in Table 7.3 reveal a mean TFP MTR of 0.410 (41.0%) for the Northern region for the 6-year period. This is interpreted as showing that on average a branch in this state group achieved only 41.0% of the total factor productivity (TFP) that it could have achieved if it had used the group technology. It suggests the existence of a technology gap between a group frontier and the branch of 59.0%. On a year by year basis there was almost negligible change in this MTR. Output technical efficiency (OTE) had a MTR of 0.709 (70.9%) with little fluctuation year by year suggesting a gap of 29.1%. This is interpreted as showing that on average a branch with its own technology was only 70.9% as output technically efficient as it could have been if it had used the group technology.

Table 7.3 — BDIST Northern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Northern Mean 2008	0.067	0.170	0.412	0.359	0.507	0.735
Northern Mean 2009	0.063	0.159	0.411	0.383	0.551	0.729
Northern Mean 2010	0.068	0.175	0.412	0.333	0.528	0.670
Northern Mean 2011	0.069	0.174	0.408	0.403	0.500	0.812
Northern Mean 2012	0.061	0.155	0.405	0.345	0.596	0.597
Northern Mean 2013	0.072	0.185	0.414	0.307	0.436	0.708
6-Year Mean	**0.067**	**0.170**	**0.410**	**0.355**	**0.520**	**0.709**

(iii) Eastern state group

From Table 7.4 (Eastern) it can be seen that the results suggest a mean TFP MTR of 0.771 (77.1%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 77.1% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 22.9%. On a year-by-year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.990 (99.0%) with little fluctuation year by year suggesting a gap of only 1% (approaching negligible). This is interpreted as showing that on average a branch with its own technology was 99.0% as output technically efficient as it could have been if it had used the group technology. OTE was 100% for three of the years.

Table 7.4 — BDIST Eastern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Eastern Mean 2008	0.082	0.106	0.771	0.422	0.422	1.000
Eastern Mean 2009	0.077	0.100	0.770	0.458	0.477	0.975
Eastern Mean 2010	0.084	0.109	0.771	0.414	0.414	1.000
Eastern Mean 2011	0.082	0.106	0.771	0.480	0.480	0.999
Eastern Mean 2012	0.085	0.110	0.772	0.448	0.448	1.000
Eastern Mean 2013	0.079	0.102	0.772	0.342	0.352	0.968
6-Year Mean	**0.082**	**0.106**	**0.771**	**0.427**	**0.432**	**0.990**

(iv) Southern state group

From Table 7.5 (Southern) it can be seen that the results suggest a mean TFP MTR of 0.438 (43.8%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 43.8% of the TFP

as it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 56.2%. On a year by year basis there was almost negligible change in this MTR. OTE had an MTR of 0.482 (48.2%) with some fluctuation year by year suggesting a gap of 51.8%. This is interpreted as showing that on average a branch using its own technology was only 48.2% as output technically efficient as it could have been if it had used the group technology.

Table 7.5 — BDIST Southern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Southern Mean 2008	0.043	0.097	0.439	0.246	0.581	0.413
Southern Mean 2009	0.045	0.103	0.439	0.277	0.494	0.549
Southern Mean 2010	0.047	0.107	0.438	0.249	0.525	0.433
Southern Mean 2011	0.050	0.114	0.438	0.326	0.457	0.695
Southern Mean 2012	0.043	0.099	0.438	0.223	0.520	0.451
Southern Mean 2013	0.046	0.104	0.438	0.219	0.599	0.350
6-Year Mean	**0.046**	**0.104**	**0.438**	**0.257**	**0.529**	**0.482**

(v) Central state group

From Table 7.6 (Central) it can be seen that the results suggest a mean TFP MTR of 0.414 (41.4%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 41.4% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 58.6%. On a year by year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.512 (51.2%) with some fluctuation year by year suggesting a gap of 48.8%. This is interpreted as showing that on average a branch using its own technology was only 51.2% as output technically efficient as it could have been if it had used the group technology.

Table 7.6 — BDIST Central summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Central Mean 2008	0.041	0.099	0.413	0.222	0.587	0.389
Central Mean 2009	0.049	0.118	0.415	0.278	0.576	0.546
Central Mean 2010	0.052	0.126	0.413	0.229	0.435	0.558
Central Mean 2011	0.042	0.103	0.414	0.233	0.558	0.427
Central Mean 2012	0.052	0.127	0.414	0.322	0.431	0.722
Central Mean 2013	0.047	0.113	0.417	0.248	0.578	0.428
6-Year Mean	**0.047**	**0.114**	**0.414**	**0.255**	**0.528**	**0.512**

(vi) Western state group

From Table 7.7 (Western) it can be seen that the results suggest a mean BDIST total factor productivity (TFP) MTR of 0.255 (25.5%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 25.5% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 74.5%. On a year-by-year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.517 (51.7%) with some fluctuation year by year suggesting a gap of 48.3%. This is interpreted as showing that on average a branch using its own technology was only 51.7% as output technically efficient as it could have been if it had used the group technology.

Table 7.7 — BDIST Western summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Western Mean 2008	0.082	0.327	0.253	0.444	0.759	0.582
Western Mean 2009	0.084	0.340	0.251	0.504	0.735	0.697
Western Mean 2010	0.069	0.270	0.258	0.340	0.690	0.483
Western Mean 2011	0.066	0.262	0.253	0.389	0.754	0.531
Western Mean 2012	0.065	0.249	0.258	0.311	0.726	0.437
Western Mean 2013	0.073	0.289	0.259	0.328	0.680	0.492
6-Year Mean	**0.073**	**0.289**	**0.255**	**0.386**	**0.724**	**0.537**

7.1.3 Extension to a meta-frontier approach (MFA) for DON

(a) Results for DON

In Tables 7.8 to 7.14 the DON summary of mean MTR by level and year at the meta-frontier and all state group levels for TFP and OTE are presented.

(i) Meta-frontier

Table 7.8 provides an overall summary of DON mean MTR by level and year.

Table 7.8 — DON summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Northern Mean 2008	0.049	0.195	0.290	0.333	0.436	0.838
Eastern Mean 2008	0.037	0.229	0.161	0.308	0.587	0.518
Southern Mean 2008	0.044	0.089	0.494	0.347	0.494	0.690
Central Mean 2008	0.034	0.188	0.183	0.247	0.842	0.294
Western Mean 2008	0.050	0.307	0.161	0.440	0.885	0.489
Meta Mean 2008	**0.043**	**0.202**	**0.258**	**0.335**	**0.649**	**0.566**
Northern Mean 2009	0.053	0.094	0.564	0.315	0.402	0.877
Eastern Mean 2009	0.040	0.249	0.161	0.295	0.628	0.457
Southern Mean 2009	0.045	0.091	0.493	0.298	0.419	0.690
Central Mean 2009	0.033	0.180	0.185	0.185	0.809	0.233
Western Mean 2009	0.056	0.342	0.158	0.449	0.757	0.604
Meta Mean 2009	**0.045**	**0.191**	**0.312**	**0.308**	**0.603**	**0.572**
Northern Mean 2010	0.049	0.088	0.566	0.412	0.518	0.853
Eastern Mean 2010	0.037	0.228	0.161	0.334	0.583	0.573
Southern Mean 2010	0.047	0.094	0.493	0.377	0.470	0.797
Central Mean 2010	0.039	0.215	0.182	0.299	0.630	0.509
Western Mean 2010	0.050	0.291	0.164	0.395	0.807	0.479
Meta Mean 2010	**0.044**	**0.183**	**0.313**	**0.363**	**0.602**	**0.642**
Northern Mean 2011	0.049	0.089	0.557	0.246	0.323	0.873
Eastern Mean 2011	0.038	0.233	0.161	0.242	0.565	0.409
Southern Mean 2011	0.046	0.092	0.496	0.323	0.583	0.516
Central Mean 2011	0.045	0.244	0.183	0.216	0.708	0.313
Western Mean 2011	0.051	0.320	0.159	0.339	0.860	0.389
Meta Mean 2011	**0.046**	**0.196**	**0.311**	**0.273**	**0.608**	**0.500**
Northern Mean 2012	0.044	0.082	0.555	0.277	0.387	0.829
Eastern Mean 2012	0.037	0.229	0.161	0.317	0.539	0.565
Southern Mean 2012	0.048	0.098	0.493	0.338	0.528	0.645
Central Mean 2012	0.046	0.257	0.184	0.393	0.680	0.548
Western Mean 2012	0.045	0.274	0.164	0.358	0.806	0.437
Meta Mean 2012	**0.044**	**0.188**	**0.311**	**0.337**	**0.588**	**0.605**
Northern Mean 2013	0.047	0.085	0.575	0.211	0.255	0.850
Eastern Mean 2013	0.036	0.221	0.162	0.224	0.600	0.361
Southern Mean 2013	0.046	0.093	0.494	0.236	0.398	0.604
Central Mean 2013	0.037	0.194	0.189	0.217	0.792	0.260
Western Mean 2013	0.046	0.265	0.166	0.240	0.943	0.253
Meta Mean 2013	**0.042**	**0.172**	**0.317**	**0.225**	**0.598**	**0.466**

From Table 7.9 (Meta) it can be seen that the results suggest a mean DON TFP MTR of 0.304 (30.4%) for the 6-year period. This is interpreted as showing that on average a state group using its group technology achieved only 30.4% of the TFP that it could have achieved if it had used the meta-technology. This suggests the existence of a technology gap between a group frontier and the meta-frontier of 69.6%. On a year-by-year basis there was little change in this MTR. OTE had an MTR of 0.558 (55.8%) with little fluctuation year by year suggesting a gap of 44.2%. This is interpreted as showing that on average the state group using its own technology was only 55.8% as output technically efficient as it could have been if it had used the meta-technology.

Table 7.9 — DON Meta summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Meta Mean 2008	0.043	0.202	0.258	0.335	0.649	0.566
Meta Mean 2009	0.045	0.191	0.312	0.308	0.603	0.572
Meta Mean 2010	0.044	0.183	0.313	0.363	0.602	0.642
Meta Mean 2011	0.046	0.196	0.311	0.273	0.608	0.500
Meta Mean 2012	0.044	0.188	0.311	0.337	0.588	0.605
Meta Mean 2013	0.042	0.172	0.317	0.225	0.598	0.466
6-Year Mean	**0.044**	**0.189**	**0.304**	**0.307**	**0.608**	**0.558**

(ii) Northern state group

From Table 7.10 (Northern) it can be seen that the results suggest a mean DON total factor productivity MTR of 0.518 (51.8%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 51.8% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 48.2%. On a year-by-year basis there was a little change in this MTR. OTE had an MTR of 0.854 (85.4%) with little fluctuation year by year suggesting a comparatively modest gap of 14.6%. This is interpreted as showing that on average a branch using its own technology was only 85.4% as output technically efficient as it could have been if it had used the group technology.

Table 7.10 — DON Northern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Northern Mean 2008	0.049	0.195	0.290	0.333	0.436	0.838
Northern Mean 2009	0.053	0.094	0.564	0.315	0.402	0.877
Northern Mean 2010	0.049	0.088	0.566	0.412	0.518	0.853
Northern Mean 2011	0.049	0.089	0.557	0.246	0.323	0.873
Northern Mean 2012	0.044	0.082	0.555	0.277	0.387	0.829
Northern Mean 2013	0.047	0.085	0.575	0.211	0.255	0.850
6-Year Mean	**0.048**	**0.106**	**0.518**	**0.299**	**0.387**	**0.854**

(iii) Eastern state group

From Table 7.11 (Eastern) it can be seen that the results suggest a mean DON total factor productivity MTR of 0.161 (16.1%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 16.1% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 83.9%. On a year-by-year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.481 (48.1%) with fluctuation year by year suggesting a gap of 51.9%. This is interpreted as showing that on average a branch using its own technology was 48.1% as output technically efficient as it could have been if it had used the group technology.

Table 7.11 — DON Eastern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Eastern Mean 2008	0.037	0.229	0.161	0.308	0.587	0.518
Eastern Mean 2009	0.040	0.249	0.161	0.295	0.628	0.457
Eastern Mean 2010	0.037	0.228	0.161	0.334	0.583	0.573
Eastern Mean 2011	0.038	0.233	0.161	0.242	0.565	0.409
Eastern Mean 2012	0.037	0.229	0.161	0.317	0.539	0.565
Eastern Mean 2013	0.036	0.221	0.162	0.224	0.600	0.361
6-Year Mean	**0.037**	**0.232**	**0.161**	**0.287**	**0.584**	**0.481**

(iv) Southern state group

From Table 7.12 (Southern) it can be seen that the results suggest a mean DON total factor productivity MTR of 0.494 (49.4%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 49.4% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 50.6%. On a year by year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.657 (65.7%) with fluctuation year by year suggesting a gap of 34.3%. This is interpreted as showing that on average a branch using its own technology was only 65.7% as output technically efficient as it could have been if it had used the group technology.

Table 7.12 — DON Southern summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Southern Mean 2008	0.044	0.089	0.494	0.347	0.494	0.690
Southern Mean 2009	0.045	0.091	0.493	0.298	0.419	0.690
Southern Mean 2010	0.047	0.094	0.493	0.377	0.470	0.797
Southern Mean 2011	0.046	0.092	0.496	0.323	0.583	0.516
Southern Mean 2012	0.048	0.098	0.493	0.338	0.528	0.645
Southern Mean 2013	0.046	0.093	0.494	0.236	0.398	0.604
6-Year Mean	**0.046**	**0.093**	**0.494**	**0.320**	**0.482**	**0.657**

(v) Central state group

From Table 7.13 (Central) it can be seen that the results suggest a mean DON total factor productivity MTR of 0.184 (18.4%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 18.4% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 81.6%. On a year-by-year basis there was almost negligible change in this MTR. Output technical efficiency had an MTR of 0.359 (35.9%) with some fluctuation year by year suggesting a gap of 64.1%. This is interpreted as showing that on average a branch using its own technology was only 35.9% as output technically efficient as it could have been if it had used the group technology.

Table 7.13 — DON Central summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Central Mean 2008	0.034	0.188	0.183	0.247	0.842	0.294
Central Mean 2009	0.033	0.180	0.185	0.185	0.809	0.233
Central Mean 2010	0.039	0.215	0.182	0.299	0.630	0.509
Central Mean 2011	0.045	0.244	0.183	0.216	0.708	0.313
Central Mean 2012	0.046	0.257	0.184	0.393	0.680	0.548
Central Mean 2013	0.037	0.194	0.189	0.217	0.792	0.260
6-Year Mean	**0.039**	**0.213**	**0.184**	**0.259**	**0.743**	**0.359**

(vi) Western state group

From Table 7.14 (Western) it can be seen that the results suggest a mean DON total factor productivity MTR of 0.162 (16.2%) for the 6-year period. This is interpreted as showing that on average a branch in the state group using its branch technology achieved only 16.2% of the TFP that it could have achieved if it had used the group technology. This suggests the existence of a technology gap between a group frontier and the branch of 83.8%. On a year-by-year basis there was little change in this MTR. Output technical efficiency had an MTR of 0.442 (44.2%) with some fluctuation year by year suggesting a gap of 55.8%. This is interpreted as showing that on average a branch with its own technology was only 44.2% as output technically efficient as it could have been if it had used the group technology.

Table 7.14 — DON Western summary of mean MTR by level and year

Level and Year	TFP Meta	TFP Group	TFP MTR	OTE Meta	OTE Group	OTE MTR
Western Mean 2008	0.050	0.307	0.161	0.440	0.885	0.489
Western Mean 2009	0.056	0.342	0.158	0.449	0.757	0.604
Western Mean 2010	0.050	0.291	0.164	0.395	0.807	0.479
Western Mean 2011	0.051	0.320	0.159	0.339	0.860	0.389
Western Mean 2012	0.045	0.274	0.164	0.358	0.806	0.437
Western Mean 2013	0.046	0.265	0.166	0.240	0.943	0.253
6-Year Mean	**0.050**	**0.300**	**0.162**	**0.370**	**0.843**	**0.442**

7.2 Summary and conclusions

In this chapter, MFA has been applied in the context of The Gideons International in Australia Incorporated (TGIA), to find productivity differences that could be attributed to differences in the grouping that has been specified earlier in the thesis. The concepts of MFA, a review of related literature and possible reasons for technology gaps at different levels of TGIA were addressed in Chapter 3.

Technology gaps of varying degree were found to exist on the basis of MTR calculations at all levels considered for BDIST total factor productivity and output technical efficiency. The MTRs ranged from 25.5% to 100%. For the Eastern state group MTR was 100% for three of the six years and 99% on average over the whole period. This was the only instance of 100% for all the MFA for BDIST and DON inclusive. Technology gaps of varying degree were also suggested as a result of MTR calculations at all levels considered for DON TFP and OTE. The MTRs ranged from 16.1% to 85.4%.

The application of MFA to TGIA extends previous research work and adds to the literature in the MFA topic area. Having presented the results of all research undertaken in this thesis in Chapter 6 and this chapter, an overall summary and conclusions for the whole thesis are provided in Chapter 8 that follows.

CHAPTER 8: SUMMARY AND CONCLUSIONS

In this final chapter there is a summary of the thesis, the research questions set out in Chapter 1 are answered and the achievement of the objectives of the thesis is addressed. A summary is also given of any new appraisals developed from the research, together with suggestions for further research.

8.1 Summary of Thesis

In this thesis the productive efficiency of the service and fundraising operations of the Australian branches of TGIA, a charitable NFP entity (charity) that operates globally in the private sector, has been researched. The ultimate aim of the thesis was to determine influential factors affecting the productivity and efficiency of charitable institutions.
The research was carried out by first constructing from TGIA databases and other sources a set of balanced panel data on input, output and other variables used in the analysis. A balanced panel dataset ensures compatibility with software applied in the analysis. There is no shortage of tabulated data at all levels of TGIA. Cross-sectional, time series and panel data were made available for the purposes of the research, and ethical issues were addressed. The structure of the organisation and the availability and other aspects of the data suited the research to which this thesis relates.

The results suggest generally low productivity and efficiency scores. Indeed, very few branches achieved maximum scores during the 6-year period 2008 to 2013. Further, the results from the Tobit regression analysis undertaken suggest that ongoing research will be required to throw more light on influential factors causing these low scores.

8.2 Summary of answers to research questions by objective

The research questions were summarised under four objectives in Chapter 1 and are addressed below. The answers to these questions should be considered in conjunction with the implications, limitations and areas for further research addressed later in this chapter.

8.2.1 Objective 1:

To measure the relative overall performance of TGIA branches' service activities of Bible distribution (BDIST) and fundraising of private donations (DON) in Australia for the period 2008 to 2013.

(a) What were the relative productivity levels of Bible distribution and fundraising of private donations of TGIA branches in Australia during the period 2008 to 2013 inclusive? This question has been answered by the results in the relevant tables and discussion in Chapter 6 for TFP and TFP* for both BDIST and DON. The relative productivity levels suggested by the results, notwithstanding the highs and lows, are now known.

(b) Have these levels changed year by year from 2008 to 2013 inclusive? The levels for TFP and TFP* for both BDIST and DON have changed little from year to year in overall general terms, with few exceptions. The results in the relevant tables and figures of descriptive statistics and plots, and the discussion in Chapter 6, have provided the evidence. The question has therefore been answered.

8.2.2 Objective 2:

To examine measures of efficiency of TGIA branches for the period 2008 to 2013.

(a) What were the relative levels of measures of efficiency of Bible distribution and fundraising of private donations of TGIA branches in Australia during the period 2008 to 2013 inclusive? The focus was placed mainly on OTE for both BDIST and DON. This question has been answered by the results in the relevant tables and discussion in Chapter 6 for OTE, and to a much lesser degree for other measures of efficiency (OSE etc.), for both BDIST and DON. The relative levels of measures of efficiency, notwithstanding the highs and lows suggested by the results, and the generally low TFP* scores are now known.

(b) Have these levels of measures of efficiency changed year by year from 2008 to 2013 inclusive? The levels for OTE for both BDIST and DON have changed from year to year in overall general terms and are generally low, with few exceptions. The results in the relevant tables and figures of descriptive statistics and plots, and the discussion in Chapter 6, have provided the evidence. The question has therefore been answered.

8.2.3 Objective 3:

To examine factors possibly affecting the performance of TGIA branches in Australia for the period 2008 to 2013.

For the factors postulated as possibly affecting the levels of productivity and of measures of efficiency of Bible distribution and fundraising of private donations performance for TGIA branches in Australia for the period 2008 to 2013, what were the magnitude, statistical significance and direction of each factor? The focus was mainly on TFP and OTE for both BDIST and DON. There were five factors considered for BDIST and six for DON. This question has been answered by the results in the relevant Tobit regression analysis tables and discussion in Chapter 6, for TFP and OTE, and to a much lesser degree for other measures of efficiency (OSE etc.), for both BDIST and DON. The magnitude, statistical significance and direction of each factor suggested by the results for the period 2008 to 2013 are now known.

8.2.4 Objective 4:

To examine the application of the meta-frontier approach (MFA) to the performance of TGIA branches in Australia for the period 2008 to 2013.

(a) What were the meta-technology ratios (MTRs) that were used to obtain estimates of total factor productivity (TFP) and output technical efficiency (OTE) for Bible distribution and fundraising of private donations of TGIA branches in Australia for the years 2008 to 2013 inclusive? The focus was specifically on TFP and OTE for both BDIST and DON. MTRs were calculated at the state group to meta levels and branch to state levels. This question has been answered by the results reported in the relevant MTR tables and discussion in Chapter 7 for TFP and OTE for both BDIST and DON. The MFA has now been examined in the context of TGIA, albeit with varying results.

(b) Have these MTRs changed year by year from 2008 to 2013 inclusive? The MTRs used to obtain estimates of TFP and OTE for both BDIST and DON changed in varying degrees from year to year in general terms, with few exceptions. The results in the relevant MTR tables and discussion in Chapter 7 have provided the evidence. The question has therefore been answered.

Given that all research questions have been answered, a reasonable conclusion would appear to be that the four objectives of the thesis have been achieved. However, there

are implications, limitations and possible areas to consider for further research, as addressed below.

8.3 Implications, limitations and areas for further research

8.3.1 Implications of results and limitations of the study

In the following summary a list is provided of the results from Chapters 6 and 7 that are considered the most notable and appear to be those that most need to be addressed by TGIA/TGI:

(a) Consistently and generally, the DEA results suggest low scores for the measures of productivity and efficiency examined for both BDIST and DON. In particular, low scores were noted for maximum achievable productivity (TFP*) in the total current environment in which TGIA operates.

(b) Few instances were detected of the TGIA branches achieving 100% OTE during the whole 6-year period, for both BDIST and DON.

(c) Very few positive trends were found for those measures for either BDIST or DON, and several negative trends emerged over parts or all the 6-year period studied. Total factor productivity appears to have generally been flat. Output technical efficiency appears to have generally fluctuated little over the period, with low scores throughout.

(d) There were a number of unpredicted results from the TRA in terms of both significance and direction for both the BDIST and DON dependent variables. In particular, consistently and generally the TRA results suggest that the number of TGIA Auxiliary prayer meetings (AUXPM) has an unpredicted negative effect on TFP and OTE. The implication of the TRA results is that additional factors, on which there may be no data at present, would need to be identified to help explain further the generally low TFP and OTE scores. However compilation of meaningful data may always prove elusive.

(e) Calculations of MTRs (see Chapter 7) suggest technology gaps in all but one case for all levels for BDIST and DON. The implication of the MTR results is that lower levels of operation (e.g. branches and states) might experience better performance if they have access to the technology of higher levels of operation (e.g. states and meta).

The results listed in the above summary should be considered against the following background.

(a) In regard to unpredicted results as in (d) above, one of the few previous studies of charities (Tofallis and Sargeant, 2000) also found low scores for technical efficiency generally. The low scores from the TGIA case study which employed DEA output VRS orientation using DPIN 3.0 (O'Donnell, 2011) should therefore not have been surprising. On the other hand, but related to the TRA rather than the DEA, the negative effect of AUXPM was the most unpredicted result in the whole TGIA case study.

(b) Also for (d) above, the TRA models in Equation 5.2 (BDIST) and Equation 5.5 (DON) in Chapter 5 were found to be significant except in four cases. All four exceptions related to dependent variables other than to the TFP and OTE that were the prime focus.

(c) The results from this study, like those of any other study, should be used with discretion and caution. In particular, TGIA/TGI is dealing with voluntary labour that is neither generally available nor working full time for TGIA/TGI. Callen (1994) suggested a possibly better indicator than the number of volunteers (GID and AUX), as suggested by Callen (1994), but it was not available. Caution should be used about this in relation to the staffing aspect when considering all results, as is also noted in other parts of this thesis.

(d) Statistical significance has been reported. It is noted that statistical significance does not necessarily imply causality, and users of the results need to be aware of this. All results should therefore be used with caution.

(e) The research reflects an evidence-based approach. The results provide evidence. The thesis does not provide and not absolute proof or truth that the results are correct beyond reproach.

(g) The data used in the study were for the six 6-year period 2008 to 2013 inclusive. Analysis of data series over a longer period may have been more beneficial. However this was not possible because those data were not available. A future study over a longer period, assuming all data would then be available, may be considered worthwhile.

Several researchers have made comments in previous papers on the ways in which leaders, managers and governing bodies at all levels can view and address the findings from research.

:

(a) Vassiloglou and Giokas (1990) in relation to a study of bank branches suggested that the main contribution from their study appeared to lie in the way in which the findings from DEA for the branches were used by bank management to follow up on the study. The authors state that the discussion took place mainly on the following three themes:

(i) The acceptability of the evaluation of specific branches;

(ii) The possibility for improving the formulation of the model, in view of the experience gained (e.g. regarding input/output specification, product classification); and

(iii) The overall benefits of the application for the bank.

The follow-up process in particular, as covered by Vassiloglou and Giokas (1990) in their study of branches of a single bank, possibly gives meaningful insight and a parallel to be mapped onto the study of TGIA branches presented in this thesis.

(b) Callen (1994) concluded that the more technically inefficient the charity the less able it is to raise money donations.

(c) Tofallis and Sargeant (2000) suggested that the results of research work would assist in improving operational stewardship of the voluntary sector (charities).

(d) Yang (2009) suggested that, among other things, bank managers must consider the external environment and the customer base of the inefficient branches when they set targets for them. Throughout the study, Yang placed special emphasis on how different output measures affect the efficiency rating, thereby providing more guidance to top management on what to manage and how to accomplish the changes. Recommendations were given to managers for guidance.

(e) O'Donnell, Fallah-Fini and Triantis (2011) showed how the meta-frontier framework can be used to make productivity comparisons within and across groups. They concluded that their productivity decomposition methodology can be applied in any empirical context where the standard meta-frontier methodology would normally be applied. They further concluded that estimated meta-technology ratios (MTR) of the type they reported in that paper will be of particular interest to managers and policy-makers who have some capacity to change the production

environment. Their work has been extended in this TGIA case study to consider both TFP and OTE for BDIST and DON. It is to be hoped that the estimated MTRs of the type reported in Chapter 7 of this thesis will be of particular interest to managers and policy-makers at TGIA/TGI who have some capacity to change the production environment.

A possible framework for TGIA to manage responses to productivity and efficiency estimates from this study based on the experience of bank branches is provided in 8.3.2 below. Topics for further research consideration are suggested in 8.3.3 below with the comments of the above researchers in mind.

8.3.2 Framework for TGIA to manage responses to measures of productivity and efficiency — prototype from the experience of bank branches

Mention was made in Chapter 1 of the possible parallels between microeconomic studies of the branches of banks and this study of TGIA. Consistent with such parallels, Chapter 4 presents a comparison between the branches of a charity and the branches of a bank.

From that exploration and comparison it has emerged that the studies of the branches of different individual banks by Vassiloglou and Giokas (1990) (VG) and Yang (2009) have provided a prototype that could be adjusted to suit the needs of TGIA. The following is a possible framework for TGIA, modelled on the VG and Yang (2009) processes:

(a) It should be possible for TGIA's management and governing body to use the findings from the present study as an avenue for evaluating the existing operations of TGIA. As TGIA operates at state/region level its top management is interested in the performance at that level as well as the meta/national level. In the present study, the TFP, OTE and MFA assessments are relevant to those levels.

(b) The DEA models estimated in this TGIA study were output-oriented under varying returns-to-scale to give the greatest flexibility with the potential for better productivity and efficiency scores, as justified by previous studies. Against this background, and assuming that a primary goal of TGIA is to maximise output, it is suggested that management could apply output-oriented models to branches that

are very inefficient, to investigate whether the targets set for them in the past have been realistic. Especially when using the output-oriented DEA models, TGIA management should consider the external environments and the customer bases of the inefficient branches when setting targets for them. TGIA management could do this by direct liaison and discussion with the leaders of these branches. The local knowledge of those leaders might uncover underlying reasons for inefficiency. Studies of socio-economic and other factors might be available for a branch territory from external sources (e.g. local government), and those could also prove beneficial.

(c) It is intended that the results from the TGIA study will be presented to TGIA, and that the discussion with TGIA management will show the potential overall benefits of the study for TGIA.

(d) Feedback on the study's evaluations will be sought from responsible personnel who have appropriate knowledge of TGIA and its operations. In particular, feedback will be sought from TGIA on:

(i) whether or not the assessments from this TGIA study appear to correspond with the evaluations TGIA management had made on the basis of information already available to it; and

(ii) any unpredicted adverse evaluations from the TGIA study encountered by those responsible at TGIA. These would need to be further explored by TGIA management, on a case by case basis.

(e) The exchange of knowledge that takes place during the follow-up process will be a very important aspect of the overall benefits to TGIA from this study.

(f) Apart from the results of this TGIA study, other benefits to management and other responsible personnel at various levels of TGIA operations will include the information exchange that will occur during the follow-up process. These discussions could be extremely beneficial because some staff will become familiar with a range of operational issues of TGIA, and others will have the opportunity to experience certain aspects and benefits of the application of quantitative techniques to their area of work.

Based on the discussion in Chapter 2 on governance, the above framework could be implemented at TGIA as follows. First, the Australian National Executive Director could brief the National Executive Committee (NEC) on the study. The NEC could

then refer the study directly to National Cabinet, or first seek input from an existing committee such as the National Finance Committee or a special ad-hoc committee formed to consider the study. The National Cabinet could then ultimately direct the National Executive Director on how to proceed. The benefit of such an approach is that it would reflect due diligence on the part of TGIA's governing body.

In applying the findings of this study and the framework above, TGIA management could also benefit by considering the following points on efficiency and effectiveness for NFPs, identified in the 2010 Report of the Productivity Commission (Productivity Commission, 2010, pp. 19–22).

- Many NFPs argue that they operate on 'the smell of an oily rag', stretching their resources to the maximum. While that is often true, the importance of process can make NFPs appear messy and inefficient to outsiders, and even to some of the insiders.
- While a trade-off between production efficiency and quality is not unique to the NFP sector, NFPs often place a relatively higher weight on quality. In some cases quality, including quality of process, is strongly linked to effectiveness of the activity, but in other cases the 'doing' can take precedence over the 'achieving'. Where these processes are central to the governance of the organisation and part of the value it provides to its volunteers and members, processes should be seen as essential outputs for the sustainability of the NFP. However, as NFPs grow and become more 'professional' in their management, this type of 'value' from process tends to diminish.
- Production efficiency tends to improve with scale, but mergers and growth can detract from valued processes, particularly in smaller organisations.
- NFPs can also be reluctant to collaborate to share support services such as back-office functions and fund raising, possibly reflecting the transaction costs associated with establishing joint approaches. This may be due to reluctance of NFPs to spend scarce funds on support activities, thus offering little opportunity for such services to develop.
- Unlike businesses, where the financial bottom line is a good measure of their effectiveness, NFPs have to rely on other signals. NFP managers may

resist honest feedback on effectiveness, or may, as with some donors, regard evaluation as wasted money.

- Philanthropy is an important mechanism for allocating resources to organisations and activities that donors see as providing the greatest value for their gift. Given that wealthier individuals have greater 'giving' power, it is their (or their foundation managers') assessment that tends to dominate this allocation.
- The productivity of an organisation improves when it raises the efficiency and effectiveness of its resource use in the short term and when it invests wisely in resources that enhance its efficiency and effectiveness in the longer term. This will improve the productivity of the sector, especially when other NFPs follow suit. However, the productivity of the sector also improves when resources shift to those organisations that make better use of resources in terms of their contribution to the wellbeing of the broader community.
- The central message here is that NFPs may face significant resource constraints to achieving efficiency and effectiveness. More difficult to address is lack of incentive for some NFPs to minimise costs in the short run, or to invest in finding out how effective their actions are. Indeed, such actions may reduce the return to the NFP management if they interfere with valued processes. In addition, at a sector level, pursuit of community-purpose does not guarantee efficient allocation of resources. In addressing these constraints and challenges, it is useful to understand what drives sector growth and development.

For TGIA the extent to which any of these points impact on efficiency and effectiveness is not known. However, they are highlighted because they are reflective of the NFP sector as a whole. It would appear quite reasonable that from TGIA's perspective they are at least worthy of consideration.

Particularly in the light of the discussion in this section, it is hoped and anticipated that the TGIA governing body and management will be receptive to discussion of the results and the implications of the study. This is with a view to possibly enhancing TGIA's performance at all levels in the future.

Based on the empirical result put forward in this study, the following suggestions could be to improve the performance of the inefficient branches of TGIA thereby allowing them to move closer to the frontier:

(a) Examine the peers for the 2013 year listed in the various appendices to this thesis. "Peers" in this context are TGIA branches that set a standard for other TGIA branches of similar size, and should be studied with a view to improve efficiency levels.

(b) Similarly to (a) for targets listed in Table 6.6 for BDIST at page 136 and in Table 6.15 at page 146 for DON, and also in various appendices. "Targets" in this context are the output levels achievable if TGIA branches are fully efficient.

(c) In conjunction with (a) and (b), examine the local environment in which the efficient TGIA branches operate e.g. demographics of local areas, background of key members of the branch, identify number of exceptionally active members in a branch. This may need to be achieved by surveys and could hopefully uncover parallels to be mapped onto at least some of the inefficient branches. The efficient branches for BDIST are listed in Table 6.2 at page 132 and for DON in Table 6.11 at page 143.

(d) Form a specialised group of experienced and long term members of TGIA to work directly with inefficient branches to encourage better performance and motivate members.

(e) Carry out more of the localised blitzes of traditional bible outlets, where willing members from all over Australia gather and carry out distribution activities, and also speak in local churches promoting membership and obtaining donations. This was done in the Melbourne area in early 2015, and church presentations are a regular feature on national and state convention weekends throughout each year at different locations,

(f) Identify and implement specialised training needs of members over and above what is already in place. This may need surveys as well.

(g) Place more emphasis on a mentoring system, particularly for new members, to encourage more activity at individual level.

It is acknowledged that some or all (a) to (g) above might already be in place at TGIA. An inescapable truth in all this however, is that, volunteers with limited availability of time and other resources are involved, and this may detract from the degree to which

TGIA could implement the suggestions. Volunteering at TGIA/TGI starts at member level and pervades the whole organisation to the most senior international level. To their credit, volunteer members of TGIA/TGI donate their time free. Most of them also self-fund all personal activities with the Gideons without seeking any reimbursement, including expensive international bible blitzes to sometimes unsafe countries. They also donate money generously to facilitate the purchase of bibles for distribution in Australia and globally, and also for the administration of the organisation. Many just would not have any more available time or financial resources to further contribute. Comments about volunteering for 80 hours per week have been heard, such is the devotion and commitment of members.

8.3.3 Areas for further research

In general terms, the models and method considered in this thesis could be applied in the context of any further research on charities and other NFP entities. Empirical analysis of the type already undertaken in the study could beneficially continue in future for TGIA over a longer period as data become available for the years 2014 onwards.

In the light of what has already been discussed, the following are some areas that could be considered for further research.

(a) Application to individual TGI countries other than Australia. Pitkin (2013) presents such an application that this author made during the course of this study. The paper was written for and subsequently published in the proceedings of a postgraduate research conference. It clearly demonstrated the application of DEA and Tobit regression analysis at a global level for an international charity. The results only partly supported the expectations for that study, but they are a starting point for further research in the topic area at the global level, for TGI and other charities operating internationally.

(b) Application at the ‘area’ level of TGIA. Each state or region of TGIA is subdivided into a number of ‘areas’. Suitable data were not readily available for inclusion in the present study, but if they become available in future such an application would be worth considering.

(c) Application to subsets of BDIST (types of Bible) and DON (sources of income) for TGIA/TGI for Australia and globally. These aspects were not explored in the current study because of data unavailability, as in (b) above.

(d) Consideration of other possible influential factors affecting productivity and efficiency scores of TGIA/TGI (e.g. as identified or suggested by surveys, expert opinion, etc.) at all levels, if suitable data are available.

(e) The potential application of MFA at all the levels covered for DEA could also be considered. In particular, and data permitting, more work might be possible on finding reasons for gaps identified by MTRs in the TGIA context (e.g. as suggested by surveys, opinion).

(f) The consistency of results obtained in the second stage using Tobit regression analysis in the TGIA study can be verified by employing the approach proposed by Simar and Wilson (2011). This approach will allow for the examination of the effects of different factors influencing the performance of the firms under the framework of truncated regression. However, as stated in Chapter 3, given that most of the literature that motivates the formation and development of the empirical models addressed in this thesis use the Tobit approach, it was opted to follow the same suit for ease of comparison of results. In this context, the limitation of the Tobit analysis was acknowledged and is flagged as an area for further analysis. This will include the estimation of bootstrapped DEA along with SFA, in order to examine the significance of estimated coefficients of the variables. The Simar and Wilson or bootstrapped DEA approach will be taken into account in the publication of journal papers. Essentially, there are two main functions of the TGIA that were considered; the service activity (i.e. distribution of bibles) and fundraising (i.e. donations). The empirical analysis focuses on both state and national level using DEA and obtained only a single measure of performance per firm. Alternatively, this process could also be regarded as network or chain process, that is, the fund raised affects the output distributed, but the performance of the firms is not necessarily the same in each sector. Therefore, it is possible to obtain indicators of performance at the “service sector” and another in the “fundraising” section. Here, one could extend the analysis and employ the network DEA approach such as that proposed by Tone and Tsutsui (2014). Verification of the consistency of results from the TGIA study could also be sought by applying stochastic frontier analysis (SFA).

(g) Explore the possibility of estimating a multi-input (GID and AUX) and multi-output (both BDIST and DON) model, thereby allowing estimation of other measures of efficiency which are not covered in the thesis, such input/output mix efficiency.

The list of possible topics above is not intended to be exhaustive. Rather it is intended to indicate where further research might be beneficially directed for TGIA/TGI and other charities.

8.4 Summary of contributions

In summarising the contribution of this thesis, the following background is noted. There is a longstanding and continuing paradigm, in relation to productivity and efficiency analysis, which originated in the seminal work of Farrell (1957). There are three main streams of productivity and efficiency analysis: namely, DEA, SFA, and index numbers (most recently embodied in DPIN). A large amount of literature examines these three streams, particularly in the areas of DEA, SFA and sensitivity comparisons. For this reason, only examples and landmark studies have been reviewed in this thesis. Additions to the literature on DEA and SFA appear to be continuing unabated. Recent and emerging themes include stochastic DEA and DEA with uncertainty.

The appraisals in this thesis can be viewed as ‘new’ because of their application to charities in general, rather than as an application of the method of assessing productive efficiency. This study has been highly successful and well worth undertaking. The research has been successful in answering the original research questions, and has achieved the following outcomes.

(a) The relative overall performance and productivity levels of the Australian service activities and fundraising of private donations of a global charity for the period 2008 to 2013 inclusive have been examined and are now known. The change in these levels from year to year in the period examined is now also known.

(b) The relative levels of efficiency of the Australian service activities and fundraising of private donations of the Australian branches of a global charity the period 2008 to 2013 inclusive have been examined and are now known. The change in these levels from year to year in the period examined is now also known.

(c) The magnitude, statistical significance and direction of each of the factors postulated to affect the levels of productivity and efficiency of the Australian service activities and fundraising of private donations performance for TGIA branches in Australia for the period 2008 to 2013 have been examined and are now known.

(d) The application of MFA to the performance of Australian service activities and fundraising of private donations of the Australian branches of a global charity for the period 2008 to 2013 has been examined. The MTRs for TFP and OTE for service activities and fundraising of private donations for the period 2008 to 2013 inclusive are now known. The changes in these ratios from year to year for the period are now also known.

This study contributes to the literature because it begins to fill a clearly identified gap in empirical research related to charities and the non-profit sector in Australia. For TGI, the Australian models developed have scope for application to other TGI countries and for adaptation to a global model for TGI (Pitkin, 2013). Similarly this could be done for other charities and NFPs in Australia and globally. The research contribution of the thesis is (a) an empirical contribution as it is the first application of DEA on charities in Australia and (b) guidelines for TGIA management to manage its efficiency and productivity levels.

The value of the research presented in this thesis is independent of Australian Government policy and its changes. Abolition of the ACNC in favour of a Centre of Excellence appears to support the perception that regulatory authorities like the ACNC are necessary. Research on the charitable and NFP sector in Australia and globally is necessary to fill knowledge gaps that exist because there has been relatively little such research so far, irrespective of the need or otherwise for regulatory authority or regulation in Australia (and globally). Ultimately, the people who manage and govern TGIA/TGI will decide what they might do about the matters and results reported and discussed in this thesis. It is again acknowledged that the organisation may already have taken some action on those matters, and it is to be hoped that the evidence from this research will at least add to what is already known by TGIA/TGI.

8.5 A Final Personal Note

At the end of this thesis an appropriate comment is the Latin expression ‘finis coronat opus’ which means ‘the end crowns the work’! This is the author’s old school motto that has encouraged and motivated him for most of his life. The end of this work and subsequent award of PhD will indeed crown the achievement of a lifelong educational goal.

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APPENDICES

Appendix 1: A Lens on Giving in Australia (2014)

A LENS
ON GIVING IN AUSTRALIA

The Australian Not for Profit sector is vast

In 2014 more than **1 in 15** Australians will work for a Not for Profit or charity.[1]

OVER **600,000**
Not for Profit organisations contribute
$43 billion (4%) of our GDP.

440,000 small unincorporated associations.
160,000 organisations with a formal legal structure.
56,000 receiving charity tax concessions.[1]

AND Australians are generous in response

The WORLD'S MOST GENEROUS

Australia **TOPPED** The World Giving Index 2012 and also headed the five year index (2007-2012). More Australians had, on average, donated money, volunteered time or helped a stranger in the past month than any other country.

76% of Australians had given money to a cause.
37% had volunteered time.[2]

GIVING their skills and expertise

VOLUNTEERING

As of 2010 the estimated number of volunteers in Australia was **6.1 million** working **713 million hours** annually.

The median weekly number of hours volunteered was **1.1 hours**.

People who volunteer are more likely to have made a donation than those who are not volunteers (**85%** compared to **72%**).

Slightly more women (**36%**) than men (**34%**) volunteered.

People aged **45-54 years** reported the highest rate of volunteering.

Employed people had a higher volunteering rate than those who were unemployed or not in the labour force.

Volunteering was more common among those living outside of a capital city.[3]

AND their money

DONATING

Australians donated about **$2.21** billion to charity in 2010-11.

It's an increase of **$248 million** (or **12.63%**) from 2009-10.

About **38%** of taxpayers - **4.79 million** - gave an average of **$461** each to charity.[4]

Donors from higher income postcodes may have donated the most in dollars but not necessarily the most as a relative share of their income.[5]

DRIVEN by purpose

PHILANTHROPY

Total foundation giving stands at between **$500 million** and **$1 billion** per annum.

Trustee companies manage more than **2,000** charitable trusts and foundations with assets of approximately **$3.2 billion.**

Private Ancillary Funds or PAFs received **$304 million in donations** in 2010-2011.

The number of registered PAFs has risen to **924** with a combined value of **$2.12 billion.** These funds distributed **$165.41 million** to a wide variety of causes from welfare to the environment.[7]

PAFs are philanthropic trust funds that can be set up as a vehicle for private giving.

PUSHING for corporates to do the same

WORKPLACE GIVING

In the 2012 financial year roughly **$56.5** million was donated through payroll giving contributions.

133,000 Australians gave through payroll deductions.

The average employee participation rate of all workplace giving programs is **4%.**

Workplace giving donors gave more than twice as much annually to charity both inside and outside the workplace.

Organisations with high employee engagement experience **2.5** times greater revenue growth than those organisations with low employee engagement.[7]

BEYOND the financial

CORPORATE VOLUNTEERING

A 2013 study[8] found that:

Up to **90%** of surveyed employees surveyed were aware of corporate volunteering options and up to **60%** participated in corporate volunteering in the last 12 months;

Corporate volunteers were very satisfied with their volunteering experience (**83%** satisfied) very likely to continue (**87%**) and very likely to recommend it to their friends (**75%**);

The most common barriers were 'not being asked' (**38%**), 'being too busy (**36%**), preferring to volunteer privately (**31%**), and preferring to donate money than to volunteer (**21%**).

[1] *Productivity Commission 2010* [2] *Charities Aid Foundation World Giving Index 2012* [3] *ABS Report on Voluntary Work, 2010* [4] *Australian Tax Office*
[5] *NAB Charitable Giving Index, August 2013* [6] *Philanthropy Australia* [7] *Australian Charities Fund* [8] *Macquarie Graduate School of Management*

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Source: Pro Bono Australia (2014). *Guide to giving: The Australian directory of not for profit organisations 2014*. Melbourne, Australia: Pro Bono Australia, p. 9. Reproduced with permission.

Appendix 2: DEA concepts applied to TGIA Bible distribution (BDIST) (Chapter 3)

The data below show the actual BDIST output and inputs for TGIA branches 1 to 4 for the year ended 31 May 2011 and are used to demonstrate the basic conceptual mathematical LP framework of DEA. The approach would be the same for fundraising of donations (DON).

Branch	Number of Bibles distributed	Number of Gideon members	Number of Auxiliary members
1	3,469	23	16
2	6,612	16	8
3	3,340	14	6
4	2,640	9	7

Let x_1 = Output 1 = number of Bibles distributed; x_2 = Input 1 = number of Gideon members; x_3 = Input 2 = number of Auxiliary members, then:

Efficiency of Branch 1 = Value of Outputs/Value of Inputs = $3469x_1/(23x_2 + 16x_3)$,
Efficiency of Branch 2 = Value of Outputs/Value of Inputs = $6612x_1/(16x_2 + 8x_3)$,
Efficiency of Branch 3 = Value of Outputs/Value of Inputs = $3340x_1/(14x_2 + 6x_3)$,
Efficiency of Branch 4 = Value of Outputs/Value of Inputs = $2240x_1/(9x_2 + 7x_3)$.

In DEA it is necessary to focus on one DMU (TGIA branch) at a time and ultimately solve a LP problem for each DMU (TGIA branch). To illustrate, the DEA problem for TGIA Branch 1 is given by:

Maximise $Z = 3469x_1/(23x_2 + 16x_3)$ (TGIA Branch 1 efficiency)
subject to $3469x_1/(23x_2 + 16x_3) \leq 1$ (TGIA Branch 1 efficiency ≤ 1) ,
$6612x_1/(16x_2 + 8x_3) \leq 1$ (TGIA Branch 2 efficiency ≤ 1) ,
$3340x_1/(14x_2 + 6x_3) \leq 1$ (TGIA Branch 3 efficiency ≤ 1) ,
$2{,}240x_1/(9x_2 + 7x_3) \leq 1$ (TGIA Branch 4 efficiency ≤ 1) ,
$x_1, x_2, x_3 \geq 0$.

This LP problem can be rewritten as:

Maximise $Z = 3469x_1 / (23x_2 + 16x_3)$ (TGIA Branch 1 efficiency)

subject to $3469x_1 - 23x_2 - 16x_3 \leq 0$ (TGIA Branch 1 efficiency ≤ 1) ,

$6612x_1 - 16x_2 - 8x_3 \leq 0$ (TGIA Branch 2 efficiency ≤ 1) ,

$3340x_1 - 14x_2 - 6x_3 \leq 0$ (TGIA Branch 3 efficiency ≤ 1) ,

$2240x_1 - 9x_2 - 7x_3 \leq 0$ (TGIA Branch 4 efficiency ≤ 1) ,

$x_1, x_2, x_3 \geq 0$.

Note that in this case the objective function is written as a ratio. Unfortunately this *ratio form* of DEA problem leads to an infinite number of solutions.

To reach a unique solution, typically the denominator in the objective function is normalised to equal 1 to establish a *multiplier form* for the DEA problem. This is achieved by adding the constraint $23x_2 + 16x_3 = 1$ to the TGIA Branch 1 LP problem. Then, as a result of introducing the normalising constraint, the DEA problem becomes:

Maximise $Z = 3469x_1$ (TGIA Branch 1 efficiency)

subject to $3469x_1 - 23x_2 - 16x_3 \leq 0$ (TGIA Branch 1 efficiency ≤ 1) ,

$6612x_1 - 16x_2 - 8x_3 \leq 0$ (TGIA Branch 2 efficiency ≤ 1) ,

$3340x_1 - 14x_2 - 6x_3 \leq 0$ (TGIA Branch 3 efficiency ≤ 1) ,

$2240x_1 - 9x_2 - 7x_3 \leq 0$ (TGIA Branch 4 efficiency ≤ 1) ,

$23x_2 + 16x_3 \leq 1$, (Normalisation) ,

$-23x_2 - 16x_3 \leq -1$, (Normalisation) ,

$x_1, x_2, x_3 \geq 0$.

In this form the LP can be solved using the simplex algorithm to get the required productivity and efficiency score for TGIA Branch 1, but the solution of LP and DEA problems is now generally automated in some software applications (e.g. DPIN, DEAP and LIMDEP). A similar process is applicable for obtaining the productivity and efficiency scores for the other branches. The example here considers a simple cross-section at a particular point in time using an input oriented CRS DEA model. The DEA problem is extendable to all TGIA branches, output orientation, panel data and VRS.

From the DEA primal multiplier form an equivalent ‘envelopment’ form can be derived using the duality in LP (Coelli et al. 2005, page 163). This is demonstrated in the extension of the simple example above to the general case below (Coelli et al. 2005, pages 162–163).

There are data available on $N > 0$ inputs and $M > 0$ outputs for each of $I > 1$ TGIA branches. For the i-th TGIA branch ($i \geq 1$), let N and M be represented by the column vectors $\mathbf{x_i}$ and $\mathbf{q_i}$ respectively (M, N, I, i are all integers). Also, let the $N \times I$ input matrix, $\mathbf{X}$, and the $N \times I$ output matrix, $\mathbf{Q}$, represent the data for all I TGIA branches.

If this generalised approach is started by using the ratio form of the DEA problem, a measure of the ratio of all outputs to all inputs, $\mathbf{u'q_i} / \mathbf{v'x_i}$, is sought, where $\mathbf{u}$ is an $M \times 1$ vector of output weights and $\mathbf{v}$ is an $N \times 1$ vector of input weights. The optimal weights are obtained by solving the LP problem:

$$\begin{aligned} &\text{Maximise} && u,v\ (\mathbf{u'q_i} / \mathbf{v'x_i}) \\ &\text{subject to} && \mathbf{u'q_j} / \mathbf{v'x_j} \leq 1 \qquad \text{for } j = 1,2,....I \\ & && \mathbf{u}, \mathbf{v} \geq 0\ . \end{aligned}$$

From this, values of $\mathbf{u}$ and $\mathbf{v}$ can be found so that the efficiency measure of the i-th TGIA branch is maximised, subject to the constraints that all measures of efficiency must be less than or equal to 1. To overcome the problem with the ratio form of giving infinite solutions, the constraint $\mathbf{v'x_i} = 1$ is imposed, and the DEA model is written in multiplier form:

$$\begin{aligned} &\text{Maximise}_{\ \mu,v} && (\boldsymbol{\mu}'\mathbf{q_i}) \\ &\text{Subject to} && \upsilon'\mathbf{x_i} = 1\ , \\ & && \boldsymbol{\mu}'\mathbf{q_j} / -\upsilon'\mathbf{x_j} \leq 0 \qquad \text{for } j = 1,2,....I\ , \\ & && \boldsymbol{\mu}, \upsilon \geq 0 \end{aligned}$$

(where $\boldsymbol{\mu}$ and υ are used rather than $\mathbf{u}$ and $\mathbf{v}$ to indicate a different LP problem).

The powerful concept of *duality* in LP can be used to derive an equivalent *envelopment form* of this *multiplier form*:

$$\text{Minimise}_{\theta,\lambda} \quad \theta$$
$$\text{subject to} \quad -\mathbf{q_i} + \mathbf{Q}\boldsymbol{\lambda} \geq 0 \,,$$
$$\theta\mathbf{x_i} - \mathbf{X}\boldsymbol{\lambda} \geq 0 \,,$$
$$\boldsymbol{\lambda} \geq 0 \,,$$

where θ is a scalar of constants and λ is an $I \times 1$ vector of constants.

This is generally the preferred form to solve (Coelli et al. 2005, page 163). In the context of TGIA, the value of θ, which satisfies the 'less than or equal to 1' requirement, obtained from the solution, would be the efficiency score of the *i*-th TGIA branch. If $\theta = 1$, it would indicate that the particular TGIA branch is technically efficient and lies on the frontier according to the Farrell (1957) definition. To obtain a value of θ for each TGIA branch, the LP problem must be solved *I* times, once for each branch.

Banker et al. (1984) did not report empirical application of the BCC model but the effect of the BCC model has been similar to that of the CCR model in that its application in empirical work is sustained to this day. The concept of the VRS DEA model and SE is covered well by Coelli et al. (2005, pages 172–174).

According to Coelli et al. (2005), Banker et al (1984) modify the CRS LP problem to account for VRS by adding the constraint $\mathbf{I1}'\boldsymbol{\lambda} = 1$, so that the VRS LP problem becomes:

$$\text{Minimise}_{\theta,\lambda} \quad \theta$$
$$\text{subject to} \quad -\mathbf{q_i} + \mathbf{Q}\boldsymbol{\lambda} \geq 0 \,,$$
$$\theta\mathbf{x_i} - \mathbf{X}\boldsymbol{\lambda} \geq 0 \,,$$
$$\mathbf{I}1'\boldsymbol{\lambda} = 1 \,,$$
$$\boldsymbol{\lambda} \geq 0 \,,$$

where $\mathbf{I}1$ is an $I \times 1$ vector of ones.

The constraint $\mathbf{I}1'\boldsymbol{\lambda} = 1$ ensures that an inefficient DMU is only 'benchmarked' against DMUs of similar size. SE scores can be calculated for each DMU under both CRS DEA and VRS DEA. Technical efficiency scores calculated using CRS DEA can be decomposed into a scale inefficiency component and a *pure* technical inefficiency

component (i.e. VRS TE). A difference in CRS technical efficiency and VRS technical efficiency scores for a particular DMU indicates that the DMU has scale inefficiency.

Coelli et al. (2005) identified a shortcoming of this calculation of SE as not determining whether it reflects IRS or DRS for a particular DMU. As to whether it is IRS or DRS can be determined by solving an additional DEA problem with non-increasing returns to scale (NIRS) imposed, achieved by substituting $\mathbf{I}1'\boldsymbol{\lambda} \leq 1$ for $\mathbf{I}1'\boldsymbol{\lambda} = 1$ in the model above. Using $\mathbf{I}1'\boldsymbol{\lambda} \leq 1$ results in a particular DMU not being 'benchmarked' against substantially larger DMUs, but permits comparison with smaller DMUs.

Appendix 3: Meta-frontier approach (MFA) (Chapter 3)

The following draws heavily on the MFA concepts adopted in Battese et al. (2004) and O'Donnell et al. (2008). Given that DMUs are mostly within 'regions' (e.g. TGIA branches within five states of Australia), it is possible to identify a 'regional frontier' using DEA on the data for DMUs from the given region. Thus, DEA can be used to construct G regional frontiers. The meta-frontier is then constructed by using DEA to analyse the data set obtained by pooling all the observations for DMUs from all the regions (e.g. TGIA branches for all Australia).

If region g consists of data on L_g DMUs over T time periods, the LP problem that is solved for the i-th DMU in an output-orientated DEA model for panel data is:

$$\max_{\varphi_{it},\lambda_{it}} \varphi_{it} , \qquad \text{(Equation A3.1)}$$

such that

$$\varphi_{it}\, q_{it} + Q_{igt}\, \lambda_{it} \geq 0 ,$$
$$x_{it} - X_{igt}\, \lambda_{it}. \geq 0 ,$$
$$\lambda_{igt} \geq 0 ,$$
$$t = 1, 2,..., T ,$$

where

q_{it} is the $M \times 1$ vector of output quantities for the i-th DMU over time period T;

x_{it} is the $N \times 1$ vector of input quantities for the i-th DMU over time period T;

Q_{igt} is the $M \times L_g$ matrix of output quantities for all L_g DMUs over time period T;

X_{igt} is the $N \times L_g$ matrix of input quantities for all L_g DMUs over time period T;

λ_{igt} is a $L_g \times 1$ vector of weights; and

φ_{igt} is a scalar.

φ_{igt} will take a value greater than or equal to 1, and $\varphi_{igt} - 1$ is the proportional increase in outputs that could be achieved by the i-th DMU in t, with input quantities held constant. Note also that $1 / \varphi_{igt}$ defines a technical efficiency score which varies between 0 and 1 (this is the output-orientated technical efficiency score).

The above LP problem (Equation A3.1) is solved L_g times; that is, once for each DMU in region g. Each LP produces φ_{igt} and λ_{igt} vectors. The φ_{igt} vector provides information on the technical efficiency score for the i-th DMU for period t, and the λ_{igt} vector provides information on the peers of the (inefficient) i-th DMU for time period t. The peers of the i-th DMU are those efficient DMUs in the region that define the facet of the frontier against which the (inefficient) i-th DMU is projected.

The meta-frontier is constructed using a DEA model based on the pooled data for all DMUs in all regions over the time period T. Since there is a total of $L = \Sigma_g L_g$ DMUs, the above LP model (Equation 3.1) is re-run with the input and output matrices with data for all DMUs for all periods t:

$$\max_{\varphi^*, \lambda^*} \varphi_{it}^*, \qquad \text{(Equation A3.2)}$$

such that

$$\varphi_{it}^* q_{it} + Q_{it}^* \lambda_{it}^* \geq 0,$$
$$x_{it} - X_{it}^* \lambda_{it}^* \geq 0,$$
$$\lambda_{it}^* \geq 0,$$

where

q_{it} is the $M \times 1$ vector of output quantities for the i-th DMU over time period T;
x_{it} is the $N \times 1$ vector of input quantities for the i-th DMU over time period T;
Q_{it}^* is the $M \times L$ matrix of output quantities for all the L DMUs over time period T;
X_{it}^* is the $N \times L$ matrix of input quantities for all the L DMUs over time period T;
λ_{it}^* is the $L \times 1$ vector of weights; and
φ_{it}^* is a scalar.

The optimum solution of the LP problem above (Equation A3.2) provides a technical efficiency score for a given DMU relative to the meta-frontier identified using data from all DMUs in all regions over time T (e.g. for TGIA all five states or ‘regions’ of Australia).

For any given DMU, φ_{it}^* is no larger than φ, because the constraints in the regional LP problem are a subset of the constraints in the meta-frontier LP problem. DMUs are

shown to be not more technically efficient when they are assessed against the meta-frontier than against the regional frontier (Battese et al. 2004).

Once the regional and meta-frontier measures are calculated, Technology Gap Ratios (TGR), which are now more commonly called meta-technology ratios (MTR), can be calculated for each DMU.

In the case of technical efficiency (TE), this is the ratio

$$MTR_{itTE} = TE_{it}^{*} / TE_{igt} , \qquad \text{(Equation A3.3)}$$

where

TE_{it}^{*} is the technical efficiency of the *i*-th DMU at time *t* in the meta-frontier case;

TE_{igt} is the technical efficiency of the *i*-th DMU at time *t* in the group *g* case;

MTR_{itTE} is the meta-technology ratio of the *i*-th DMU at time *t*;

$TE_{it}^{*} \leq TE_{igt}$;

$0 < TE_{it}^{*}$, TE_{itg} , $MTR_{itTE} \leq 1$.

For example, if $TE_{it}^{*} = 0.6$ and $TE_{igt} = 0.8$, then $MTR_{itTE} = 0.75$. This is interpreted as showing that the *i*-th DMU with group *g* technology is only 75% as technically efficient as it could be if using the meta-frontier technology. Generally, MTRs that have values less than 1 indicate the existence of a technology gap between a group frontier and the meta-frontier.

Appendix 4: BDIST mean productivity and efficiency scores by level and year: five regions and national (Chapter 6)

Level	Year	TFP	TFPE	OTE	OSE	OME	ROSE	OSME	ITE	ISE	IME	RISE	ISME	RME
Meta	2008	0.063	0.249	0.339	0.798	1.000	0.765	0.765	0.373	0.675	0.959	0.678	0.650	0.963
(i.e. National/	2009	0.063	0.343	0.375	0.928	1.000	0.915	0.915	0.460	0.746	0.967	0.761	0.736	0.986
All Australia)	2010	0.066	0.213	0.323	0.715	1.000	0.683	0.683	0.385	0.582	0.951	0.582	0.557	0.960
	2011	0.065	0.318	0.384	0.882	1.000	0.846	0.846	0.484	0.582	0.938	0.679	0.645	0.960
	2012	0.063	0.228	0.337	0.716	1.000	0.683	0.683	0.418	0.581	0.928	0.589	0.556	0.956
	2013	0.064	0.239	0.289	0.888	1.000	0.849	0.849	0.415	0.591	0.945	0.587	0.564	0.955
	6-Year	**0.064**	**0.265**	**0.341**	**0.821**	**1.000**	**0.790**	**0.790**	**0.423**	**0.641**	**0.948**	**0.646**	**0.618**	**0.963**
Northern	2008	0.170	0.376	0.507	0.800	1.000	0.718	0.718	0.593	0.665	0.895	0.663	0.599	0.888
	2009	0.159	0.395	0.551	0.794	1.000	0.715	0.715	0.628	0.658	0.971	0.613	0.594	0.897
	2010	0.175	0.369	0.528	0.780	1.000	0.691	0.691	0.643	0.608	0.907	0.599	0.541	0.879
	2011	0.174	0.345	0.500	0.788	1.000	0.670	0.670	0.610	0.627	0.917	0.587	0.531	0.845
	2012	0.155	0.364	0.596	0.686	1.000	0.619	0.619	0.631	0.624	0.940	0.600	0.563	0.902
	2013	0.185	0.295	0.436	0.774	1.000	0.660	0.660	0.624	0.555	0.914	0.511	0.471	0.848
	6-Year	**0.170**	**0.357**	**0.520**	**0.771**	**1.000**	**0.679**	**0.679**	**0.621**	**0.623**	**0.924**	**0.595**	**0.550**	**0.876**
Eastern	2008	0.106	0.327	0.422	0.826	1.000	0.803	0.803	0.505	0.681	0.976	0.680	0.662	0.976
	2009	0.101	0.421	0.477	0.922	1.000	0.906	0.906	0.585	0.713	0.971	0.725	0.701	0.983
	2010	0.109	0.277	0.414	0.723	1.000	0.685	0.685	0.465	0.636	0.971	0.621	0.600	0.960
	2011	0.106	0.417	0.480	0.904	1.000	0.892	0.892	0.558	0.748	0.991	0.744	0.737	0.988
	2012	0.110	0.319	0.448	0.726	1.000	0.715	0.715	0.539	0.612	0.980	0.618	0.606	0.988
	2013	0.102	0.302	0.352	0.895	1.000	0.872	0.872	0.530	0.591	1.000	0.572	0.572	0.977
	6-Year	**0.106**	**0.344**	**0.432**	**0.833**	**1.000**	**0.812**	**0.812**	**0.530**	**0.664**	**0.982**	**0.660**	**0.646**	**0.979**

(Appendix 4 Continues on Next Page)

Level	Year	TFP	TFPE	OTE	OSE	OME	ROSE	OSME	ITE	ISE	IME	RISE	ISME	RME
Southern	2008	0.097	0.429	0.581	0.807	1.000	0.742	0.742	0.556	0.834	0.956	0.811	0.771	0.917
	2009	0.103	0.264	0.494	0.534	1.000	0.534	0.534	0.464	0.577	0.999	0.578	0.577	1.000
	2010	0.108	0.328	0.525	0.618	1.000	0.618	0.618	0.478	0.698	0.979	0.711	0.698	1.000
	2011	0.114	0.327	0.457	0.768	1.000	0.750	0.750	0.542	0.630	0.850	0.725	0.616	0.976
	2012	0.099	0.395	0.520	0.817	1.000	0.797	0.797	0.575	0.698	0.912	0.744	0.683	0.976
	2013	0.105	0.305	0.599	0.668	1.000	0.501	0.501	0.582	0.702	0.873	0.613	0.532	0.755
	6-Year	**0.104**	**0.341**	**0.529**	**0.702**	**1.000**	**0.657**	**0.657**	**0.533**	**0.690**	**0.928**	**0.697**	**0.646**	**0.937**
Central	2008	0.099	0.386	0.588	0.842	1.000	0.723	0.723	0.731	0.602	0.741	0.658	0.503	0.848
	2009	0.118	0.368	0.576	0.807	1.000	0.717	0.717	0.721	0.558	0.813	0.590	0.486	0.875
	2010	0.126	0.301	0.435	0.827	1.000	0.724	0.724	0.677	0.505	0.951	0.446	0.430	0.874
	2011	0.103	0.452	0.558	0.865	1.000	0.822	0.822	0.681	0.689	0.967	0.678	0.656	0.949
	2012	0.127	0.328	0.431	0.881	1.000	0.801	0.801	0.532	0.635	0.955	0.597	0.574	0.911
	2013	0.113	0.424	0.577	0.847	1.000	0.786	0.786	0.677	0.652	0.795	0.752	0.602	0.920
	6-Year	**0.114**	**0.376**	**0.528**	**0.845**	**1.000**	**0.762**	**0.762**	**0.670**	**0.607**	**0.870**	**0.620**	**0.542**	**0.896**
Western	2008	0.327	0.556	0.759	0.966	1.000	0.746	0.746	0.839	0.817	0.904	0.687	0.628	0.771
	2009	0.340	0.524	0.735	0.869	1.000	0.731	0.731	0.804	0.758	0.921	0.682	0.630	0.837
	2010	0.270	0.531	0.690	0.932	1.000	0.772	0.772	0.893	0.691	0.910	0.619	0.573	0.818
	2011	0.262	0.427	0.754	0.701	1.000	0.592	0.592	0.850	0.571	0.914	0.523	0.485	0.826
	2012	0.249	0.447	0.726	0.751	1.000	0.608	0.608	0.822	0.571	0.889	0.579	0.513	0.812
	2013	0.289	0.463	0.680	0.846	1.000	0.686	0.686	0.781	0.705	0.877	0.659	0.577	0.813
	6-Year	**0.289**	**0.491**	**0.724**	**0.844**	**1.000**	**0.689**	**0.689**	**0.832**	**0.698**	**0.902**	**0.625**	**0.568**	**0.813**

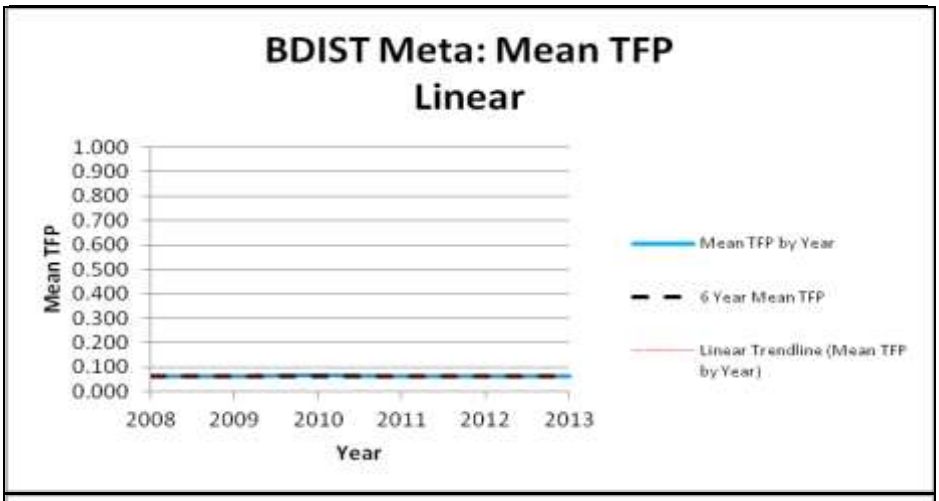
Appendix 5: BDIST TFP descriptive statistics and plots of productivity and efficiency scores (Chapter 6)

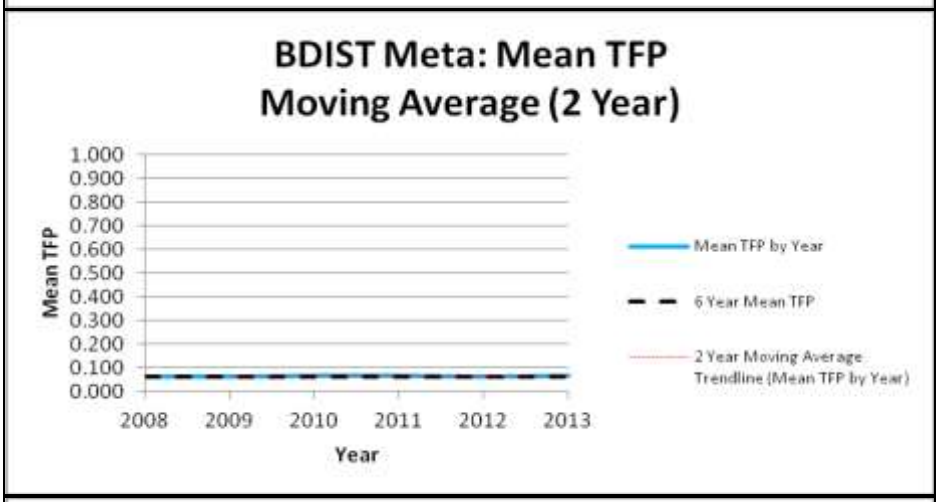
As a preliminary note, in the appendices below descriptive statistics for all BDIST mean TFP and OTE at the meta and group levels year by year for the 6-year period are provided. The three plots displayed in each case (linear, 2 year and 3 year moving average) are presented because of a likely perceived interest by end users of the findings of the study. From this, trends over the 6-year period studied can be examined, focusing on the more important measures of TFP and OTE.

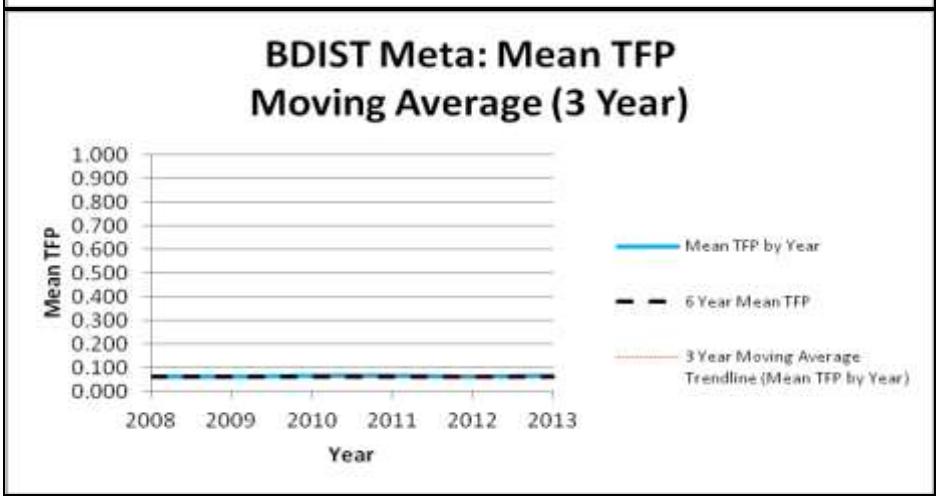
From Appendix 5.1 (BDIST mean TFP for meta by year) it can be seen that mean TFP by year over the 6-year period showed little variation and low scores can be noted, with an overall 6-year mean TFP of 0.064 (6.4%). This is the observed TFP. All plots reflect this with the graphical representations almost converging to a flat straight line. In Appendices 5.2 to 5.6, representing the five state groups, a generally similar pattern for mean TFP as the meta level is shown. Even though the 6-year mean for each state group is higher than the meta, it is still low in magnitude.

Appendix 5.1 — BDIST mean TFP for meta by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.063	0.046	0.003	0.254	121	0
2009	0.063	0.042	0.004	0.183	121	0
2010	0.066	0.049	0.005	0.308	121	0
2011	0.065	0.044	0.004	0.203	121	0
2012	0.063	0.043	0.007	0.275	121	0
2013	0.064	0.042	0.007	0.269	121	0
6 Years	**0.064**	**0.044**	**0.003**	**0.308**	**726**	**0**

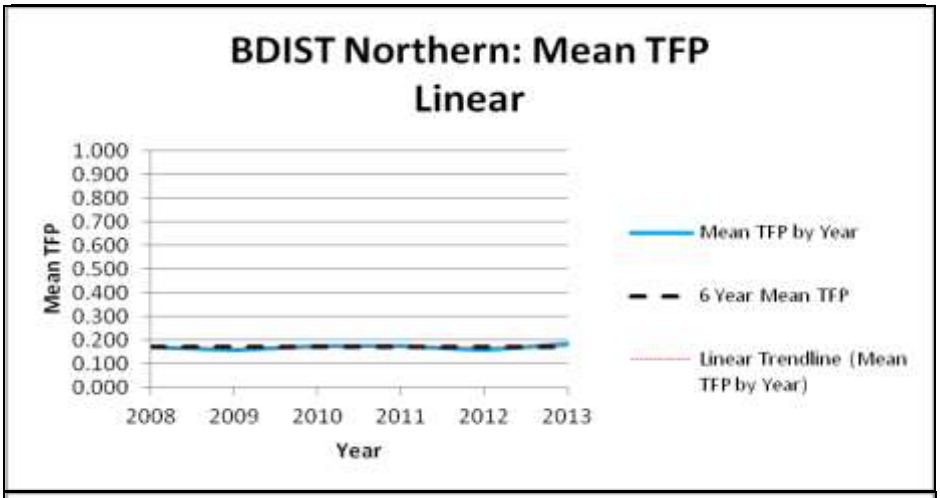


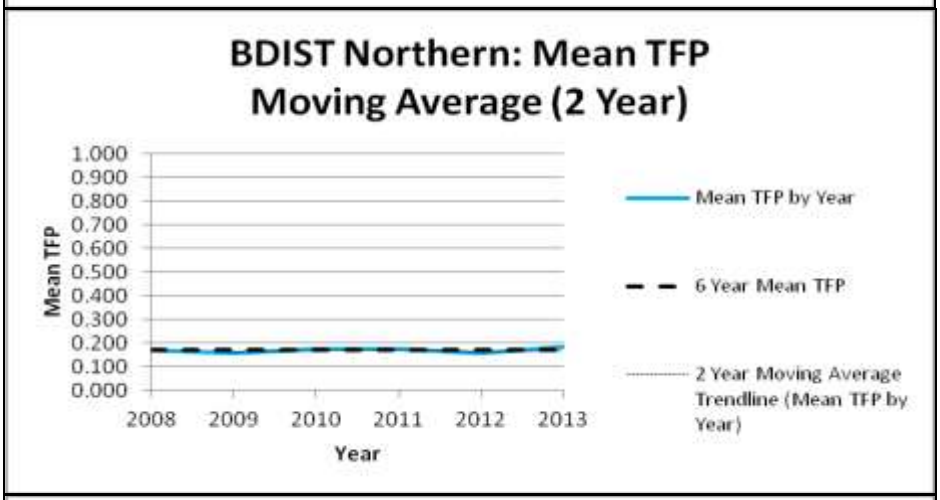


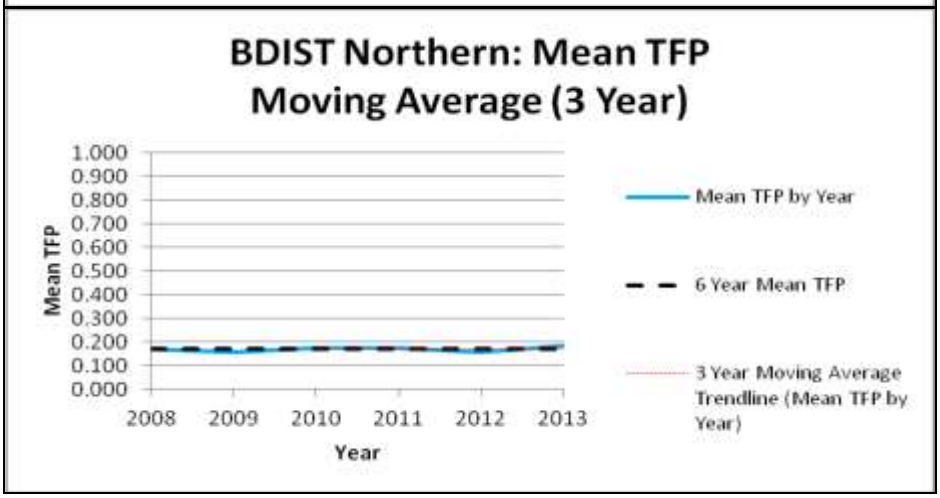


Appendix 5.2 — BDIST mean TFP for Northern region by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.170	0.126	0.019	0.452	30	0
2009	0.159	0.104	0.012	0.401	30	0
2010	0.175	0.126	0.012	0.473	30	0
2011	0.174	0.128	0.022	0.505	30	0
2012	0.155	0.099	0.026	0.427	30	0
2013	0.185	0.135	0.021	0.625	30	0
6 Years	**0.170**	**0.119**	**0.012**	**0.625**	**180**	**0**

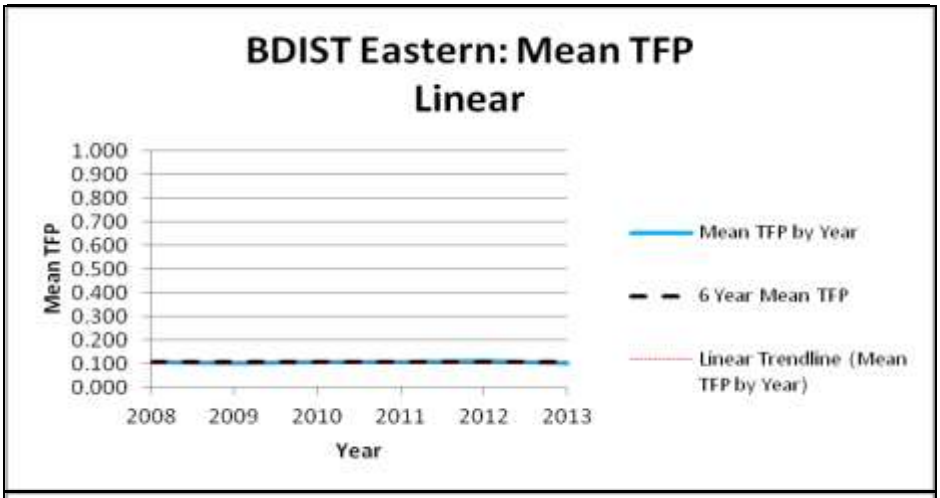


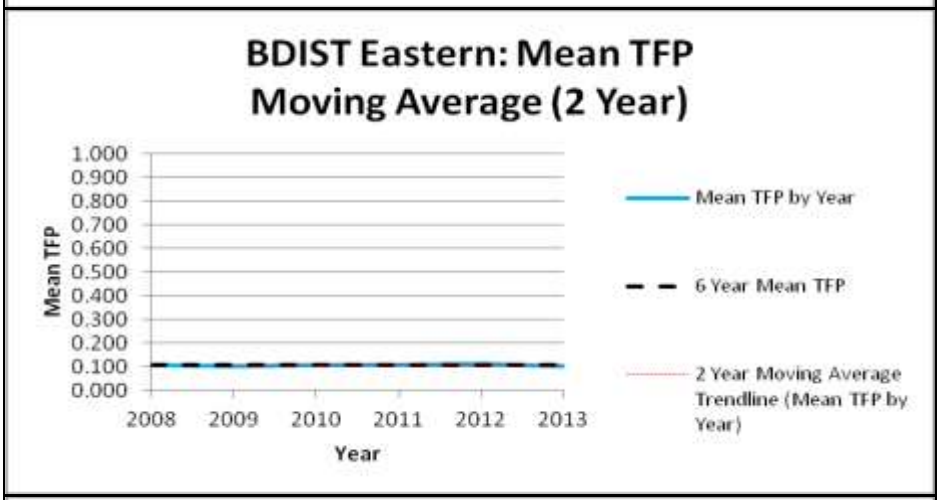


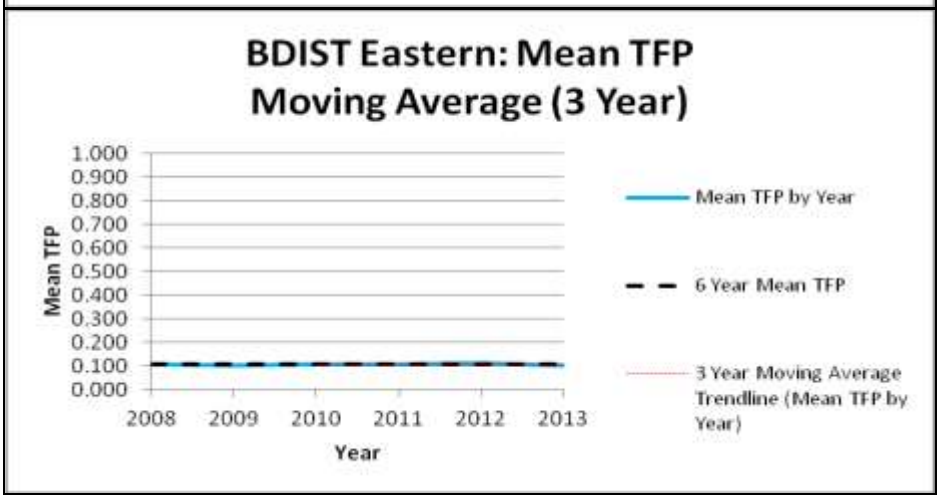


Appendix 5.3 — BDIST mean TFP for Eastern region by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.106	0.070	0.032	0.325	35	0
2009	0.101	0.058	0.023	0.239	35	0
2010	0.109	0.079	0.024	0.393	35	0
2011	0.106	0.062	0.013	0.255	35	0
2012	0.110	0.063	0.026	0.345	35	0
2013	0.102	0.056	0.044	0.338	35	0
6 Years	**0.106**	**0.065**	**0.013**	**0.393**	**210**	**0**

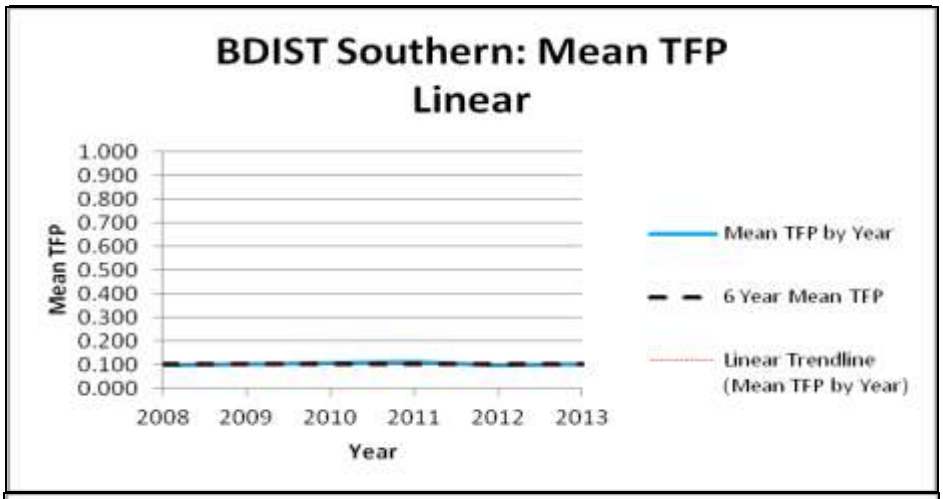


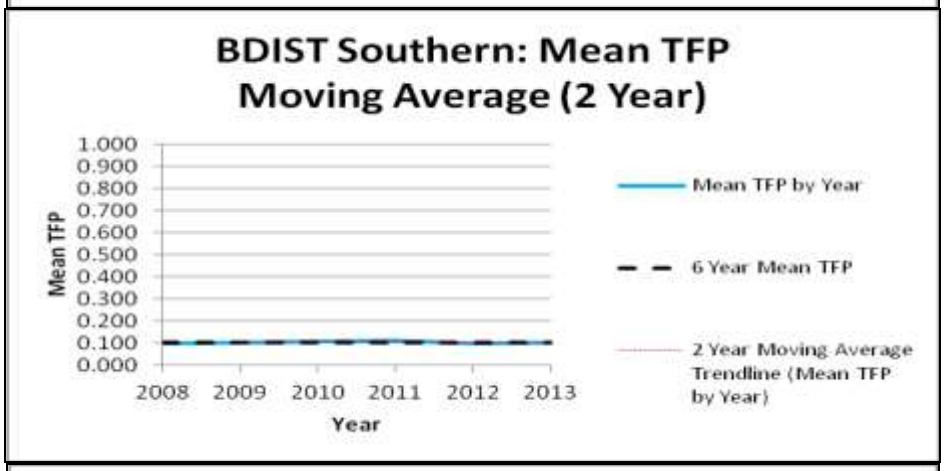


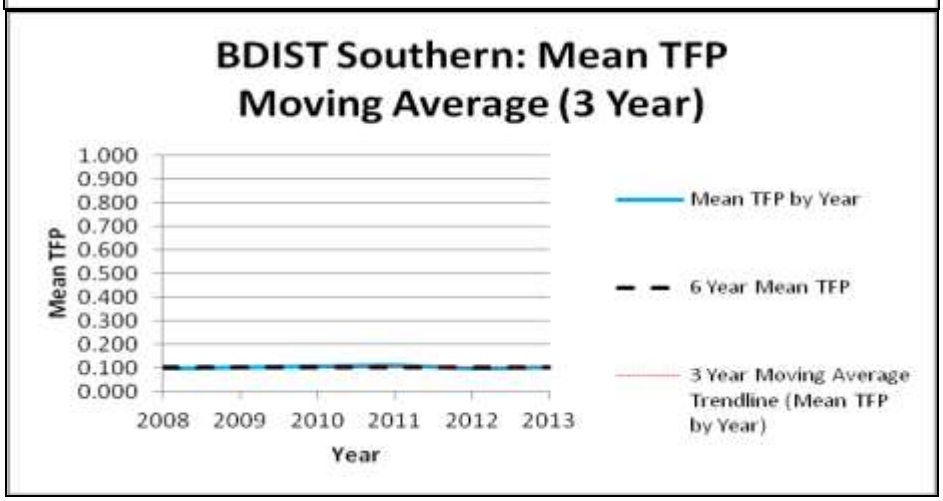


Appendix 5.4 — BDIST mean TFP for Southern region by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.097	0.054	0.006	0.227	32	0
2009	0.103	0.077	0.025	0.389	32	0
2010	0.108	0.077	0.034	0.328	32	0
2011	0.114	0.079	0.012	0.349	32	0
2012	0.099	0.058	0.031	0.249	32	0
2013	0.105	0.068	0.031	0.342	32	0
6 Years	**0.104**	**0.069**	**0.006**	**0.389**	**192**	**0**

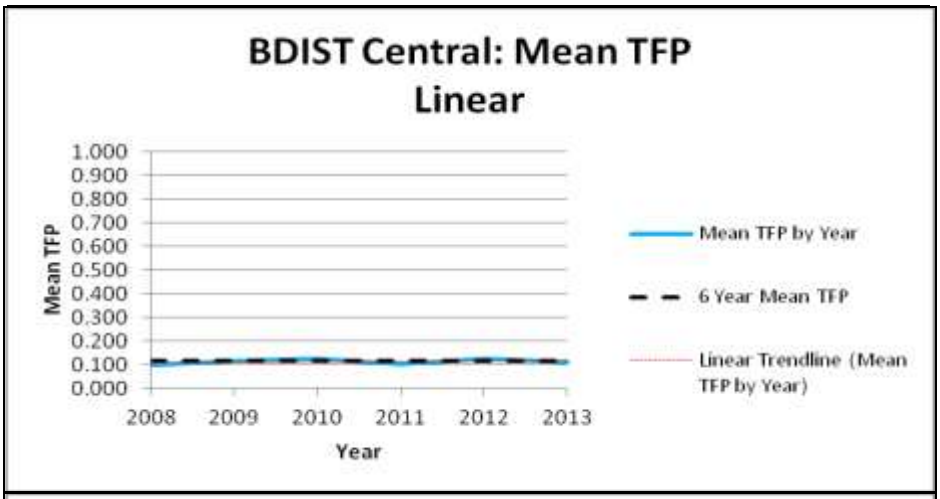


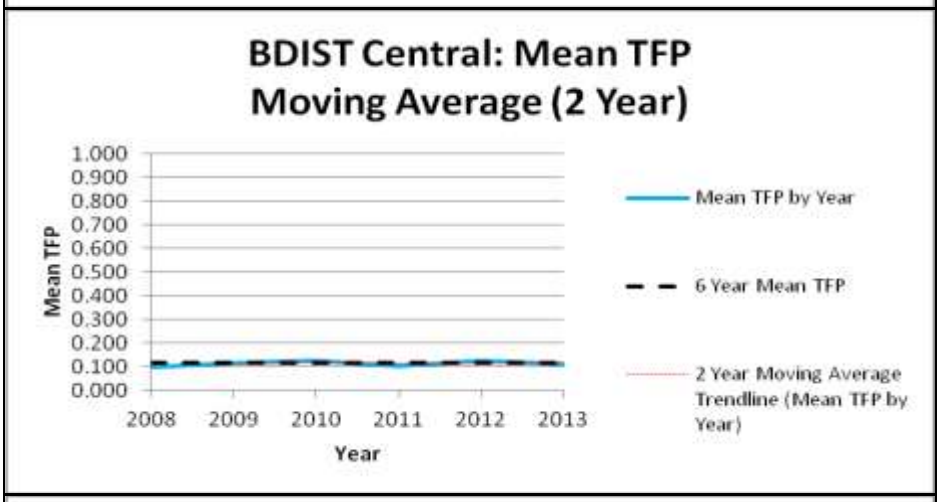


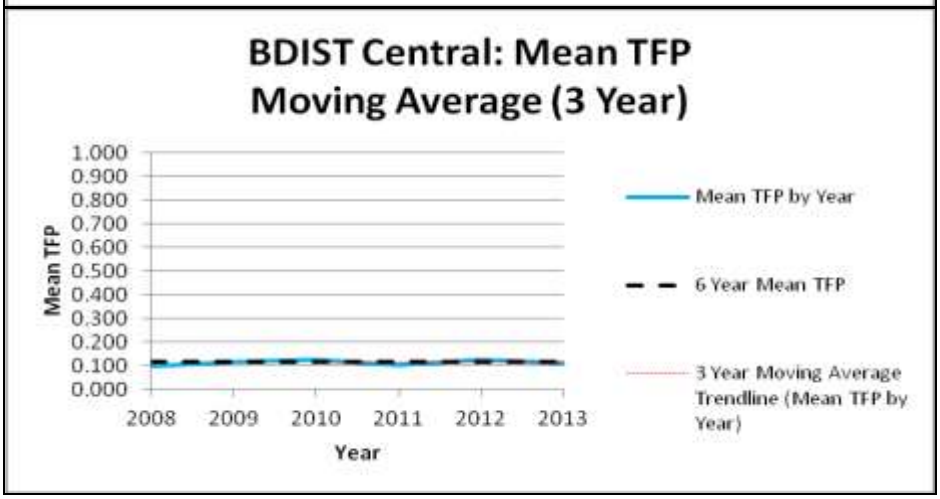


Appendix 5.5 — BDIST mean TFP for Central region by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.099	0.071	0.016	0.257	14	0
2009	0.118	0.086	0.027	0.320	14	0
2010	0.126	0.101	0.020	0.418	14	0
2011	0.103	0.054	0.036	0.228	14	0
2012	0.127	0.106	0.025	0.388	14	0
2013	0.113	0.072	0.036	0.267	14	0
6 Years	**0.114**	**0.082**	**0.016**	**0.418**	**84**	**0**

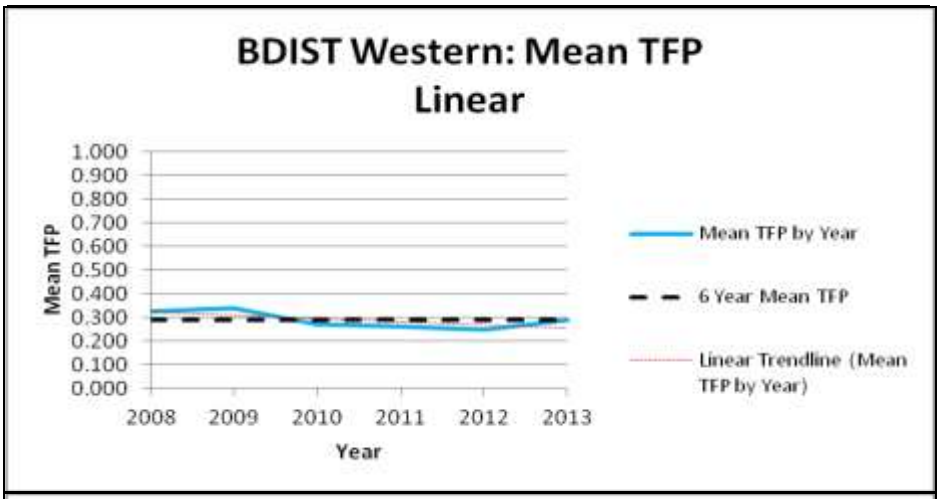


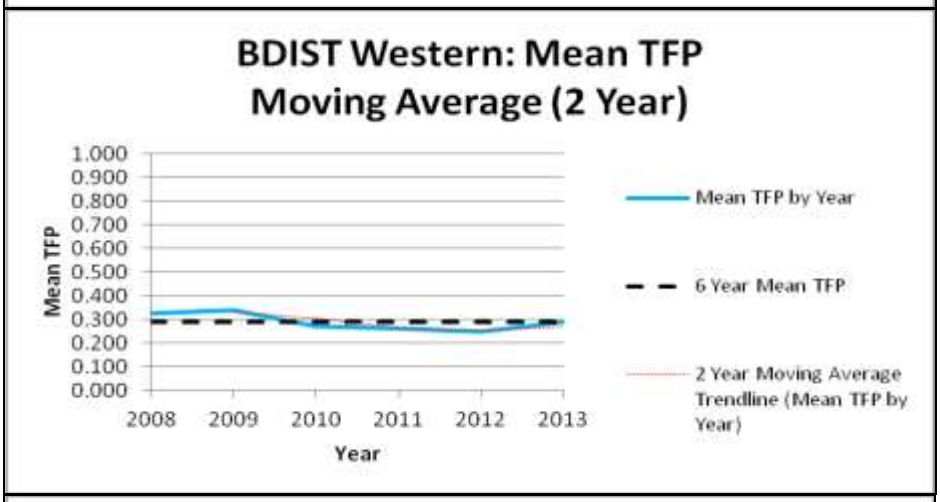


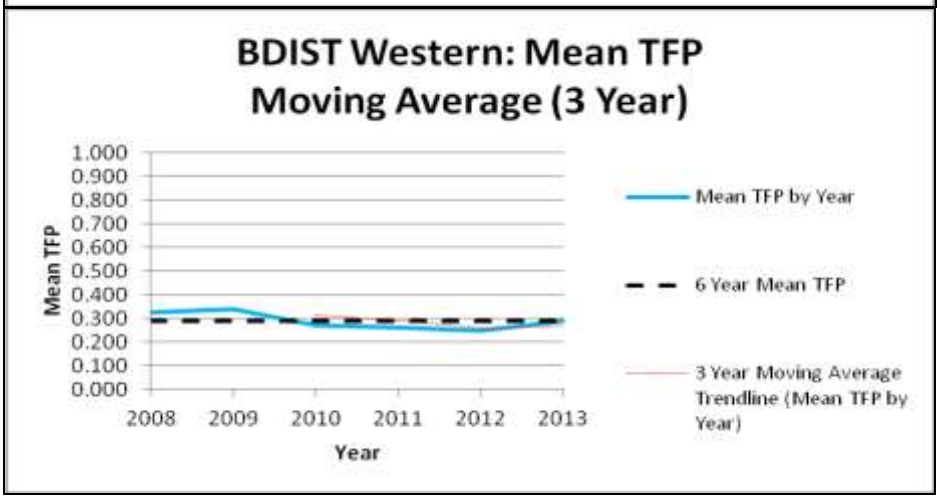


Appendix 5.6 — BDIST mean TFP for Western region by year

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.327	0.172	0.035	0.588	10	0
2009	0.340	0.184	0.085	0.648	10	0
2010	0.270	0.168	0.032	0.508	10	0
2011	0.262	0.181	0.014	0.613	10	0
2012	0.249	0.174	0.025	0.557	10	0
2013	0.289	0.179	0.026	0.624	10	0
6 Years	**0.289**	**0.172**	**0.014**	**0.648**	**60**	**0**





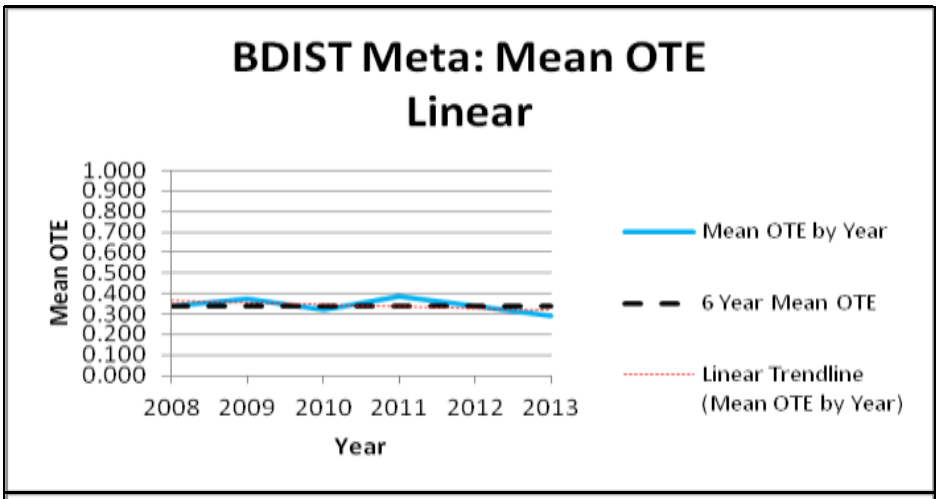


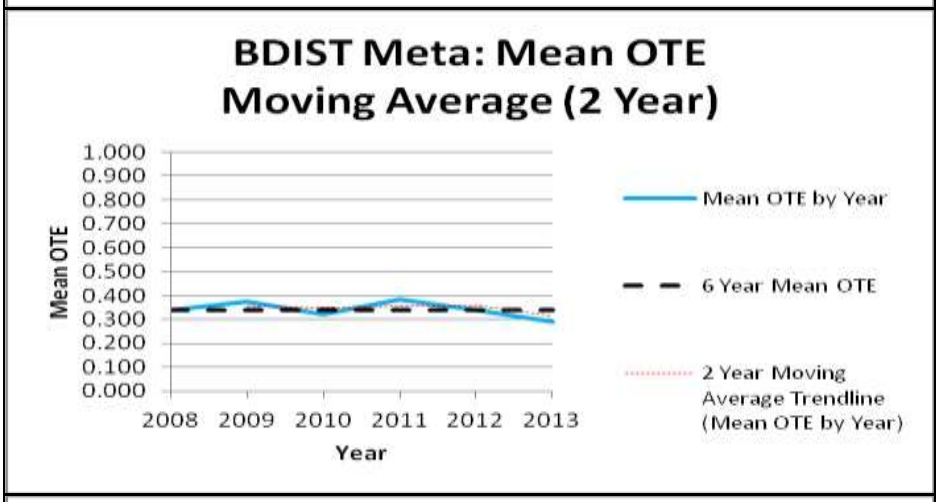
Appendix 6: BDIST OTE descriptive statistics and plots of productivity and efficiency scores (Chapter 6)

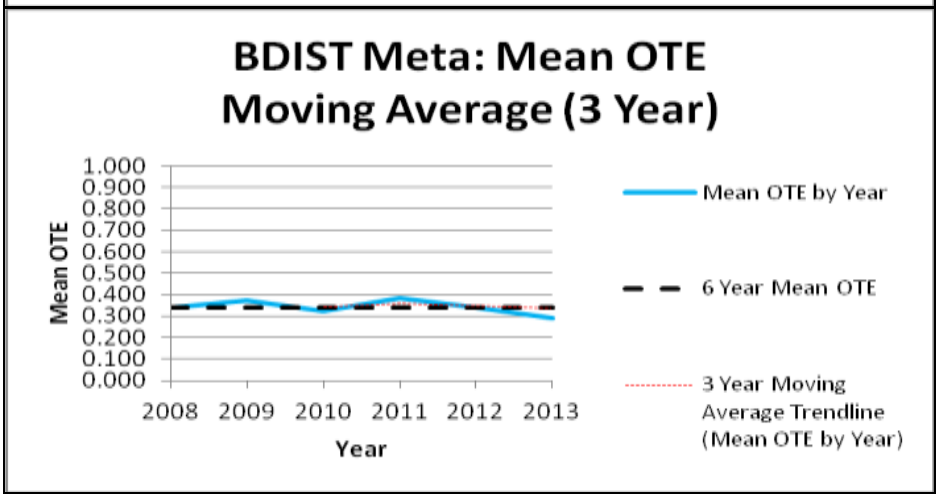
From Appendix 6.1 (BDIST mean OTE for meta by year) it can be seen that mean OTE by year over the 6-year period had some fluctuations with a distinct negative trend since 2011. The overall 6-year mean OTE was 0.341 (34.1%). The interpretation of this is that it suggests that output (BDIST) could have increased by 65.9% without any change in the available level of inputs (number of Gideon and Auxiliary members). From Appendix 6.2 (Northern), 6.3 (Eastern) and 6.6 (Western) a generally similar pattern for mean OTE as the meta level is shown. From Appendix 6.4 (Southern) and 6.5 (Central) a positive trend is evident.

Appendix 6.1 — BDIST mean OTE for meta by year

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.339	0.232	0.023	1.000	121	0
2009	0.375	0.240	0.029	1.000	121	0
2010	0.323	0.241	0.028	1.000	121	0
2011	0.384	0.256	0.019	1.000	121	0
2012	0.337	0.224	0.032	1.000	121	0
2013	0.289	0.200	0.030	1.000	121	0
6 Years	**0.341**	**0.234**	**0.019**	**1.000**	**726**	**0**

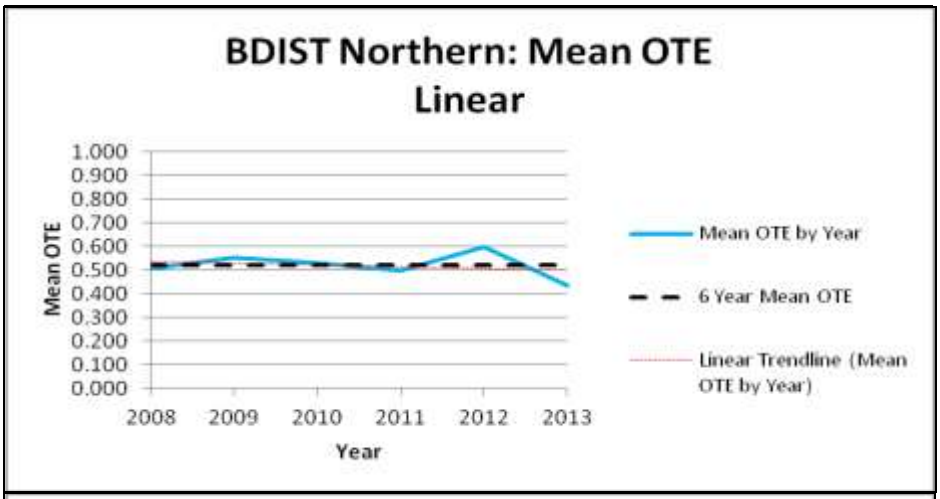


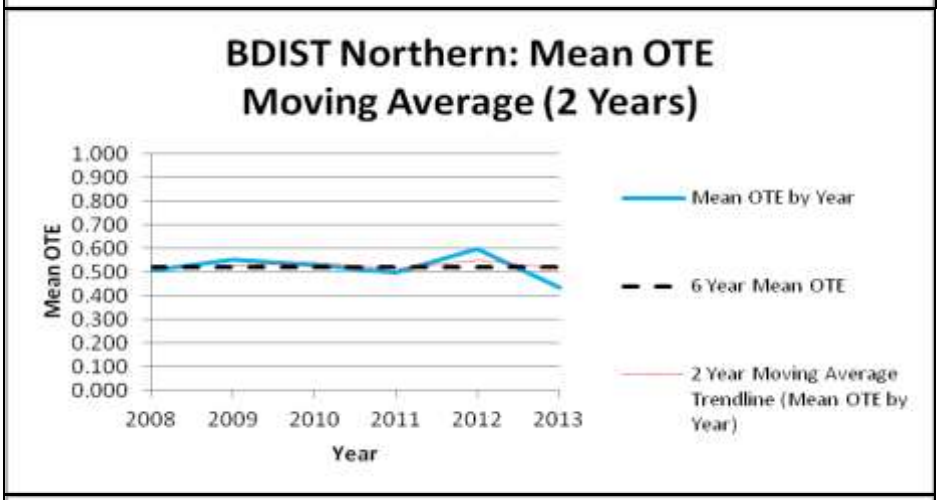


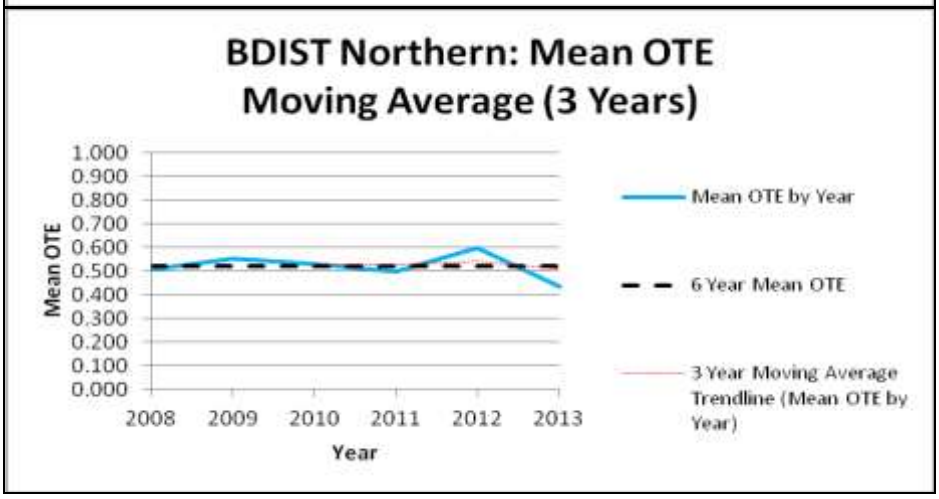


Appendix 6.2 — BDIST mean OTE for Northern region by year

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.507	0.298	0.074	1.000	30	0
2009	0.551	0.327	0.041	1.000	30	0
2010	0.528	0.298	0.039	1.000	30	0
2011	0.500	0.300	0.067	1.000	30	0
2012	0.596	0.288	0.095	1.000	30	0
2013	0.436	0.265	0.048	1.000	30	0
6 Years	**0.520**	**0.296**	**0.039**	**1.000**	**180**	**0**

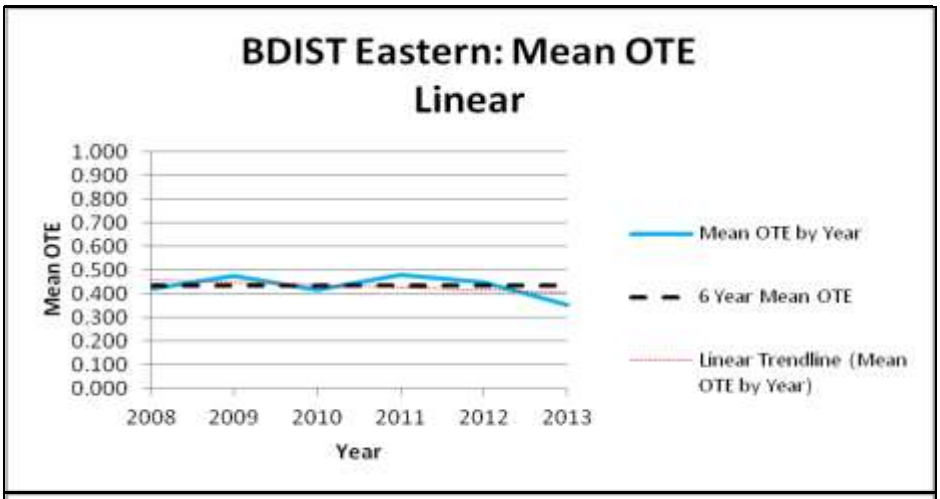


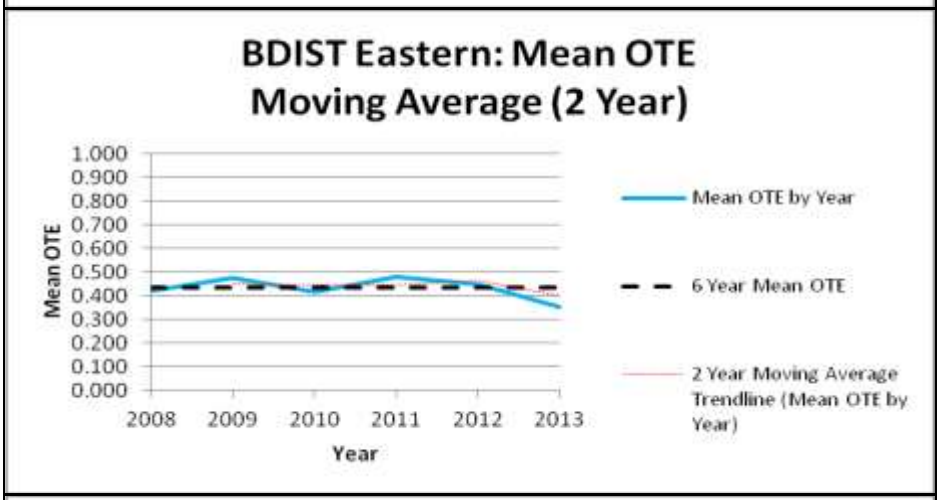


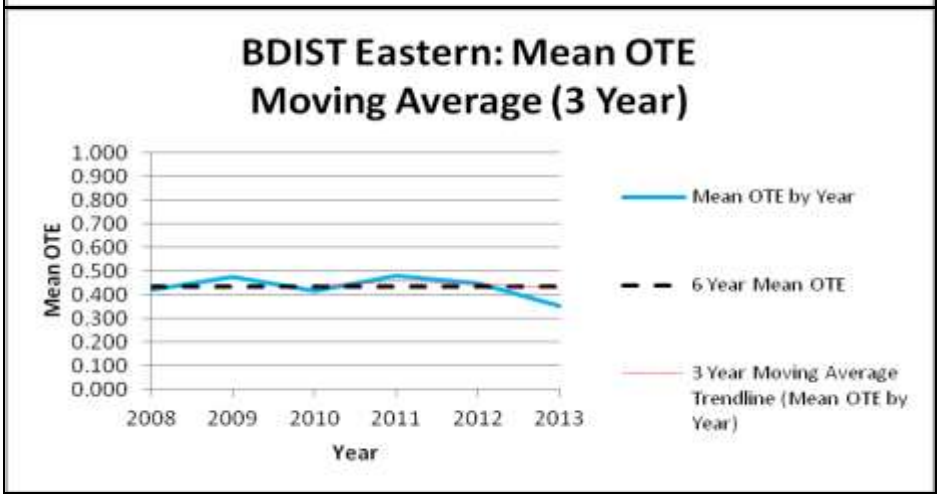


Appendix 6.3 — BDIST mean OTE for Eastern region

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.422	0.263	0.098	1.000	35	0
2009	0.477	0.278	0.101	1.000	35	0
2010	0.414	0.279	0.078	1.000	35	0
2011	0.480	0.279	0.051	1.000	35	0
2012	0.448	0.242	0.104	1.000	35	0
2013	0.352	0.200	0.140	1.000	35	0
6 Years	**0.432**	**0.259**	**0.051**	**1.000**	**210**	**0**

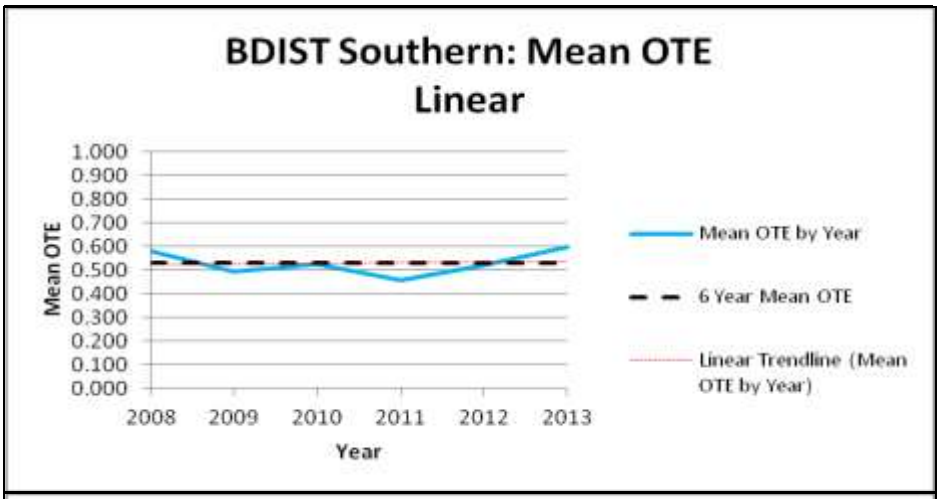


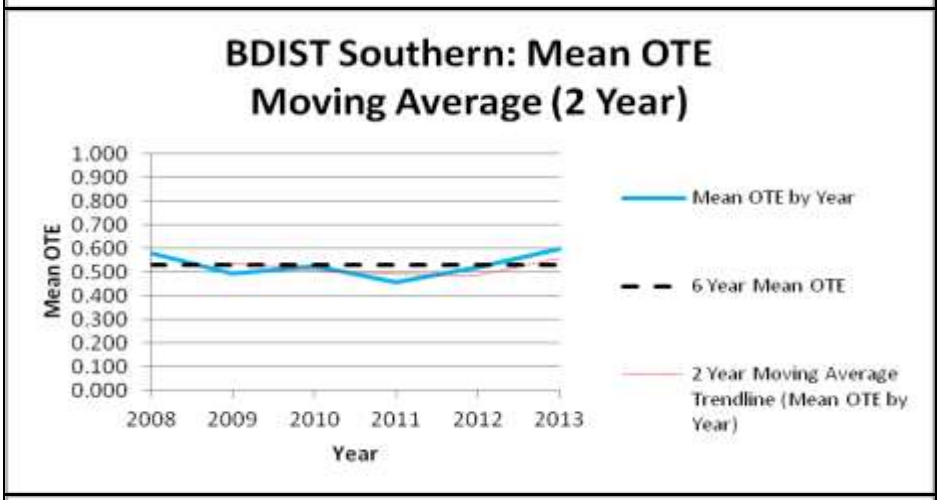


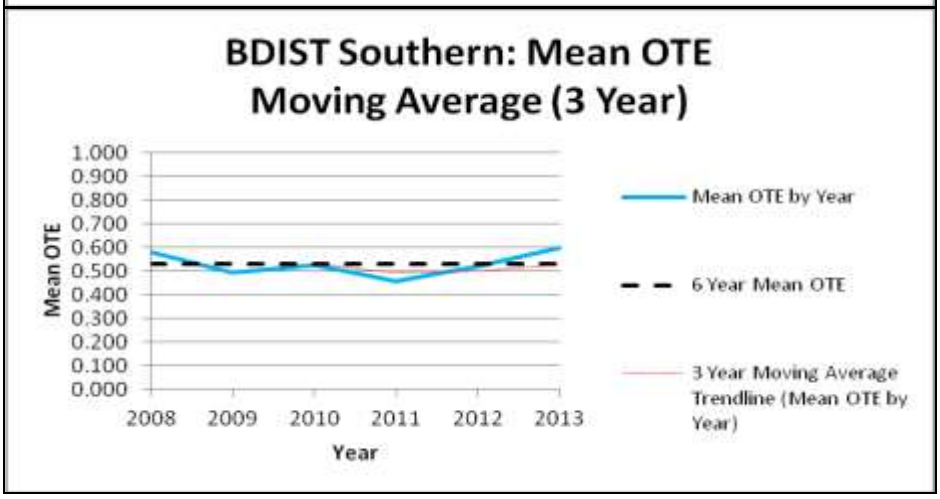


Appendix 6.4 — BDIST mean OTE for Southern region

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.581	0.270	0.045	1.000	32	0
2009	0.494	0.267	0.107	1.000	32	0
2010	0.525	0.280	0.179	1.000	32	0
2011	0.457	0.280	0.130	1.000	32	0
2012	0.520	0.292	0.139	1.000	32	0
2013	0.599	0.244	0.249	1.000	32	0
6 Years	**0.529**	**0.273**	**0.045**	**1.000**	**192**	**0**

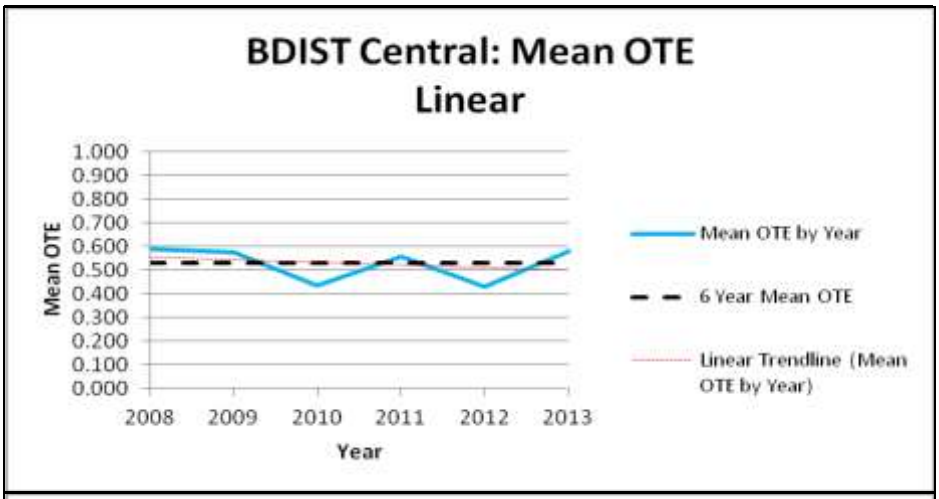


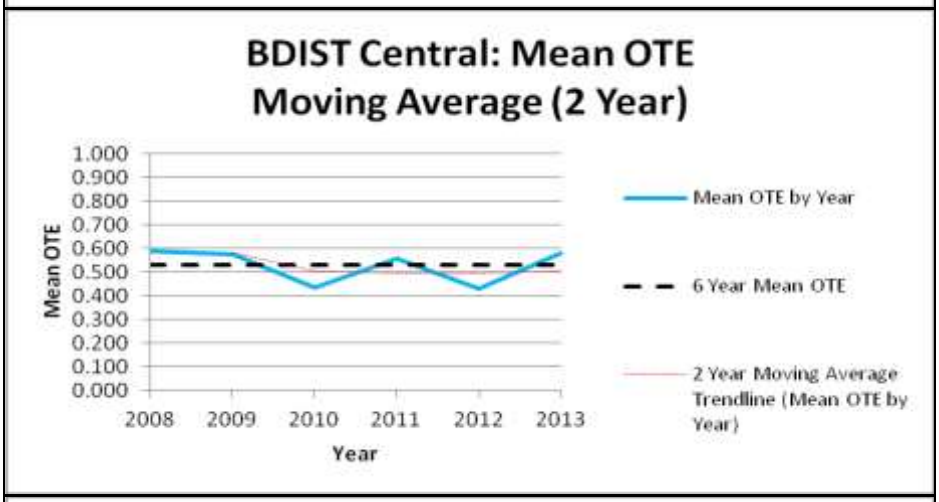


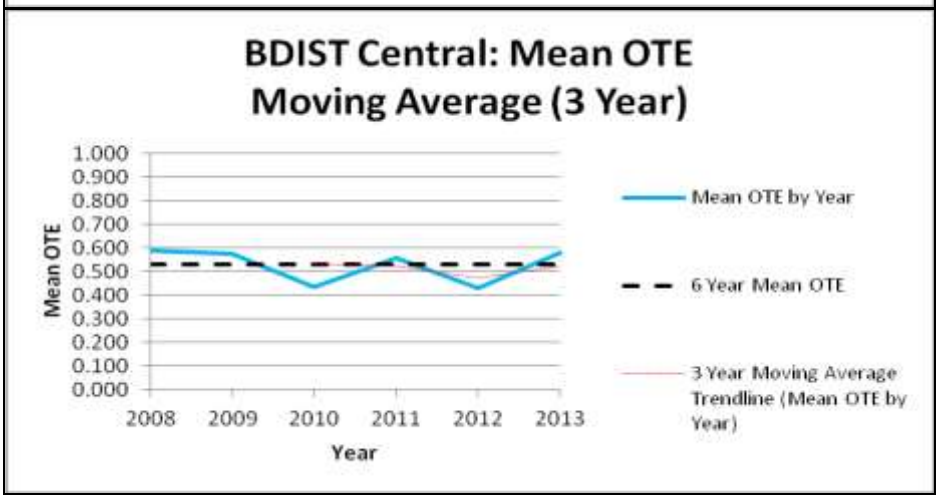


Appendix 6.5 — BDIST Mean OTE for Central region

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.588	0.364	0.083	1.000	14	0
2009	0.576	0.375	0.093	1.000	14	0
2010	0.435	0.303	0.054	1.000	14	0
2011	0.558	0.274	0.182	1.000	14	0
2012	0.431	0.346	0.072	1.000	14	0
2013	0.577	0.352	0.142	1.000	14	0
6 Years	**0.528**	**0.334**	**0.054**	**1.000**	**84**	**0**

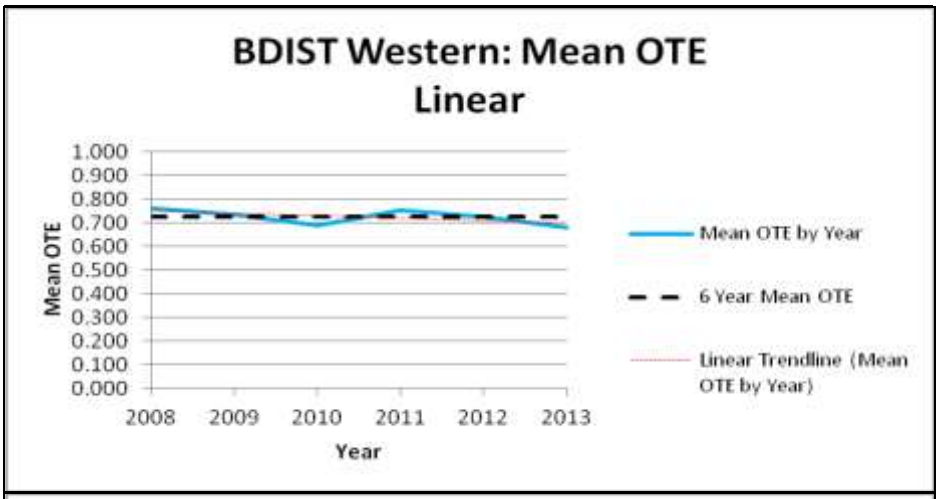


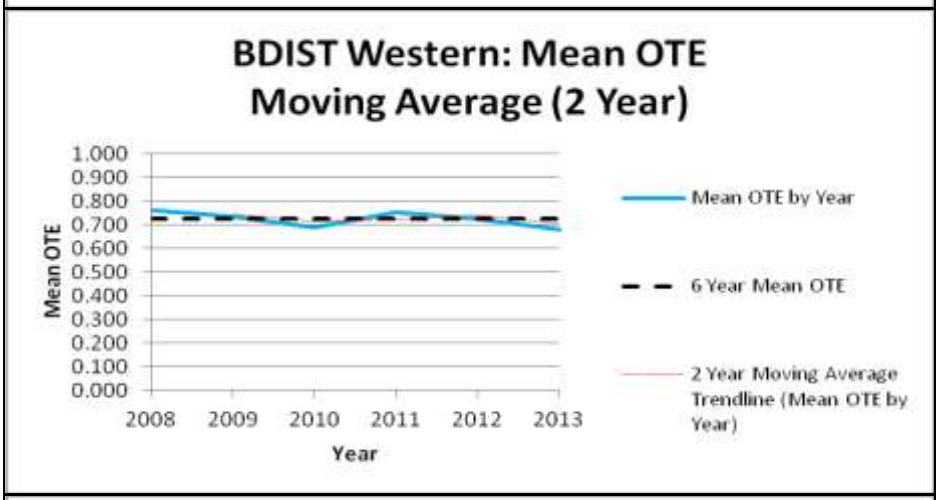


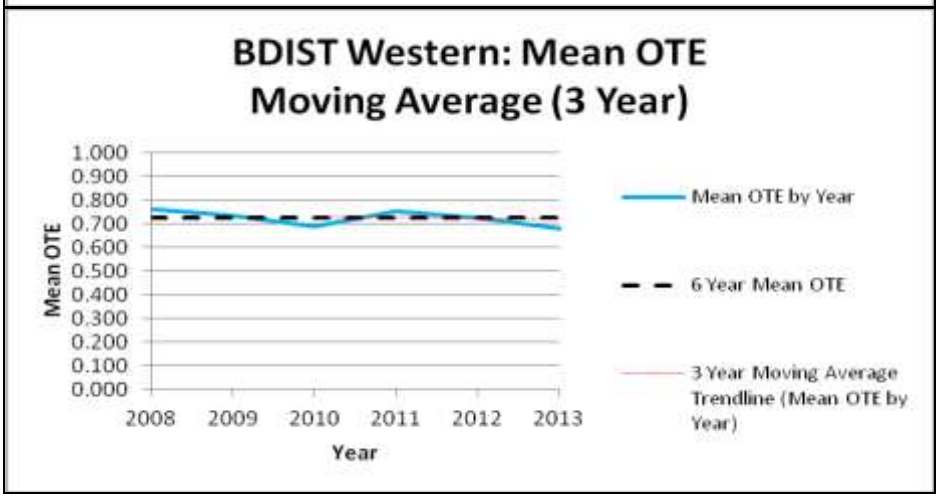


Appendix 6.6 — BDIST mean OTE for Western region

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.759	0.343	0.069	1.000	10	0
2009	0.735	0.342	0.188	1.000	10	0
2010	0.690	0.359	0.068	1.000	10	0
2011	0.754	0.352	0.030	1.000	10	0
2012	0.726	0.379	0.060	1.000	10	0
2013	0.680	0.351	0.055	1.000	10	0
6 Years	**0.724**	**0.341**	**0.030**	**1.000**	**60**	**0**







Appendix 7: BDIST 2013 slacks at meta level and equivalent state group levels (Chapter 6)

Appendix 7.1 — BDIST 2013 slacks at meta level (M) and equivalent Northern group level (N)

Meta Branch Code (M))	Equivalent Northern Branch Code (N)	BDIST Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	BDIST Output Slacks at Northern Level	GID Input Slacks at Northern Level	AUX Input Slacks at Northern Level
1N	1N	0	2	14	0	8	10
2N	2N	0	0	10	0	3	6
3N	3N	0	6	13	0	12	9
4N	4N	0	1	6	0	7	2
5N	5N	0	0	4	0	2	0
6N	6N	0	4	15	0	10	11
7N	7N	0	0	4	0	4	0
8N	8N	0	0	9	0	5	5
9N	9N	0	2	6	0	8	2
10N	10N	0	0	4	0	4	0
11N	11N	0	0	8	0	6	4
12N	12N	0	3	2	0	8	0
13N	13N	0	0	14	0	5	10
14N	14N	0	9	16	0	15	12
15N	15N	0	0	4	0	0	0
16N	16N	0	0	3	0	0	0
17N	17N	0	0	7	0	5	3
18N	18N	0	3	7	0	9	3
19N	19N	0	1	10	0	7	6
20N	20N	0	0	4	0	0	1
21N	21N	0	8	16	0	14	12
22N	22N	0	0	2	0	0	0
23N	23N	0	0	2	0	0	0
24N	24N	0	8	17	0	14	13
25N	25N	0	0	4	0	0	2
26N	26N	0	0	12	0	2	8
27N	27N	0	0	10	0	6	6
28N	28N	0	0	2	0	0	0
29N	29N	0	0	5	0	0	1
30N	30N	0	0	7	0	3	3
	Mean	**0**	**2**	**8**	**0**	**5**	**4**

Appendix 7.2 — BDIST 2013 slacks at meta level (M) and equivalent Eastern group level (E)

Meta Branch Code (M))	Equivalent Eastern Branch Code (N)	BDIST Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	BDIST Output Slacks at Eastern Level	GID Input Slacks at Eastern Level	AUX Input Slacks at Eastern Level
31M	1E	0	0	3	0	0	5
32M	2E	0	0	11	0	0	11
33M	3E	0	0	9	0	0	11
34M	4E	0	0	10	0	0	11
35M	5E	0	0	7	0	0	10
36M	6E	0	0	7	0	0	7
37M	7E	0	3	7	0	3	7
38M	8E	0	4	5	0	4	5
39M	9E	0	0	0	0	0	1
40M	10E	0	6	8	0	6	8
41M	11E	0	0	2	0	0	3
42M	12E	0	0	4	0	0	7
43M	13E	0	0	9	0	0	12
44M	14E	0	0	2	0	0	5
45M	15E	0	4	12	0	4	12
46M	16E	0	0	0	0	0	2
47M	17E	0	0	7	0	0	7
48M	18E	0	0	7	0	0	7
49M	19E	0	0	0	0	0	0
50M	20E	0	0	1	0	0	5
51M	21E	0	0	3	0	0	3
52M	22E	0	0	2	0	0	5
53M	23E	0	0	3	0	0	6
54M	24E	0	0	4	0	0	5
55M	25E	0	0	0	0	0	0
56M	26E	0	0	2	0	0	4
57M	27E	0	0	1	0	0	3
58M	28E	0	0	4	0	0	5
59M	29E	0	0	5	0	0	5
60M	30E	0	2	0	0	2	0
61M	31E	0	0	4	0	0	6
62M	32E	0	0	0	0	0	0
63M	33E	0	6	9	0	6	9
64M	34E	0	0	3	0	0	4
65M	35E	0	0	4	0	0	7
	Mean	**0**	**1**	**4**	**0**	**1**	**6**

Appendix 7.3 — BDIST 2013 slacks at meta level (M) and equivalent Southern group level (S)

Meta Branch Code (M))	Equivalent Southern Branch Code (N)	BDIST Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	BDIST Output Slacks at Southern Level	GID Input Slacks at Southern Level	AUX Input Slacks at Southern Level
66M	1S	0	1	13	0	2	0
67M	2S	0	5	10	0	10	0
68M	3S	0	0	0	0	1	0
69M	4S	0	0	3	0	9	0
70M	5S	0	0	0	0	0	0
71M	6S	0	0	2	0	4	0
72M	7S	0	0	0	0	0	0
73M	8S	0	2	9	0	9	0
74M	9S	0	3	15	0	1	0
75M	10S	0	0	5	0	1	0
76M	11S	0	0	3	0	4	0
77M	12S	0	0	6	0	2	0
78M	13S	0	0	1	0	0	0
79M	14S	0	0	0	0	0	0
80M	15S	0	10	21	0	0	0
81M	16S	0	0	10	0	4	0
82M	17S	0	0	5	0	2	0
83M	18S	0	0	3	0	4	0
84M	19S	0	2	14	0	2	0
85M	20S	0	0	3	0	3	0
86M	21S	0	0	4	0	5	0
87M	22S	0	0	0	0	2	0
88M	23S	0	0	3	0	0	0
89M	24S	0	12	20	0	3	0
90M	25S	0	0	1	0	3	0
91M	26S	0	0	5	0	8	0
92M	27S	0	0	5	0	6	0
93M	28S	0	8	11	0	12	0
94M	29S	0	14	14	0	14	0
95M	30S	0	0	8	0	5	0
96M	31S	0	0	7	0	5	0
97M	32S	0	0	4	0	2	0
	Mean	**0**	**2**	**6**	**0**	**4**	**0**

Appendix 7.4 — BDIST 2013 Slacks at meta level (M) and equivalent Central group level (C)

Meta Branch Code (M))	Equivalent Central Branch Code (N)	BDIST Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	BDIST Output Slacks at Central Level	GID Input Slacks at Central Level	AUX Input Slacks at Central Level
98M	1C	0	0	6	0	0	1
99M	2C	0	0	5	0	0	1
100M	3C	0	0	5	0	1	0
101M	4C	0	0	7	0	0	0
102M	5C	0	0	5	0	0	3
103M	6C	0	15	14	0	15	7
104M	7C	0	0	0	0	0	0
105M	8C	0	0	9	0	0	2
106M	9C	0	0	9	0	0	4
107M	10C	0	0	0	0	0	0
108M	11C	0	0	3	0	0	0
109M	12C	0	0	1	0	0	0
110M	13C	0	0	6	0	0	0
111M	14C	0	0	5	0	0	0
	Mean	**0**	**1**	**5**	**0**	**1**	**1**

Appendix 7.5 — BDIST 2013 slacks at meta level (M) and equivalent Western group level (W)

Meta Branch Code (M))	Equivalent Western Branch Code (N)	BDIST Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	BDIST Output Slacks at Western Level	GID Input Slacks at Western Level	AUX Input Slacks at Western Level
112M	1W	0	6	10	0	12	10
113M	2W	0	0	1	0	0	0
114M	3W	0	0	2	0	0	1
115M	4W	0	0	6	0	0	6
116M	5W	0	0	4	0	1	4
117M	6W	0	0	3	0	0	3
118M	7W	0	0	0	0	0	0
119M	8W	0	0	0	0	1	0
120M	9W	0	0	4	0	0	4
121M	10W	0	0	0	0	0	0
	Mean	**0**	**1**	**3**	**0**	**1**	**3**

Appendix 8: BDIST 2013 peers at meta level and regional group levels and equivalents (Chapter 6)

Appendix 8.1A — BDIST 2013 peers at meta level (M) with Northern group (N) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Northern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
1M	49M	19E				
2M	49M	19E	107M	10C		
3M	49M	19E				
4M	49M	19E				
5M	49M	19E	107M	10C		
6M	49M	19E				
7M	107M	10C	49M	19E		
8M	107M	10C	49M	19E		
9M	49M	19E				
10M	107M	10C	49M	19E		
11M	49M	19E				
12M	49M	19E				
13M	107M	10C	49M	19E		
14M	49M	19E				
15M	107M	10C	49M	19E		
16M	49M	19E	107M	10C		
17M	49M	19E	107M	10C		
18M	49M	19E				
19M	49M	19E				
20M	49M	19E	107M	10C		
21M	49M	19E				
22M	49M	19E	107M	10C		
23M	107M	10C	49M	19E		
24M	49M	19E				
25M	107M	10C	49M	19E		
26M	107M	10C	49M	19E		
27M	49M	19E				
28M	107M	10C	49M	19E		
29M	49M	19E	107M	10C		
30M	107M	10C	49M	19E		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.1B — BDIST 2013 peers at Northern group level (N) with meta level (M) equivalents

	Northern Peer Code (N) with Equivalent Meta Branch Code (M)					
Northern Group Branch Code	**Northern Peer 1 Code (N)**	**Equivalent Meta Code (M)**	**Northern Peer 2 Code (N)**	**Equivalent Meta Code (M)**	**Northern Peer 3 Code (N)**	**Equivalent Meta Code (M)**
1N	15N	15M				
2N	15N	15M				
3N	15N	15M				
4N	15N	15M				
5N	15N	15M				
6N	15N	15M				
7N	15N	15M				
8N	15N	15M				
9N	15N	15M				
10N	15N	15M				
11N	15N	15M				
12N	28N	28M				
13N	15N	15M				
14N	15N	15M				
15N	15N	15M				
16N	23N	23M	15N	15M	28N	28M
17N	15N	15M				
18N	15N	15M				
19N	15N	15M				
20N	15N	15M	23N	23M		
21N	15N	15M				
22N	23N	23M	28N	28M		
23N	23N	23M				
24N	15N	15M				
25N	23N	23M				
26N	15N	15M				
27N	15N	15M				
28N	28N	28M				
29N	15N	15M	23N	23M		
30N	15N	15M				

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.2A — BDIST 2013 peers at meta level (M) with Eastern group (E) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Eastern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
31M	107M	10C	49M	19E		
32M	49M	19E				
33M	107M	10C	49M	19E		
34M	107M	10C	49M	19E		
35M	49M	19E	107M	10C		
36M	49M	19E				
37M	49M	19E				
38M	49M	19E				
39M	49M	19E	107M	10C	62M	32E
40M	49M	19E				
41M	107M	10C	49M	19E		
42M	107M	10C	49M	19E		
43M	107M	10C	49M	19E		
44M	49M	19E	107M	10C		
45M	49M	19E				
46M	49M	19E	62M	32E	17M	17N
47M	49M	19E				
48M	49M	19E				
49M	49M	19E				
50M	107M	10C	49M	19E		
51M	107M	10C	49M	19E		
52M	107M	10C	49M	19E		
53M	107M	10C	49M	19E		
54M	49M	19E	107M	10C		
55M	62M	32E	49M	19E	17M	17N
56M	107M	10C	49M	19E		
57M	107M	10C	49M	19E		
58M	107M	10C	49M	19E		
59M	107M	10C	49M	19E		
60M	49M	19E	62M	32E		
61M	107M	10C	49M	19E		
62M	62M	32E				
63M	49M	19E				
64M	107M	10C	49M	19E		
65M	49M	19E	107M	10C		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.2B — BDIST 2013 peers at Eastern group level (E) with meta level (M) equivalents

	Eastern Peer Code (E) with Equivalent Meta Branch Code (M)					
Eastern Group Branch Code	**Eastern Peer 1 Code (E)**	**Equivalent Meta Code (M)**	**Eastern Peer 2 Code (E)**	**Equivalent Meta Code (M)**	**Eastern Peer 3 Code (E)**	**Equivalent Meta Code (M)**
1E	19E	49M	32E	62M		
2E	19E	49M				
3E	32E	62M	19E	49M		
4E	32E	62M	19E	49M		
5E	32E	62M	19E	49M		
6E	19E	49M				
7E	19E	49M				
8E	19E	49M				
9E	32E	62M	19E	49M		
10E	19E	49M				
11E	19E	49M	32E	62M		
12E	32E	62M	19E	49M		
13E	32E	62M	19E	49M		
14E	19E	49M	32E	62M		
15E	19E	49M				
16E	32E	62M	19E	49M		
17E	19E	49M				
18E	19E	49M				
19E	19E	49M				
20E	32E	62M	19E	49M		
21E	32E	62M	19E	49M		
22E	32E	62M	19E	49M		
23E	32E	62M	19E	49M		
24E	32E	62M	19E	49M		
25E	19E	49M	32E	62M		
26E	32E	62M	19E	49M		
27E	32E	62M	19E	49M		
28E	19E	49M	32E	62M		
29E	19E	49M	32E	62M		
30E	19E	49M	32E	62M		
31E	32E	62M	19E	49M		
32E	32E	62M				
33E	19E	49M				
34E	32E	62M	19E	49M		
35E	32E	62M	19E	49M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.3A — BDIST 2013 peers at meta level (M) with Southern group (S) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Southern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
66M	49M	19E				
67M	49M	19E				
68M	49M	19E	107M	10C		
69M	49M	19E	107M	10C		
70M	49M	19E	107M	10C		
71M	49M	19E	107M	10C		
72M	49M	19E	107M	10C		
73M	49M	19E				
74M	49M	19E				
75M	107M	10C	49M	19E		
76M	107M	10C	49M	19E		
77M	107M	10C	49M	19E		
78M	107M	10C	49M	19E		
79M	49M	19E	62M	32E	17M	17N
80M	49M	19E				
81M	49M	19E	107M	10C		
82M	107M	10C	49M	19E		
83M	107M	10C	49M	19E		
84M	49M	19E				
85M	49M	19E	107M	10C		
86M	107M	10C	49M	19E		
87M	49M	19E	62M	32E	17M	17N
88M	107M	10C	49M	19E		
89M	49M	19E				
90M	49M	19E	107M	10C		
91M	107M	10C	49M	19E		
92M	107M	10C	49M	19E		
93M	49M	19E				
94M	49M	19E				
95M	49M	19E	107M	10C		
96M	49M	19E	107M	10C		
97M	107M	10C	49M	19E		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.3B — BDIST 2013 peers at Southern group level (S) with meta level (M) equivalents

	Southern Peer Code (S) with Equivalent Meta Branch Code (M)					
Southern Group Branch Code	**Southern Peer 1 Code (S)**	**Equivalent Meta Code (M)**	**Southern Peer 2 Code (S)**	**Equivalent Meta Code (M)**	**Southern Peer 3 Code (S)**	**Equivalent Meta Code (M)**
1S	23S	88M	15S	80M		
2S	15S	80M	23S	88M		
3S	23S	88M	14S	79M		
4S	23S	88M				
5S	5S	70M				
6S	23S	88M	14S	79M		
7S	14S	79M	5S	70M	23S	88M
8S	23S	88M	15S	80M		
9S	23S	88M	15S	80M		
10S	15S	80M	23S	88M		
11S	23S	88M				
12S	15S	80M	23S	88M		
13S	23S	88M	14S	79M		
14S	14S	79M				
15S	15S	80M				
16S	23S	88M	15S	80M		
17S	23S	88M	15S	80M		
18S	23S	88M				
19S	23S	88M	15S	80M		
20S	23S	88M				
21S	23S	88M	15S	80M		
22S	14S	79M				
23S	23S	88M				
24S	23S	88M	15S	80M		
25S	23S	88M	14S	79M		
26S	23S	88M	15S	80M		
27S	15S	80M	23S	88M		
28S	15S	80M	23S	88M		
29S	23S	88M	15S	80M		
30S	23S	88M	15S	80M		
31S	15S	80M	23S	88M		
32S	15S	80M	23S	88M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.4A — BDIST 2013 peers at meta level (M) with Central group (C) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Central Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
98M	49M	19E	107M	10C		
99M	107M	10C	49M	19E		
100M	107M	10C	49M	19E		
101M	49M	19E				
102M	107M	10C	49M	19E		
103M	49M	19E				
104M	49M	19E	107M	10C		
105M	49M	19E	107M	10C		
106M	49M	19E	107M	10C		
107M	107M	10C				
108M	107M	10C	49M	19E		
109M	49M	19E	107M	10C		
110M	107M	10C	49M	19E		
111M	49M	19E	107M	10C		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.4B — BDIST 2013 peers at Central group level (C) with meta level (M) equivalents

	Central Peer Code (C) with Equivalent Meta Branch Code (M)					
Central Group Branch Code	**Central Peer 1 Code (C)**	**Equivalent Meta Code (M)**	**Central Peer 2 Code (C)**	**Equivalent Meta Code (M)**	**Central Peer 3 Code (C)**	**Equivalent Meta Code (M)**
1C	13C	110M	10C	107M		
2C	13C	110M	10C	107M		
3C	12C	109M	13C	110M		
4C	4C	101M				
5C	10C	107M	13C	110M		
6C	4C	101M				
7C	7C	104M				
8C	13C	110M	4C	101M		
9C	13C	110M	10C	107M		
10C	10C	107M				
11C	13C	110M	7C	104M		
12C	12C	109M				
13C	13C	110M				
14C	13C	110M	10C	107M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.5A — BDIST 2013 peers at meta level (M) with Western group (W) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Western Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
112M	49M	19E				
113M	107M	10C	49M	19E		
114M	107M	10C	49M	19E		
115M	107M	10C	49M	19E		
116M	107M	10C	49M	19E		
117M	49M	19E	107M	10C		
118M	49M	19E	62M	32E	17M	17N
119M	49M	19E	62M	32E	17M	17N
120M	49M	19E	107M	10C		
121M	49M	19E	107M	10C		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 8.5B — BDIST 2013 peers at Western group (W) level with meta level (M) equivalents

	Western Peer Code (W) with Equivalent Meta Branch Code (M)					
Western Group Branch Code	**Western Peer 1 Code (W)**	**Equivalent Meta Code (M)**	**Western Peer 2 Code (W)**	**Equivalent Meta Code (M)**	**Western Peer 3 Code (W)**	**Equivalent Meta Code (M)**
1W	10W	121M				
2W	2W	113M				
3W	10W	121M	2W	113M		
4W	2W	113M	10W	121M		
5W	10W	121M				
6W	10W	121M	2W	113M		
7W	7W	118M				
8W	7W	118M				
9W	2W	113M	10W	121M		
10W	10W	121M				

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 9: BDIST 2013 targets at meta level and regional group levels (Chapter 6)

Appendix 9.1 — BDIST 2013 targets at meta level (M) and equivalent Northern group level (N)

Meta Branch Code (M)	Equivalent Northern Branch Code (N)	Target at Meta Level	Equivalent Target at Northern Group Level
1M	1N	13305	8620
2M	2N	11285	8620
3M	3N	13305	8620
4M	4N	13305	8620
5M	5N	10611	8620
6M	6N	13305	8620
7M	7N	11958	8620
8M	8N	12632	8620
9M	9N	13305	8620
10M	10N	11958	8620
11M	11N	13305	8620
12M	12N	13305	5466
13M	13N	12632	8620
14M	14N	13305	8620
15M	15N	9264	8620
16M	16N	6571	5713
17M	17N	12632	8620
18M	18N	13305	8620
19M	19N	13305	8620
20M	20N	7244	6583
21M	21N	13305	8620
22M	22N	4551	3101
23M	23N	3204	2510
24M	24N	13305	8620
25M	25N	3204	2510
26M	26N	10611	8620
27M	27N	13305	8620
28M	28N	9938	5466
29M	29N	7918	7262
30M	30N	11285	8620
Totals		**330641**	**228252**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 9.2 — BDIST 2013 targets at meta level (M) and equivalent Eastern group level (E)

Meta Branch Code (M)	Equivalent Eastern Branch Code (E)	Target at Meta Level	Equivalent Target at Eastern Group Level
31M	1E	7244	6834
32M	2E	13305	13305
33M	3E	9264	8991
34M	4E	11958	11867
35M	5E	5897	5396
36M	6E	13305	13305
37M	7E	13305	13305
38M	8E	13305	13305
39M	9E	5556	5396
40M	10E	13305	13305
41M	11E	10611	10429
42M	12E	5897	5396
43M	13E	6571	6115
44M	14E	6571	6115
45M	15E	13305	13305
46M	16E	6400	6115
47M	17E	13305	13305
48M	18E	13305	13305
49M	19E	13305	13305
50M	20E	3877	3239
51M	21E	12632	12586
52M	22E	5897	5396
53M	23E	5897	5396
54M	24E	10611	10429
55M	25E	4711	4677
56M	26E	9264	8991
57M	27E	7244	6834
58M	28E	9938	9710
59M	29E	12632	12586
60M	30E	5216	5216
61M	31E	7918	7553
62M	32E	2520	2520
63M	33E	13305	13305
64M	34E	9938	9710
65M	35E	6571	6115
Totals		**323887**	**316662**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 9.3 — BDIST 2013 targets at meta level (M) and equivalent Southern group level (S)

Meta Branch Code (M)	Equivalent Southern Branch Code (S)	Target at Meta Level	Equivalent Target at Southern Group Level
66M	1S	13305	3086
67M	2S	13305	2902
68M	3S	3877	1760
69M	4S	9264	2471
70M	5S	1857	510
71M	6S	5897	2234
72M	7S	2530	1135
73M	8S	13305	2840
74M	9S	13305	3209
75M	10S	5897	2594
76M	11S	5897	2471
77M	12S	7244	2656
78M	13S	3204	1997
79M	14S	3033	1523
80M	15S	13305	3578
81M	16S	12632	2902
82M	17S	6571	2594
83M	18S	5897	2471
84M	19S	13305	3148
85M	20S	5224	2471
86M	21S	7244	2533
87M	22S	4380	1523
88M	23S	3204	2471
89M	24S	13305	3517
90M	25S	5224	1997
91M	26S	10611	2594
92M	27S	9264	2594
93M	28S	13305	2963
94M	29S	13305	3148
95M	30S	11285	2779
96M	31S	10611	2717
97M	32S	5224	2533
Totals		**265817**	**79917**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 9.4 — BDIST 2013 targets at meta level (M) and equivalent Central group level (C)

Meta Branch Code (M)	Equivalent Central Branch Code (C)	Target at Meta Level	Equivalent Target at Central Group Level
98M	1C	8591	3774
99M	2C	7244	3230
100M	3C	10611	3962
101M	4C	13305	5136
102M	5C	3204	1598
103M	6C	13305	5136
104M	7C	3877	770
105M	8C	12632	5000
106M	9C	9264	4046
107M	10C	510	510
108M	11C	7244	2680
109M	12C	7918	1451
110M	13C	10611	4590
111M	14C	8591	3774
Totals		**116908**	**45657**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 9.5 — BDIST 2013 targets at meta level (M) and equivalent Western group level (W)

Meta Branch Code (M)	Equivalent Western Branch Code (W)	Target at Meta Level	Equivalent Target at Western Group Level
112M	1W	13305	4764
113M	2W	2530	2025
114M	3W	5224	3121
115M	4W	6571	3668
116M	5W	9938	4764
117M	6W	6571	3668
118M	7W	8420	2233
119M	8W	9094	2233
120M	9W	7244	3942
121M	10W	9264	4764
Totals		**78161**	**35183**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 10: DON mean productivity and efficiency scores by level and year: five regions and national (Chapter 6)

Level	Year	TFP	TFPE	OTE	OSE	OME	ROSE	OSME	ITE	ISE	IME	RISE	ISME	RME
Meta	2008	0.042	0.232	0.328	0.892	1.000	0.747	0.747	0.416	0.673	0.943	0.595	0.560	0.843
(i.e. National/	2009	0.045	0.205	0.301	0.866	1.000	0.735	0.735	0.447	0.576	0.947	0.511	0.484	0.850
All Australia)	2010	0.044	0.231	0.366	0.681	1.000	0.654	0.654	0.391	0.642	0.941	0.652	0.625	0.965
	2011	0.044	0.171	0.269	0.808	1.000	0.727	0.727	0.490	0.405	0.876	0.410	0.365	0.909
	2012	0.044	0.217	0.325	0.862	1.000	0.735	0.735	0.490	0.540	0.881	0.506	0.452	0.861
	2013	0.042	0.160	0.224	0.880	1.000	0.784	0.784	0.410	0.457	0.789	0.492	0.403	0.900
	6-Year	**0.044**	**0.203**	**0.302**	**0.831**	**1.000**	**0.730**	**0.730**	**0.441**	**0.549**	**0.896**	**0.528**	**0.482**	**0.888**
Northern	2008	0.086	0.283	0.436	0.776	1.000	0.732	0.732	0.637	0.482	0.899	0.499	0.452	0.935
	2009	0.094	0.246	0.402	0.752	1.000	0.697	0.697	0.616	0.437	0.958	0.419	0.404	0.925
	2010	0.088	0.338	0.518	0.850	1.000	0.699	0.699	0.664	0.628	0.939	0.546	0.509	0.827
	2011	0.089	0.174	0.323	0.717	1.000	0.633	0.633	0.609	0.396	0.906	0.315	0.287	0.876
	2012	0.082	0.222	0.387	0.746	1.000	0.683	0.683	0.627	0.326	0.930	0.385	0.359	0.905
	2013	0.085	0.163	0.255	0.770	1.000	0.658	0.658	0.624	0.332	0.931	0.296	0.282	0.850
	6-Year	**0.088**	**0.238**	**0.387**	**0.768**	**1.000**	**0.684**	**0.684**	**0.629**	**0.433**	**0.927**	**0.410**	**0.382**	**0.886**
Eastern	2008	0.229	0.483	0.587	0.851	1.000	0.845	0.845	0.686	0.702	0.968	0.724	0.700	0.994
	2009	0.249	0.482	0.628	0.856	1.000	0.789	0.789	0.726	0.715	0.952	0.695	0.659	0.924
	2010	0.228	0.449	0.583	0.869	1.000	0.795	0.795	0.627	0.765	0.963	0.729	0.707	0.920
	2011	0.233	0.411	0.565	0.802	1.000	0.763	0.763	0.634	0.683	0.982	0.664	0.652	0.954
	2012	0.229	0.384	0.539	0.847	1.000	0.741	0.741	0.648	0.682	0.971	0.610	0.592	0.885
	2013	0.221	0.463	0.600	0.880	1.000	0.785	0.785	0.716	0.720	0.977	0.664	0.641	0.898
	6-Year	**0.232**	**0.445**	**0.584**	**0.851**	**1.000**	**0.786**	**0.786**	**0.673**	**0.711**	**0.969**	**0.681**	**0.658**	**0.929**

(Appendix 10 Continues on Next Page)

Level	Year	TFP	TFPE	OTE	OSE	OME	ROSE	OSME	ITE	ISE	IME	RISE	ISME	RME
Southern	2008	0.089	0.357	0.494	0.801	1.000	0.763	0.763	0.516	0.727	0.977	0.710	0.691	0.946
	2009	0.091	0.268	0.419	0.749	1.000	0.671	0.671	0.504	0.627	0.969	0.575	0.550	0.902
	2010	0.094	0.247	0.471	0.555	1.000	0.555	0.555	0.482	0.528	0.950	0.555	0.528	1.000
	2011	0.092	0.407	0.583	0.899	1.000	0.750	0.750	0.671	0.735	0.910	0.666	0.606	0.840
	2012	0.098	0.406	0.528	0.872	1.000	0.819	0.819	0.635	0.694	0.965	0.668	0.645	0.942
	2013	0.093	0.272	0.398	0.759	1.000	0.749	0.749	0.566	0.514	0.944	0.536	0.505	0.981
	6-Year	**0.093**	**0.326**	**0.482**	**0.773**	**1.000**	**0.718**	**0.718**	**0.562**	**0.637**	**0.953**	**0.618**	**0.588**	**0.935**
Central	2008	0.213	0.627	0.842	0.843	1.000	0.756	0.756	0.846	0.829	0.925	0.804	0.746	0.891
	2009	0.180	0.571	0.809	0.796	1.000	0.727	0.727	0.855	0.740	0.918	0.729	0.677	0.898
	2010	0.215	0.410	0.630	0.749	1.000	0.699	0.699	0.758	0.593	0.929	0.595	0.559	0.925
	2011	0.244	0.471	0.708	0.758	1.000	0.700	0.700	0.758	0.686	0.971	0.654	0.636	0.908
	2012	0.257	0.481	0.680	0.849	1.000	0.740	0.740	0.700	0.806	0.924	0.762	0.705	0.868
	2013	0.195	0.596	0.792	0.854	1.000	0.761	0.761	0.803	0.854	0.873	0.857	0.761	0.890
	6-Year	**0.213**	**0.526**	**0.744**	**0.808**	**1.000**	**0.731**	**0.731**	**0.787**	**0.751**	**0.923**	**0.734**	**0.681**	**0.896**
Western	2008	0.308	0.626	0.885	0.816	1.000	0.711	0.711	0.861	0.849	0.915	0.806	0.643	0.870
	2009	0.342	0.515	0.757	0.773	1.000	0.712	0.712	0.816	0.697	0.944	0.665	0.643	0.901
	2010	0.291	0.601	0.807	0.830	1.000	0.724	0.724	0.903	0.767	0.935	0.718	0.679	0.862
	2011	0.320	0.665	0.860	0.857	1.000	0.786	0.786	0.901	0.802	0.946	0.776	0.736	0.915
	2012	0.274	0.578	0.806	0.807	1.000	0.725	0.725	0.875	0.733	0.971	0.678	0.658	0.897
	2013	0.265	0.732	0.943	0.870	1.000	0.775	0.775	0.909	0.914	0.918	0.879	0.816	0.881
	6-Year	**0.300**	**0.619**	**0.843**	**0.826**	**1.000**	**0.739**	**0.739**	**0.877**	**0.793**	**0.938**	**0.754**	**0.713**	**0.888**

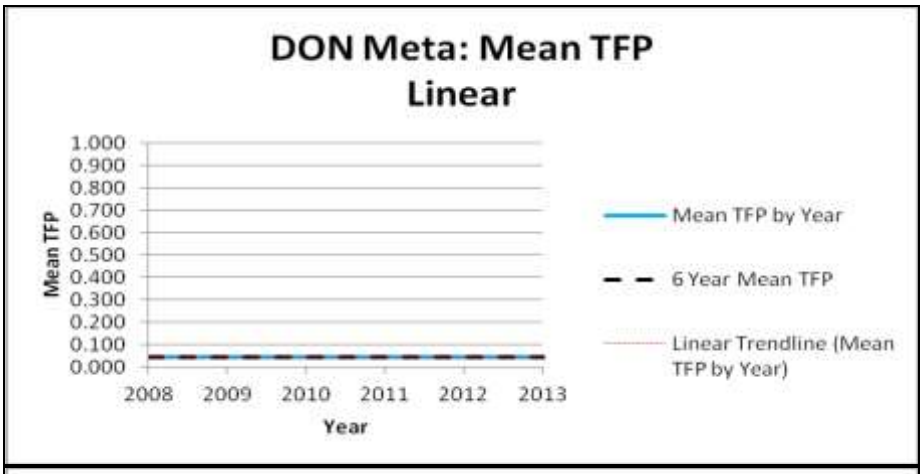
Appendix 11: DON TFP descriptive statistics and plots of productivity and efficiency scores (Chapter 6)

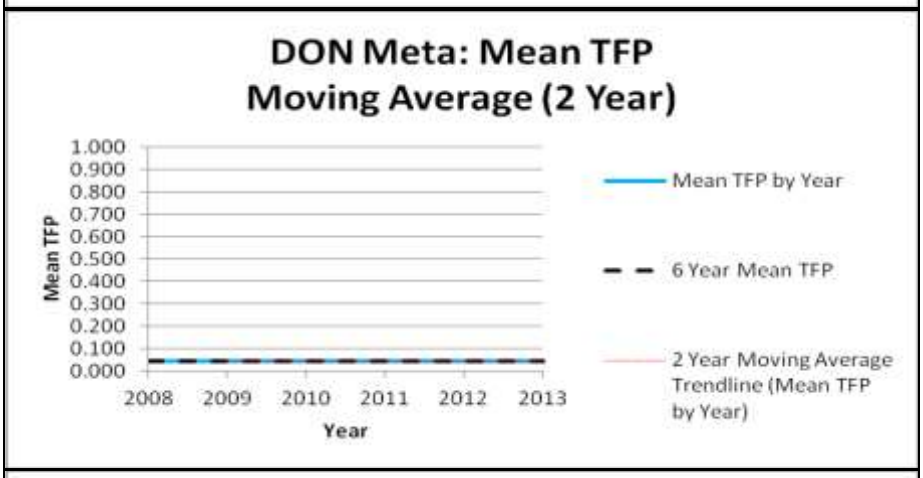
As a preliminary note, in the appendices below descriptive statistics for all DON mean TFP and OTE at the meta and group levels year by year for the 6-year period are provided. The three plots displayed in each case (linear, 2 year and 3 year moving average) are presented because of a likely perceived interest by end users of the findings of the study. From this, trends over the 6-year period studied can be examined, focusing on the more important measures of TFP and OTE.

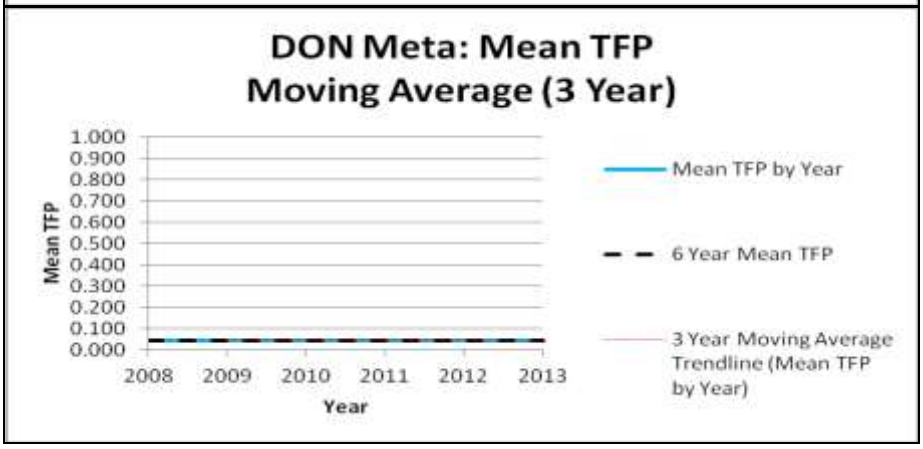
From Appendix 11.1 (DON mean TFP for meta by year) it can be seen that mean TFP by year over the 6-year period showed little variation and low scores can be noted, with an overall 6-year mean TFP of 0.044 (4.4%). This is the observed TFP. All plots reflect this with the graphical representations almost converging to a flat straight line. Appendices 11.2 to 11.6 representing the five state groups show a generally similar pattern for mean TFP as the meta level even though the 6-year mean for each state group is higher but still low in magnitude. There is some suggestion of improvement for the Central and Western Groups (Appendices 11.5 and 11.6) during the earlier part of the period but a distinct negative trend appeared to have emerged by the end of the 2013 year for both those groups.

Appendix 11.1 — DON mean TFP for meta by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.042	0.025	0.011	0.183	121	0
2009	0.045	0.030	0.007	0.219	121	0
2010	0.044	0.027	0.009	0.189	121	0
2011	0.044	0.029	0.009	0.259	121	0
2012	0.044	0.027	0.011	0.201	121	0
2013	0.042	0.032	0.005	0.264	121	0
6 Years	**0.044**	**0.028**	**0.005**	**0.264**	**726**	**0**

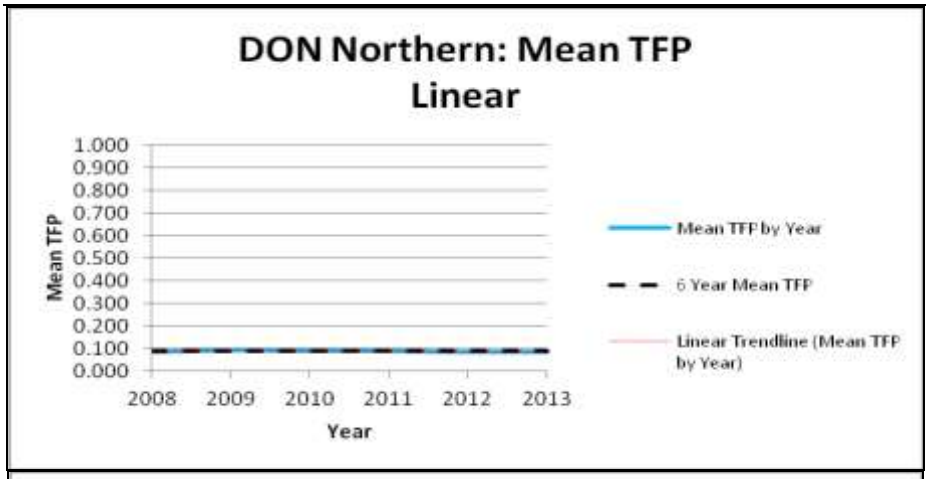


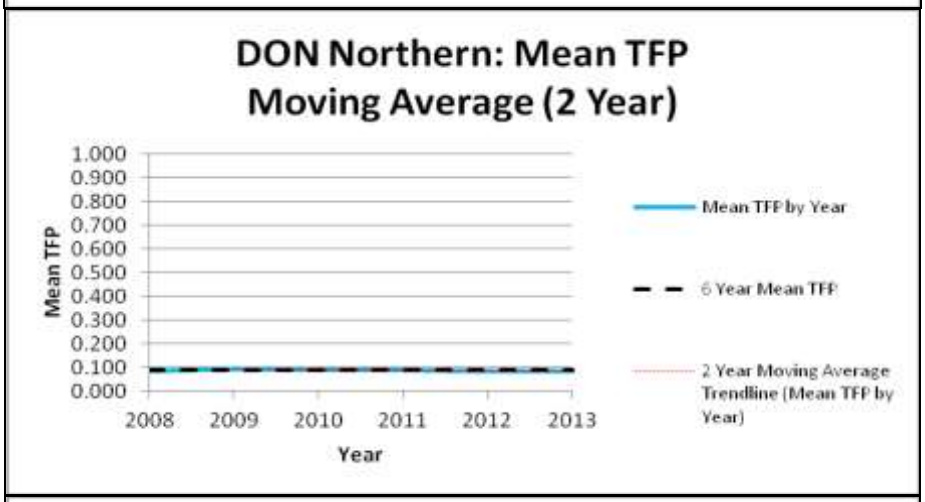


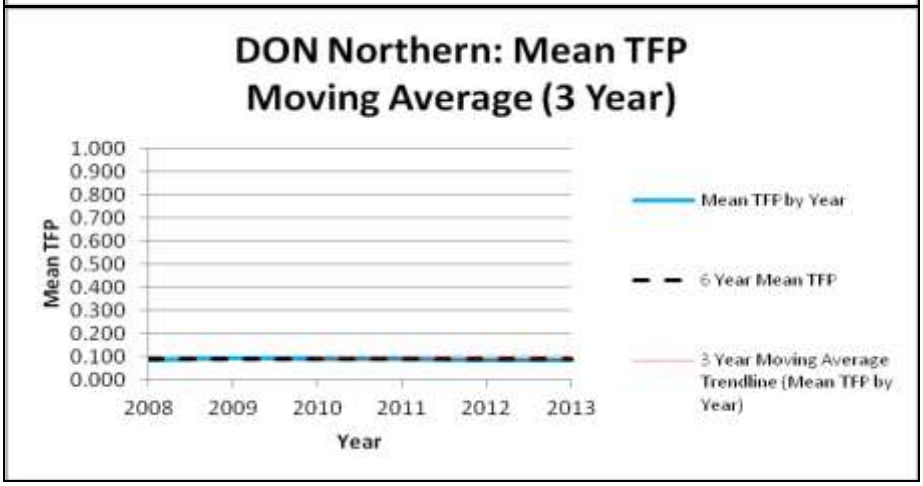


Appendix 11.2 — DON mean TFP for Northern by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.086	0.051	0.025	0.304	30	0
2009	0.094	0.069	0.023	0.383	30	0
2010	0.088	0.049	0.023	0.261	30	0
2011	0.089	0.088	0.025	0.509	30	0
2012	0.082	0.067	0.021	0.371	30	0
2013	0.085	0.091	0.007	0.523	30	0
6 Years	**0.088**	**0.070**	**0.007**	**0.523**	**180**	**0**

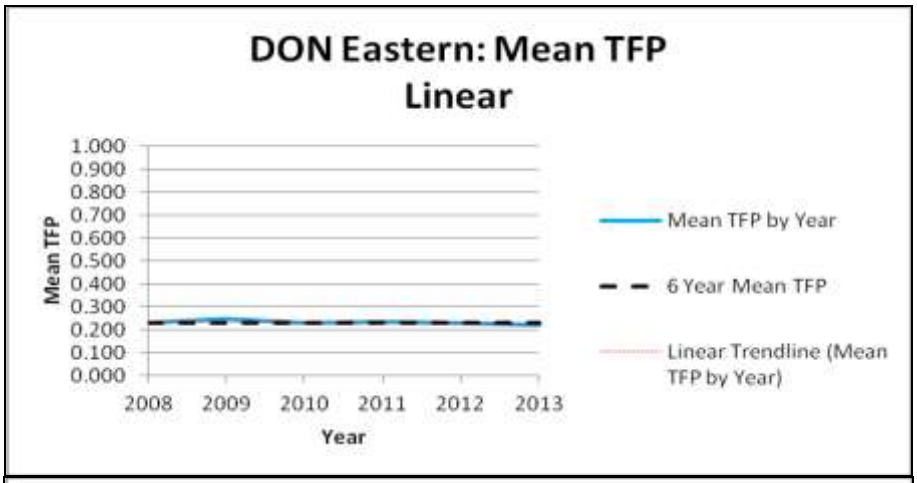


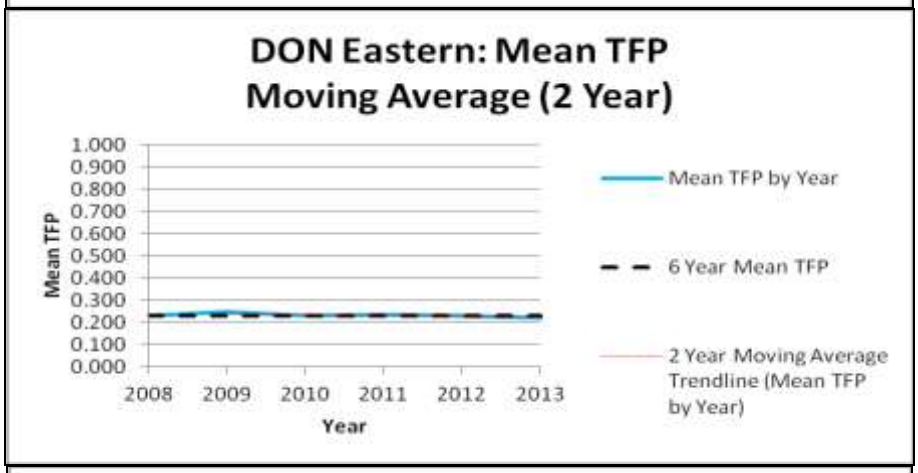


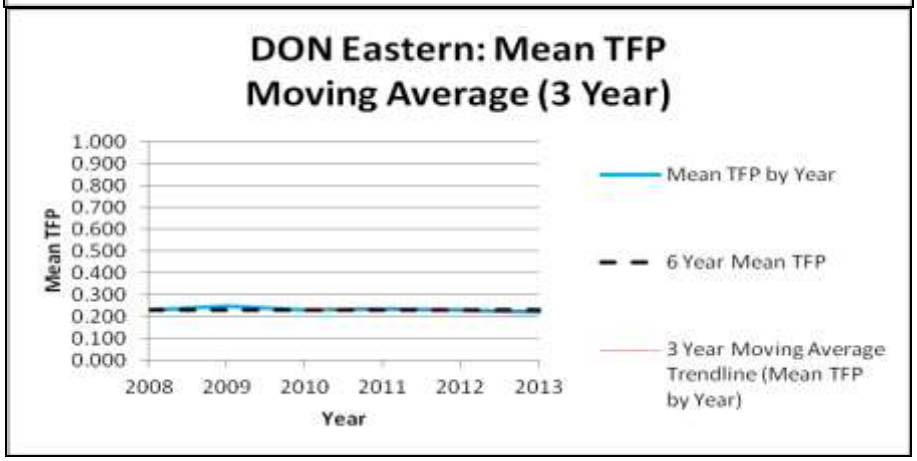


Appendix 11.3 — DON mean TFP for Eastern by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.229	0.109	0.069	0.474	35	0
2009	0.249	0.119	0.085	0.518	35	0
2010	0.228	0.110	0.057	0.507	35	0
2011	0.233	0.103	0.093	0.568	35	0
2012	0.229	0.127	0.067	0.597	35	0
2013	0.221	0.110	0.059	0.478	35	0
6 Years	**0.232**	**0.112**	**0.057**	**0.597**	**210**	**0**

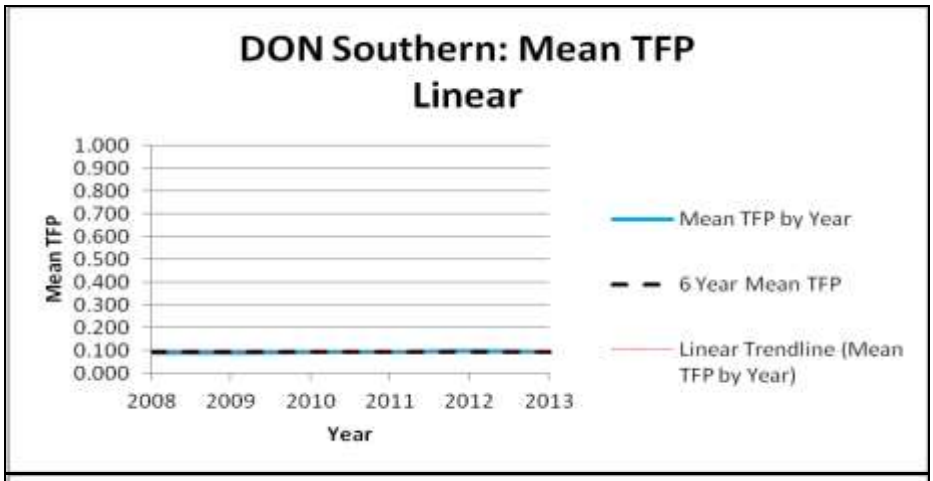


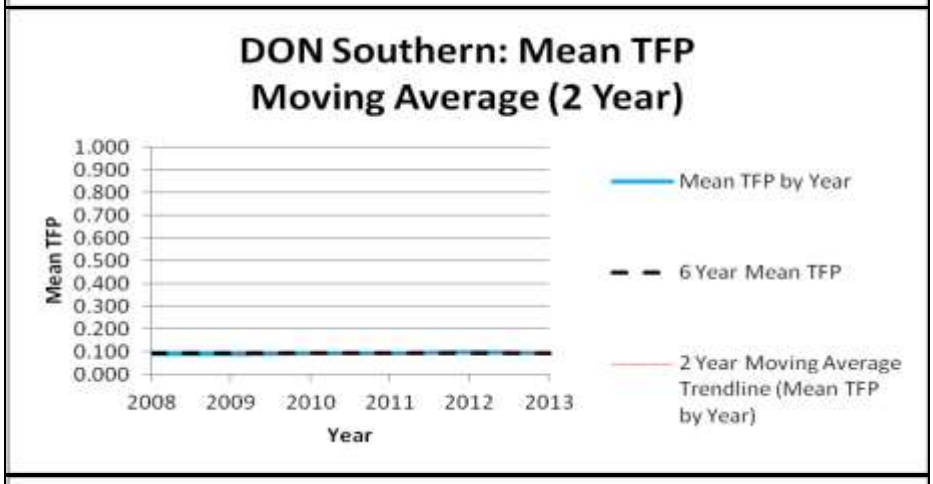


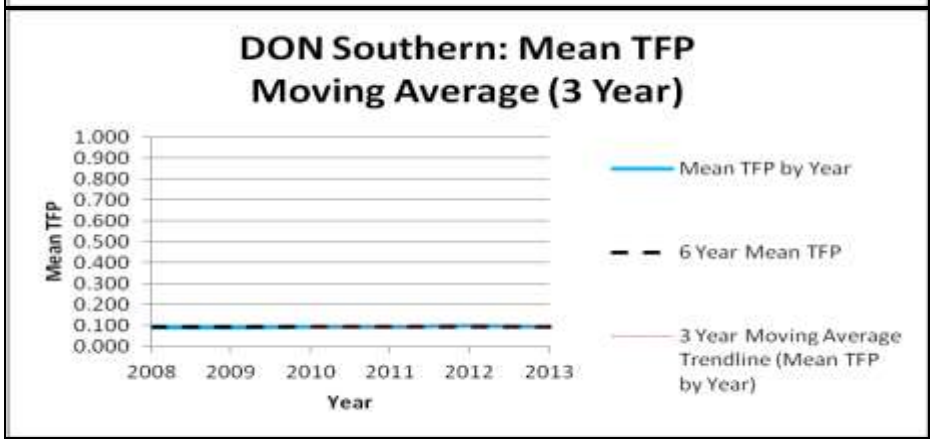


Appendix 11.4 — DON mean TFP for Southern by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.089	0.056	0.027	0.250	32	0
2009	0.091	0.062	0.018	0.338	32	0
2010	0.094	0.072	0.030	0.382	32	0
2011	0.092	0.049	0.022	0.226	32	0
2012	0.098	0.055	0.030	0.242	32	0
2013	0.093	0.070	0.030	0.341	32	0
6 Years	**0.093**	**0.061**	**0.018**	**0.382**	**192**	**0**

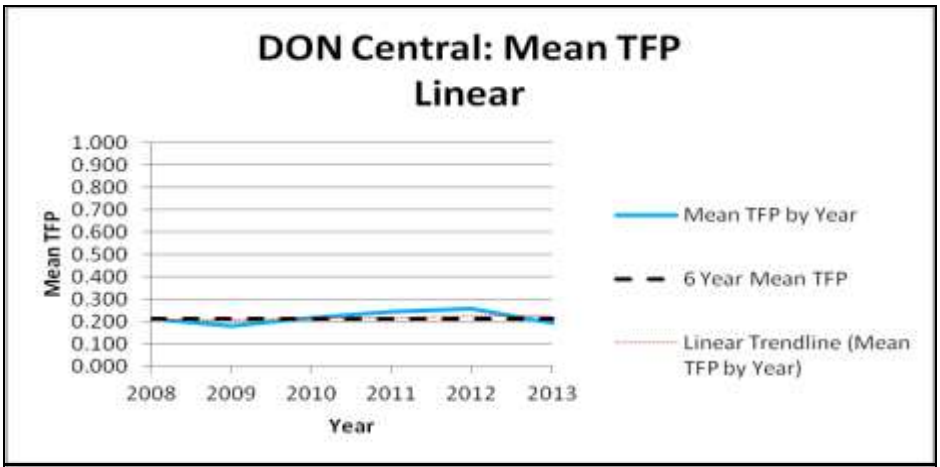


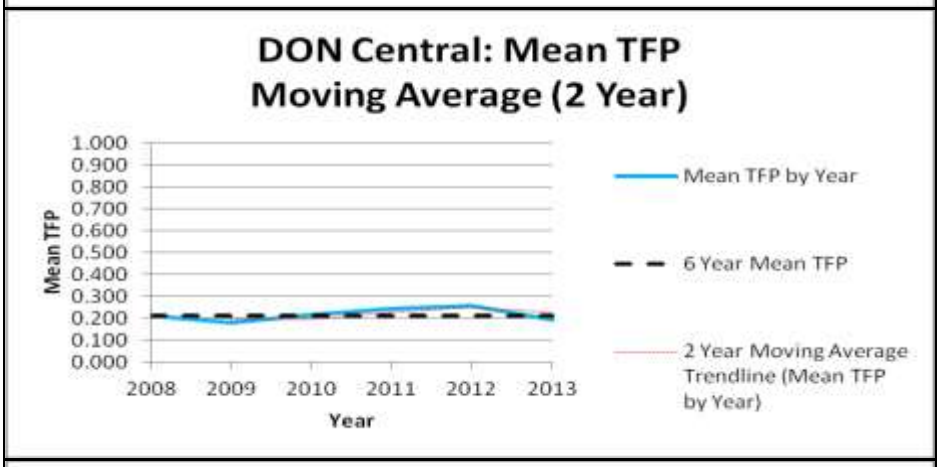


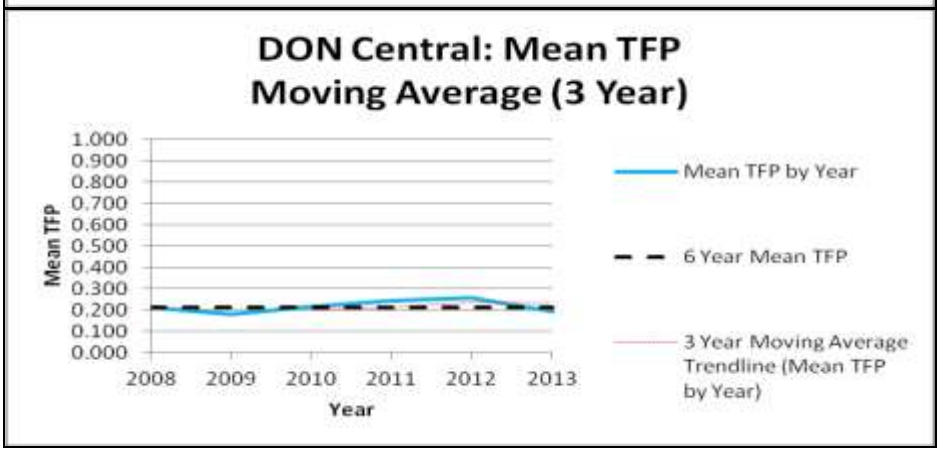


Appendix 11.5 — DON mean TFP for Central by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.213	0.098	0.046	0.534	84	0
2009	0.180	0.082	0.046	0.314	14	0
2010	0.215	0.120	0.075	0.524	14	0
2011	0.244	0.122	0.081	0.519	14	0
2012	0.257	0.110	0.122	0.534	14	0
2013	0.195	0.067	0.082	0.326	14	0
6 Years	**0.213**	**0.098**	**0.046**	**0.534**	**84**	**0**

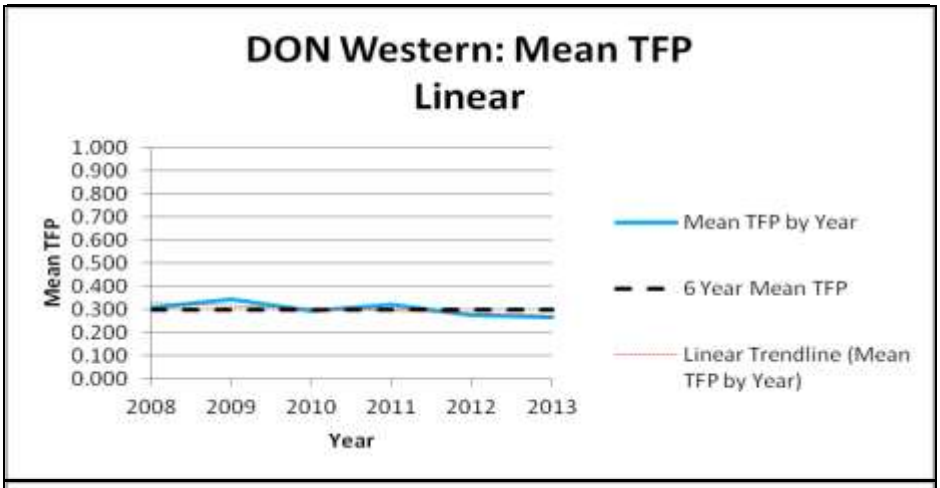


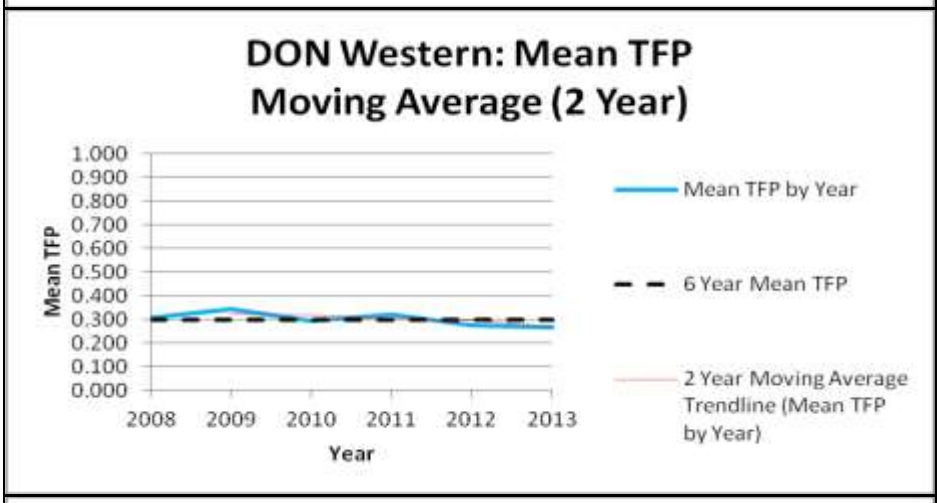


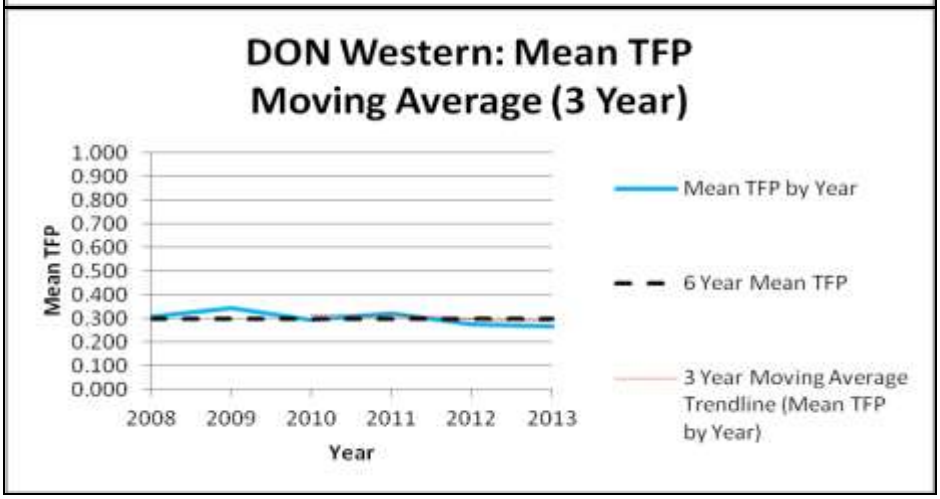


Appendix 11.6 — DON mean TFP for Western by year descriptive statistics and plot

Year	Mean TFP	Std Dev	Min	Max	Cases	Missing
2008	0.308	0.112	0.166	0.492	10	0
2009	0.342	0.178	0.108	0.664	10	0
2010	0.291	0.143	0.079	0.485	10	0
2011	0.320	0.118	0.143	0.481	10	0
2012	0.274	0.112	0.111	0.475	10	0
2013	0.265	0.084	0.106	0.362	10	0
6 Years	**0.300**	**0.125**	**0.079**	**0.664**	**60**	**0**





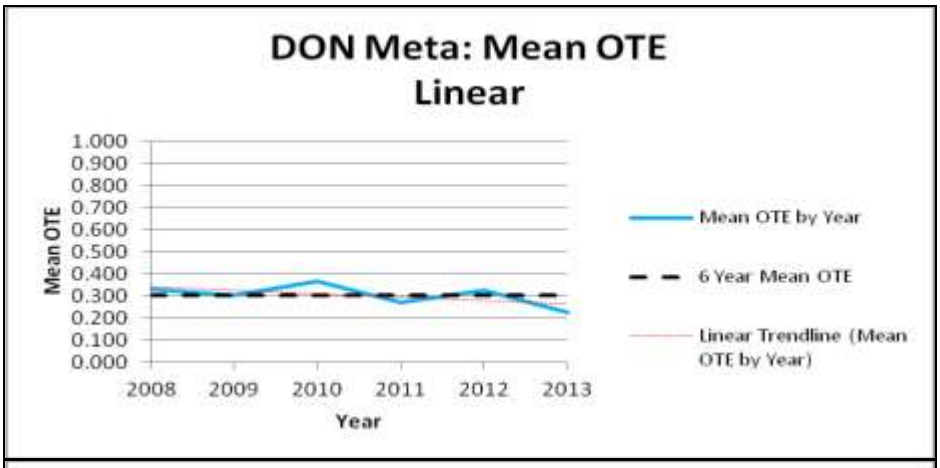


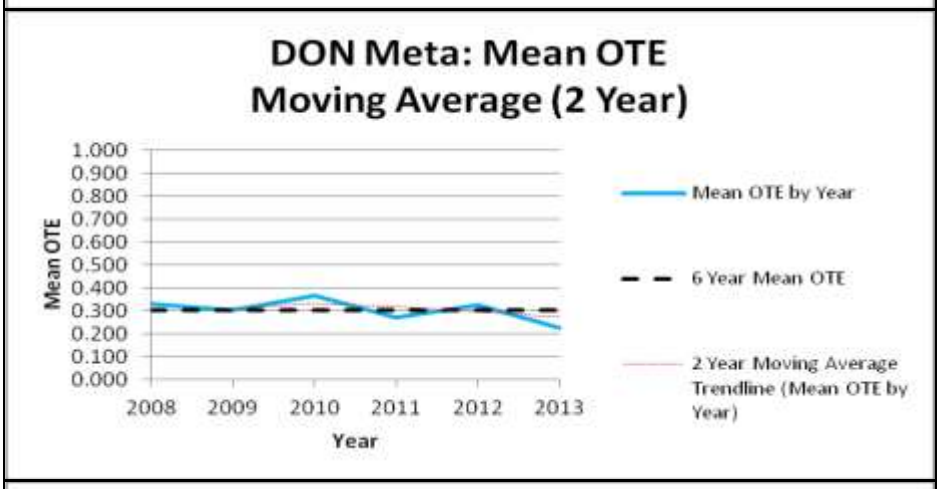
Appendix 12: DON OTE descriptive statistics and plots of productivity and efficiency scores (Chapter 6)

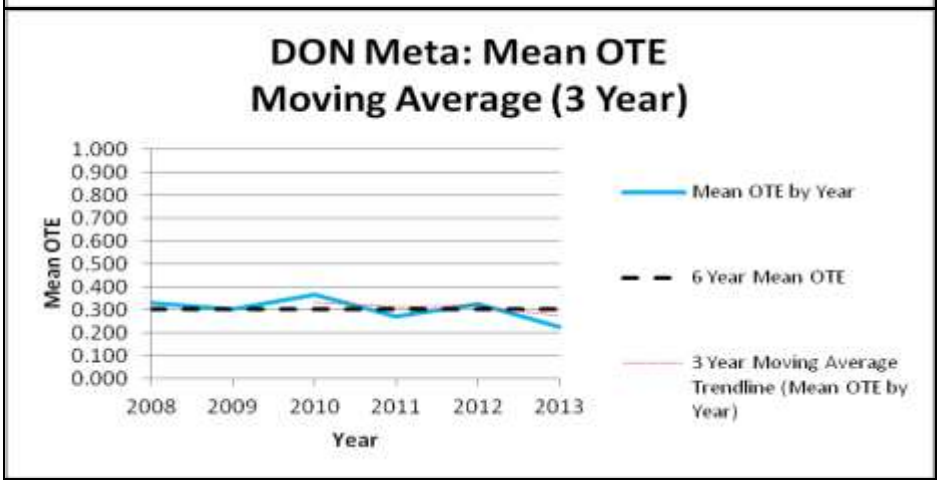
From Appendix 12.1 (DON mean OTE for meta by year) it can be seen that mean OTE by year over the 6-year period had fluctuations with a distinct negative trend by the end of the 2013 year. The overall 6-year mean OTE was 0.302 (30.2%). The interpretation of this is that it suggests that output (DON) could have increased by 69.8% without any change in the available level of inputs (numbers of Gideon and Auxiliary members). In Appendices 12.2 (Northern) and 12.4 (Southern) a generally similar pattern is shown for mean OTE as for the meta level, although the fluctuations are more pronounced for both groups. On examination of Appendices 12.3 (Eastern), 12.5 (Central) and 12.6 (Western), it can be seen that positive trends by the end of the 2013 year are suggested.

Appendix 12.1 — DON mean OTE for meta by year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.328	0.196	0.076	1.000	121	0
2009	0.301	0.210	0.043	1.000	121	0
2010	0.366	0.220	0.082	1.000	121	0
2011	0.269	0.212	0.044	1.000	121	0
2012	0.325	0.220	0.069	1.000	121	0
2013	0.224	0.195	0.022	1.000	121	0
6 Years	**0.302**	**0.213**	**0.022**	**1.000**	**726**	**0**

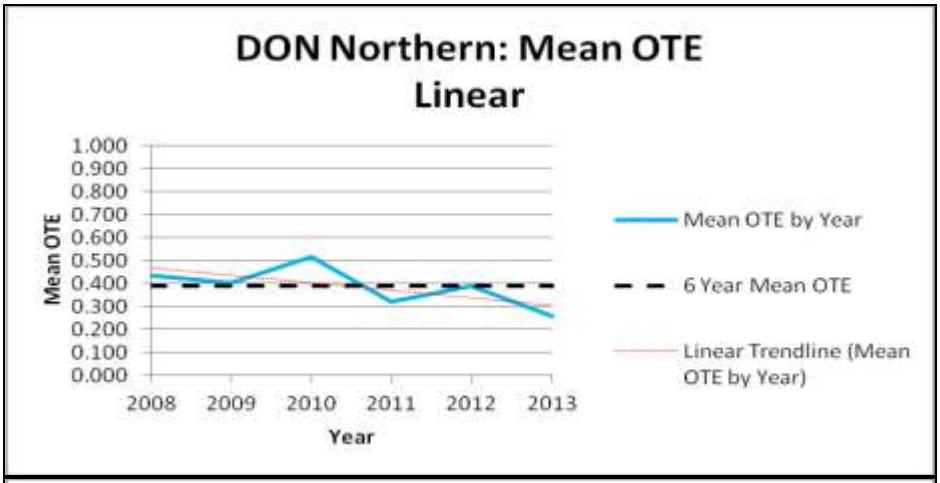


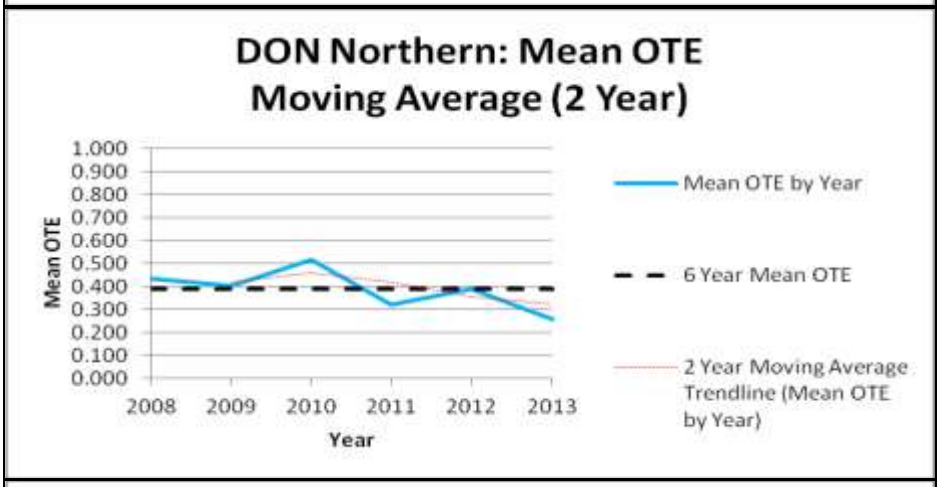


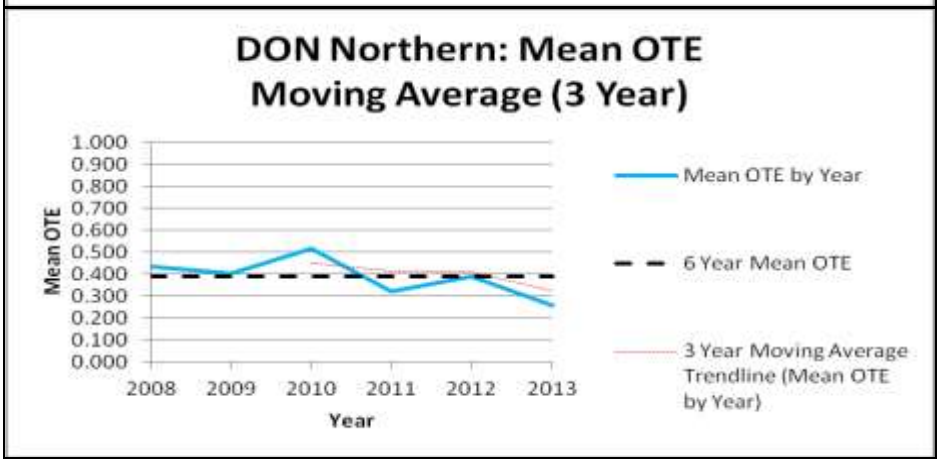


Appendix 12.2 — DON mean OTE for Northern by year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.436	0.258	0.089	1.000	30	0
2009	0.402	0.297	0.070	1.000	30	0
2010	0.518	0.294	0.106	1.000	30	0
2011	0.323	0.302	0.074	1.000	30	0
2012	0.387	0.302	0.089	1.000	30	0
2013	0.255	0.228	0.044	1.000	30	0
6 Years	**0.387**	**0.290**	**0.044**	**1.000**	**180**	**0**

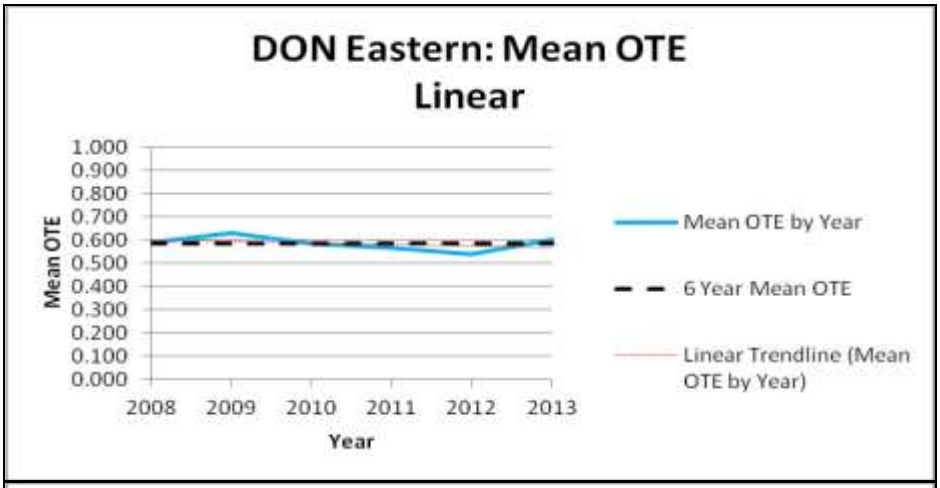


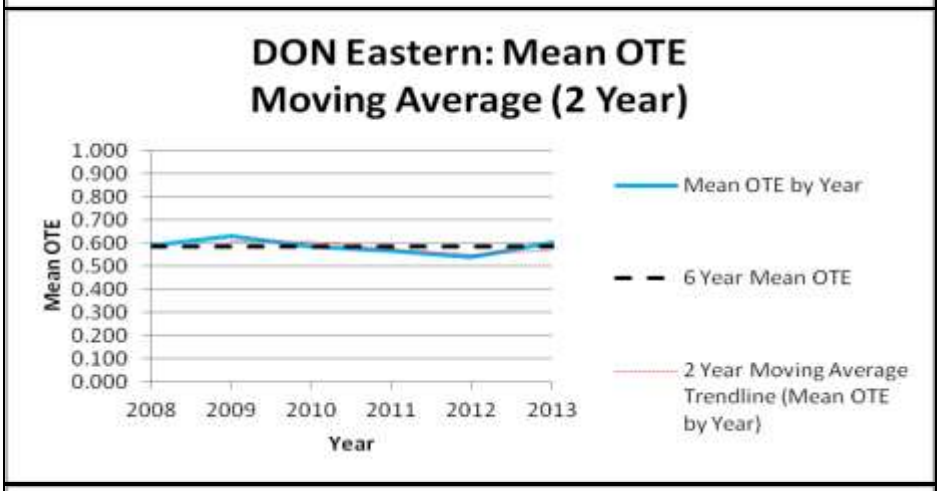


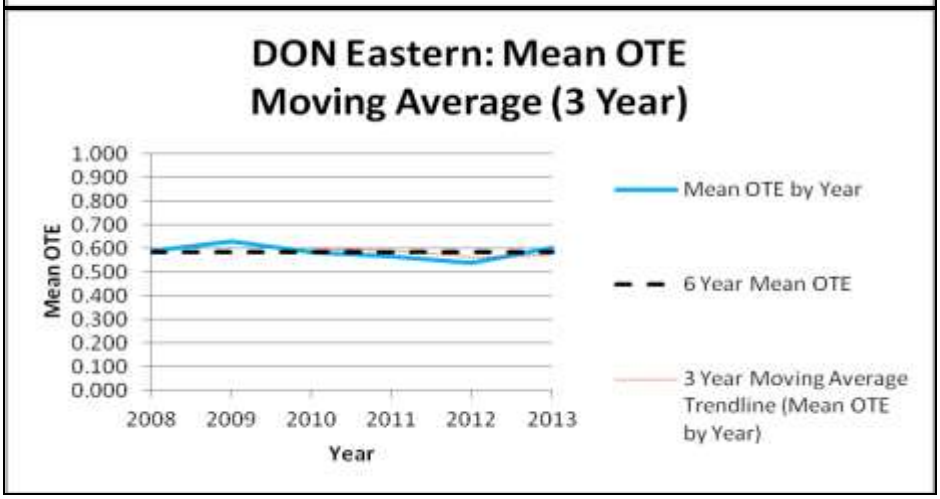


Appendix 12.3 — DON mean OTE for Eastern year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.587	0.280	0.162	1.000	35	0
2009	0.628	0.279	0.199	1.000	35	0
2010	0.583	0.288	0.174	1.000	35	0
2011	0.565	0.267	0.164	1.000	35	0
2012	0.539	0.284	0.132	1.000	35	0
2013	0.600	0.280	0.150	1.000	35	0
6 Years	**0.584**	**0.277**	**0.132**	**1.000**	**210**	**0**

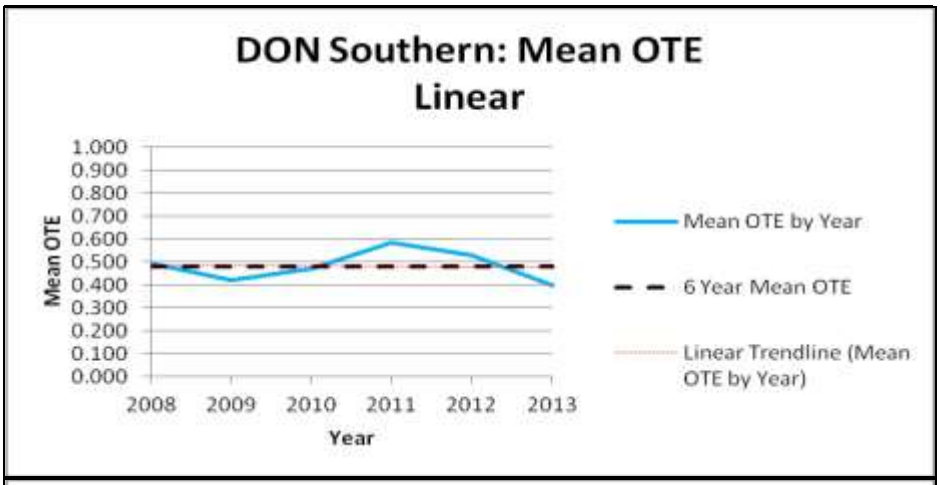


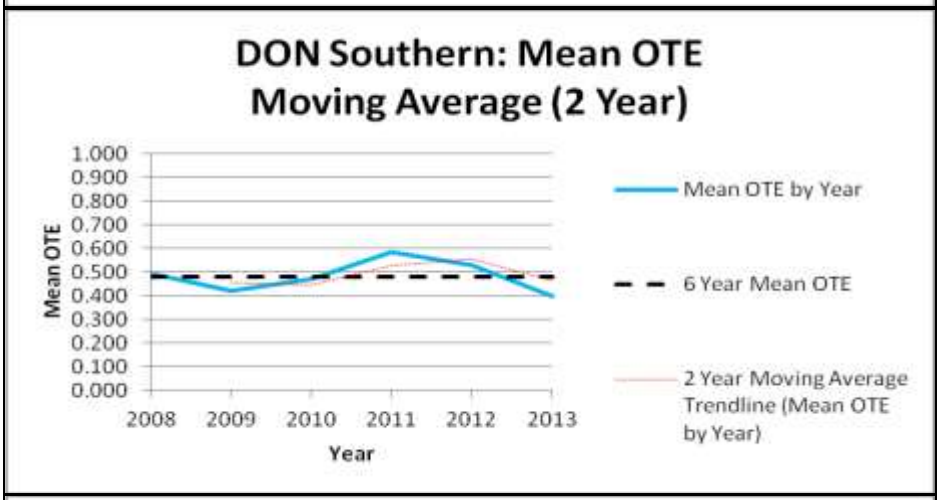


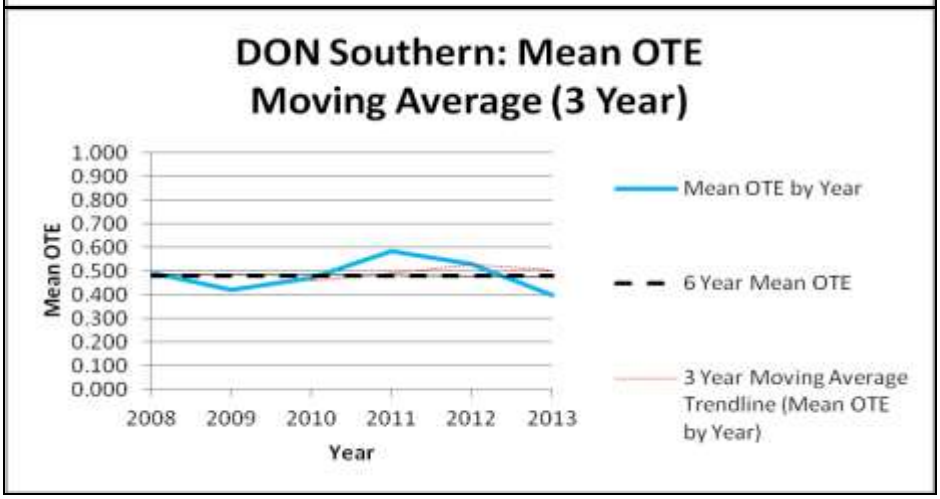


Appendix 12.4 — DON mean OTE for Southern by year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.494	0.290	0.128	1.000	32	0
2009	0.419	0.276	0.075	1.000	32	0
2010	0.471	0.298	0.089	1.000	32	0
2011	0.583	0.312	0.118	1.000	32	0
2012	0.528	0.291	0.131	1.000	32	0
2013	0.398	0.289	0.129	1.000	32	0
6 Years	**0.482**	**0.296**	**0.075**	**1.000**	**192**	**0**

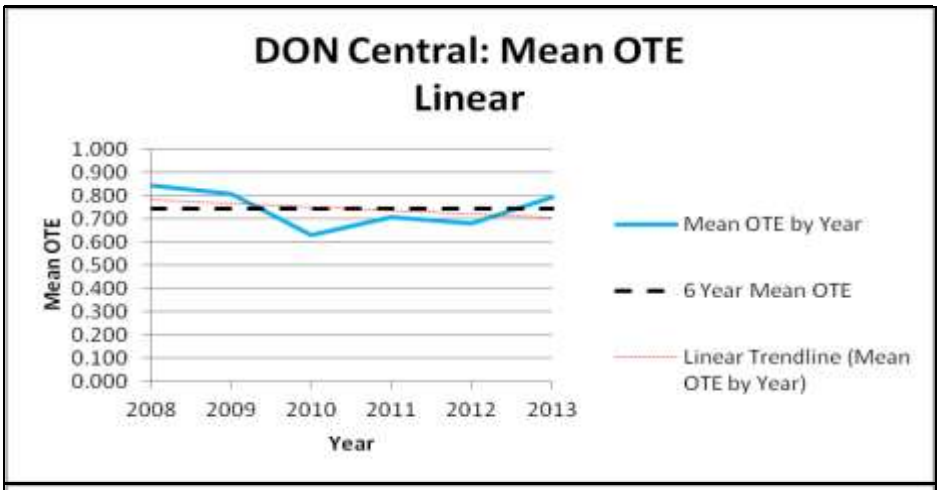


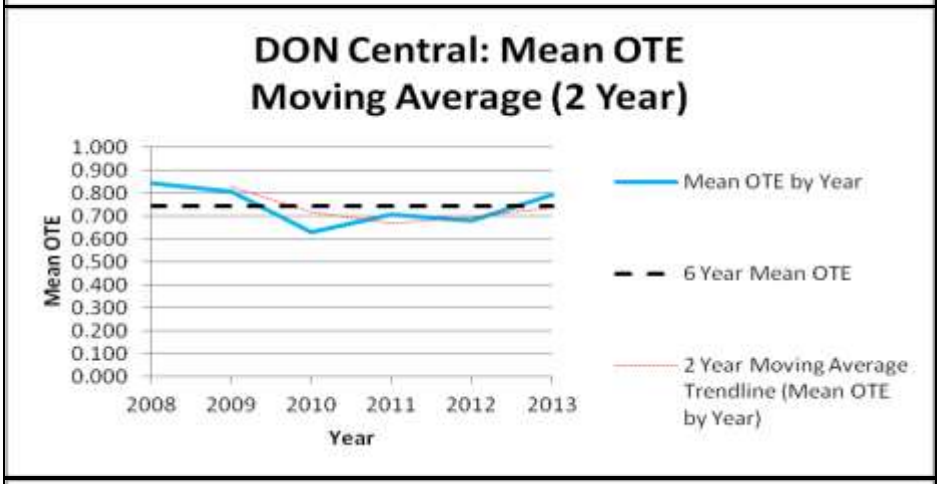


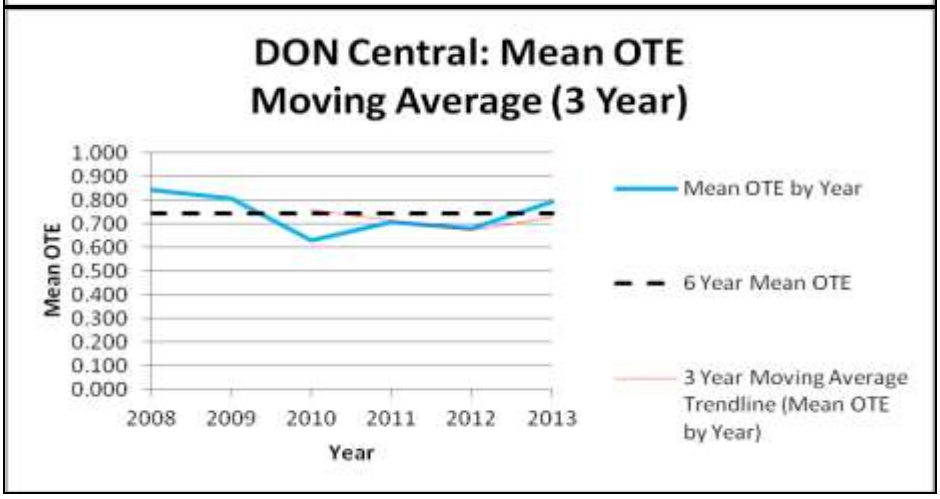


Appendix 12.5 — DON mean OTE for Central by year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.842	0.201	0.478	1.000	14	0
2009	0.809	0.191	0.402	1.000	14	0
2010	0.630	0.254	0.273	1.000	14	0
2011	0.708	0.246	0.372	1.000	14	0
2012	0.680	0.234	0.326	1.000	14	0
2013	0.792	0.177	0.476	1.000	14	0
6 Years	**0.744**	**0.226**	**0.273**	**1.000**	**84**	**0**

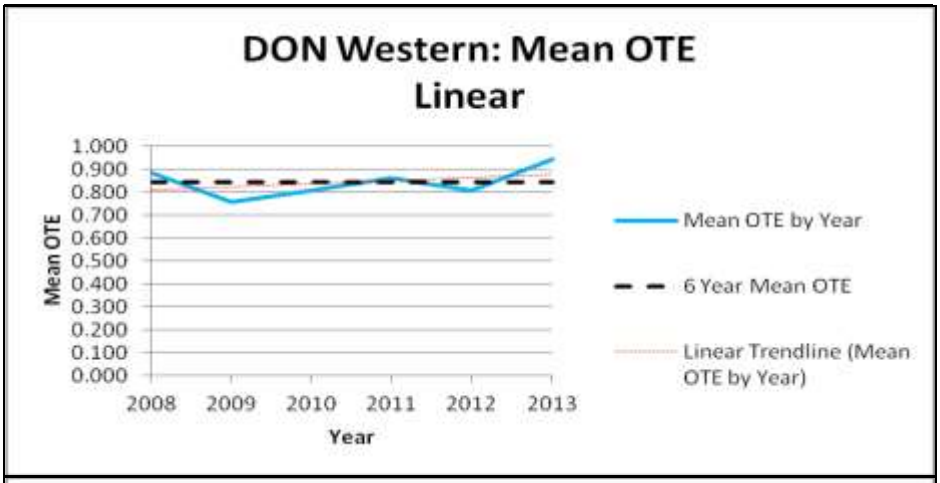


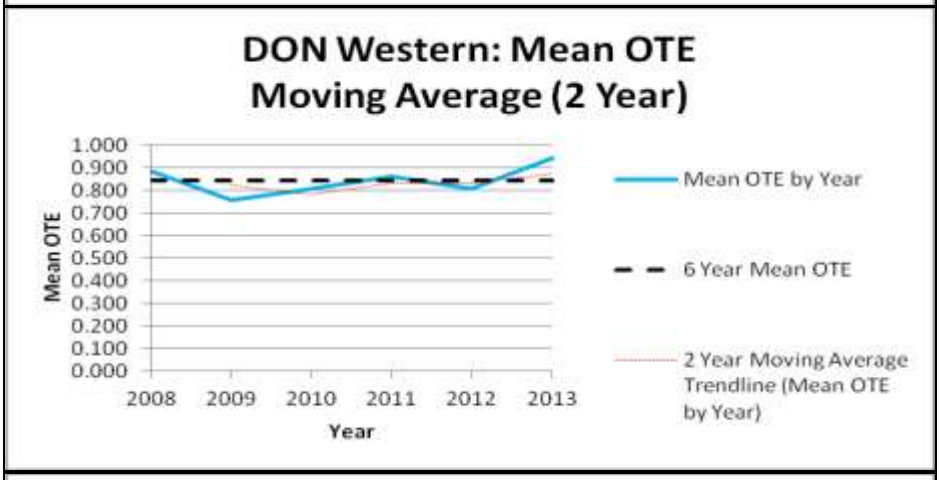


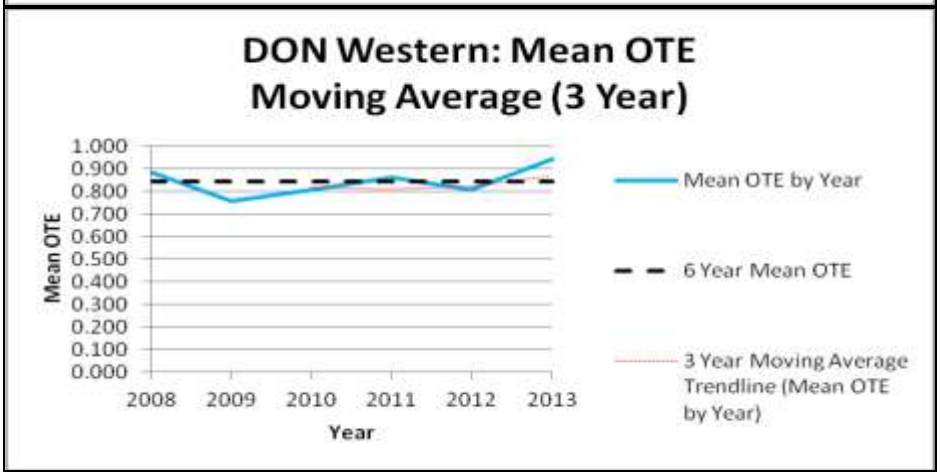


Appendix 12.6 — DON mean OTE for Western by year descriptive statistics and plot

Year	Mean OTE	Std Dev	Min	Max	Cases	Missing
2008	0.885	0.202	0.472	1.000	10	0
2009	0.757	0.291	0.272	1.000	10	0
2010	0.807	0.274	0.294	1.000	10	0
2011	0.860	0.251	0.337	1.000	10	0
2012	0.806	0.260	0.397	1.000	10	0
2013	0.943	0.092	0.775	1.000	10	0
6 Years	**0.843**	**0.236**	**0.272**	**1.000**	**60**	**0**







Appendix 13: DON 2013 slacks at meta level and equivalent state group levels (Chapter 6)

Appendix 13.1 — DON 2013 slacks at meta level (M) and equivalent Northern group level (N)

Meta Branch Code (M))	Equivalent Northern Branch Code (N)	DON Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	DON Output Slacks at Northern Level	GID Input Slacks at Northern Level	AUX Input Slacks at Northern Level
1N	1N	0	3	7	0	3	7
2N	2N	0	0	4	0	0	4
3N	3N	0	7	6	0	7	6
4N	4N	0	3	0	0	5	0
5N	5N	0	1	0	0	5	0
6N	6N	0	5	8	0	5	8
7N	7N	0	3	0	0	7	0
8N	8N	0	0	2	0	0	2
9N	9N	0	4	0	0	6	0
10N	10N	0	3	0	0	7	0
11N	11N	0	1	1	0	1	1
12N	12N	0	10	0	0	18	0
13N	13N	0	0	7	0	0	7
14N	14N	0	10	9	0	10	9
15N	15N	0	0	0	0	3	0
16N	16N	0	0	0	0	2	0
17N	17N	0	0	0	0	0	0
18N	18N	0	4	0	0	4	0
19N	19N	0	2	3	0	2	3
20N	20N	0	0	0	0	0	0
21N	21N	0	9	9	0	9	9
22N	22N	0	0	0	0	2	0
23N	23N	0	0	0	0	0	0
24N	24N	0	9	10	0	9	10
25N	25N	0	0	2	0	0	2
26N	26N	0	0	6	0	0	6
27N	27N	0	1	3	0	1	3
28N	28N	0	2	0	0	10	0
29N	29N	0	0	1	0	0	1
30N	30N	0	0	1	0	0	1
	Mean	**0**	**3**	**3**	**0**	**4**	**3**

Appendix 13.2 — DON 2013 slacks at meta level (M) and equivalent Eastern group level (E)

Meta Branch Code (M))	Equivalent Eastern Branch Code (N)	DON Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	DON Output Slacks at Eastern Level	GID Input Slacks at Eastern Level	AUX Input Slacks at Eastern Level
31M	1E	0	0	0	0	0	0
32M	2E	0	1	4	0	0	4
33M	3E	0	0	4	0	0	5
34M	4E	0	0	3	0	0	4
35M	5E	0	0	4	0	0	6
36M	6E	0	1	0	0	0	0
37M	7E	0	4	0	0	0	0
38M	8E	0	8	0	0	2	0
39M	9E	0	1	0	0	0	0
40M	10E	0	7	1	0	3	1
41M	11E	0	3	0	0	0	0
42M	12E	0	0	1	0	0	3
43M	13E	0	0	6	0	0	7
44M	14E	0	0	0	0	0	0
45M	15E	0	5	5	0	1	5
46M	16E	0	1	0	0	0	0
47M	17E	0	1	0	0	0	0
48M	18E	0	1	0	0	0	0
49M	19E	0	10	0	0	0	0
50M	20E	0	0	0	0	0	4
51M	21E	0	5	0	0	0	0
52M	22E	0	0	0	0	0	1
53M	23E	0	0	0	0	0	2
54M	24E	0	1	0	0	0	0
55M	25E	0	2	0	0	0	0
56M	26E	0	1	0	0	0	0
57M	27E	0	0	0	0	0	0
58M	28E	0	0	0	0	0	0
59M	29E	0	3	0	0	0	0
60M	30E	0	5	0	0	3	0
61M	31E	0	0	0	0	0	1
62M	32E	0	0	0	0	0	0
63M	33E	0	7	2	0	3	2
64M	34E	0	1	0	0	0	0
65M	35E	0	0	1	0	0	2
	Mean	**0**	**2**	**1**	**0**	**0**	**1**

Appendix 13.3 — DON 2013 slacks at meta level (M) and equivalent Southern group level (S)

Meta Branch Code (M))	Equivalent Southern Branch Code (N)	DON Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	DON Output Slacks at Southern Level	GID Input Slacks at Southern Level	AUX Input Slacks at Southern Level
66M	1S	0	2	6	0	0	0
67M	2S	0	6	3	0	8	0
68M	3S	0	0	0	0	0	0
69M	4S	0	0	0	0	5	0
70M	5S	0	0	0	0	0	0
71M	6S	0	0	0	0	1	0
72M	7S	0	0	0	0	0	0
73M	8S	0	3	2	0	6	0
74M	9S	0	4	8	0	0	0
75M	10S	0	0	2	0	0	2
76M	11S	0	0	0	0	0	0
77M	12S	0	0	2	0	0	2
78M	13S	0	0	0	0	0	1
79M	14S	0	0	0	0	0	0
80M	15S	0	11	14	0	0	0
81M	16S	0	0	3	0	2	0
82M	17S	0	0	2	0	0	2
83M	18S	0	0	0	0	0	0
84M	19S	0	3	7	0	0	0
85M	20S	0	0	0	0	0	1
86M	21S	0	0	0	0	0	0
87M	22S	0	0	0	0	2	0
88M	23S	0	0	1	0	0	3
89M	24S	0	13	13	0	3	0
90M	25S	0	0	0	0	1	0
91M	26S	0	0	0	0	4	0
92M	27S	0	0	0	0	2	0
93M	28S	0	9	4	0	9	0
94M	29S	0	15	7	0	12	0
95M	30S	0	0	2	0	2	0
96M	31S	0	0	1	0	2	0
97M	32S	0	0	1	0	0	2
	Mean	**0**	**2**	**2**	**0**	**2**	**0**

Appendix 13.4 — DON 2013 slacks at meta level (M) and equivalent Central group level (C)

Meta Branch Code (M))	Equivalent Central Branch Code (N)	DON Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	DON Output Slacks at Central Level	GID Input Slacks at Central Level	AUX Input Slacks at Central Level
98M	1C	0	0	1	0	0	1
99M	2C	0	0	1	0	0	1
100M	3C	0	0	0	0	3	0
101M	4C	0	1	0	0	4	1
102M	5C	0	0	3	0	0	3
103M	6C	0	16	7	0	19	8
104M	7C	0	0	0	0	5	0
105M	8C	0	0	2	0	3	3
106M	9C	0	0	4	0	0	4
107M	10C	0	0	0	0	0	0
108M	11C	0	0	0	0	3	0
109M	12C	0	1	0	0	9	0
110M	13C	0	0	0	0	0	0
111M	14C	0	0	0	0	0	0
	Mean	**0**	**1**	**1**	**0**	**3**	**2**

Appendix 13.5 — DON 2013 slacks at meta level (M) and equivalent Western group level (W)

Meta Branch Code (M))	Equivalent Western Branch Code (N)	DON Output Slacks at Meta Level	GID Input Slacks at Meta Level	AUX Input Slacks at Meta Level	DON Output Slacks at Western Level	GID Input Slacks at Western Level	AUX Input Slacks at Western Level
112M	1W	0	7	3	0	15	6
113M	2W	0	0	0	0	0	0
114M	3W	0	0	0	0	0	0
115M	4W	0	0	3	0	0	2
116M	5W	0	0	0	0	4	0
117M	6W	0	0	0	0	0	0
118M	7W	0	4	0	0	0	0
119M	8W	0	5	0	0	0	0
120M	9W	0	0	0	0	0	0
121M	10W	0	4	0	0	0	0
	Mean	**0**	**2**	**1**	**0**	**2**	**1**

Appendix 14: DON 2013 peers at meta level with state group equivalents (Chapter 6)

Appendix 14.1A — DON 2013 peers at meta level (M) with Northern group (N) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Northern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
1M	17M	17N				
2M	107M	10C	17M	17N		
3M	17M	17N				
4M	17M	17N	62M	32E		
5M	62M	32E	17M	17N		
6M	17M	17N				
7M	62M	32E	17M	17N		
8M	17M	17N				
9M	62M	32E	17M	17N		
10M	62M	32E	17M	17N		
11M	17M	17N				
12M	62M	32E	17M	17N		
13M	17M	17N				
14M	17M	17N				
15M	17M	17N	62M	32E	68M	3S
16M	17M	17N	107M	10C	68M	3S
17M	17M	17N				
18M	17M	17N				
19M	17M	17N				
20M	17M	17N	107M	10C		
21M	17M	17N				
22M	107M	10C	17M	17N	68M	3S
23M	17M	17N	107M	10C		
24M	17M	17N				
25M	17M	17N	107M	10C		
26M	107M	10C	17M	17N		
27M	17M	17N				
28M	62M	32E	17M	17N		
29M	17M	17N	107M	10C		
30M	107M	10C	17M	17N		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.1B — DON 2013 peers at Northern group level (N) with meta level (M) equivalents

	Northern Peer Code (N) with Equivalent Meta Branch Code (M)					
Northern Group Branch Code	**Northern Peer 1 Code (N)**	**Equivalent Meta Code (M)**	**Northern Peer 2 Code (N)**	**Equivalent Meta Code (M)**	**Northern Peer 3 Code (N)**	**Equivalent Meta Code (M)**
1N	15N	15M				
2N	15N	15M				
3N	15N	15M				
4N	15N	15M				
5N	15N	15M				
6N	15N	15M				
7N	15N	15M				
8N	15N	15M				
9N	15N	15M				
10N	15N	15M				
11N	15N	15M				
12N	28N	23M				
13N	15N	15M				
14N	15N	15M				
15N	15N	15M				
16N	23N	23M	15N	15M	28N	28M
17N	15N	15M				
18N	15N	15M				
19N	15N	15M				
20N	15N	15M	23N	23M		
21N	15N	15M				
22N	23N	23M	28N	28M		
23N	23N	23M				
24N	15N	15M				
25N	23N	23M				
26N	15N	15M				
27N	15N	15M				
28N	28N	28M				
29N	15N	15M	23N	23M		
30N	15N	15M				

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.2A — DON 2013 peers at meta level (M) with Eastern group (E) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Eastern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
31M	17M	17N	107M	10C	68M	3S
32M	17M	17N				
33M	107M	10C	17M	17N		
34M	17M	17N	107M	10C		
35M	107M	10C	17M	17N		
36M	17M	17N				
37M	17M	17N				
38M	17M	17N	62M	32E		
39M	62M	32E	17M	17N		
40M	17M	17N				
41M	62M	32E	17M	17N		
42M	107M	10C	17M	17N		
43M	17M	17N	107M	10C		
44M	17M	17N	62M	32E	68M	3S
45M	17M	17N				
46M	62M	32E	17M	17N		
47M	17M	17N				
48M	17M	17N				
49M	62M	32E	17M	17N		
50M	17M	17N	107M	10C	68M	3S
51M	62M	32E	17M	17N		
52M	17M	17N	107M	10C	68M	3S
53M	107M	10C	17M	17N	68M	
54M	62M	32E	17M	17N		
55M	62M	32E	17M	17N		
56M	17M	17N	62M	32E		
57M	17M	17N	62M	32E	68M	3S
58M	17M	17N	62M	32E	68M	3S
59M	17M	17N	62M	32E		
60M	17M	17N	62M	32E		
61M	107M	10C	17M	17N	68M	3S
62M	62M	32E				
63M	17M	17N				
64M	17M	17N	62M	32E		
65M	107M	10C	17M	17N		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.2B — DON 2013 peers at Eastern group level (E) with meta level (M) equivalents

	Eastern Peer Code (E) with Equivalent Meta Branch Code (M)					
Eastern Group Branch Code	**Eastern Peer 1 Code (E)**	**Equivalent Meta Code (M)**	**Eastern Peer 2 Code (E)**	**Equivalent Meta Code (M)**	**Eastern Peer 3 Code (E)**	**Equivalent Meta Code (M)**
1E	1E	31M				
2E	6E	36M				
3E	6E	36M	1E	31M		
4E	6E	36M	1E	31M		
5E	1E	31M	32E	62M		
6E	6E	36M				
7E	7E	37M				
8E	7E	37M	19E	49M		
9E	25E	55M	26E	56M	1E	31M
10E	7E	37M				
11E	26E	56M	19E	49M	7E	37M
12E	1E	31M	32E	62M		
13E	1E	31M	32E	62M		
14E	1E	31M	32E	62M		
15E	7E	37M				
16E	26E	56M	1E	31M	25E	55M
17E	6E	36M				
18E	6E	36M				
19E	19E	49M				
20E	32E	62M	1E	31M		
21E	26E	56M	19E	49M	7E	37M
22E	1E	31M	32E	62M		
23E	1E	31M	32E	62M		
24E	6E	36M	26E	56M	1E	31M
25E	25E	55M				
26E	26E	56M				
27E	26E	56M	1E	31M	25E	31M
28E	26E	56M	6E	36M	1E	31M
29E	26E	56M	7E	37M	6E	36M
30E	25E	55M				
31E	6E	36M	1E	31M		
32E	32E	62M				
33E	7E	37M				
34E	6E	36M	26E	56M	1E	31M
35E	1E	31M	32E	62M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.3A — DON 2013 peers at meta level (M) with Southern group (S) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Southern Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
66M	17M	17N				
67M	17M	17N				
68M	68M	3S				
69M	62M	32E	17M	17N		
70M	68M	3S	107M	10C		
71M	17M	17N	107M	10C	68M	3S
72M	107M	10C	68M	3S		
73M	17M	17N				
74M	17M	17N				
75M	17M	17N	107M	10C		
76M	107M	10C	17M	17N	68M	3S
77M	107M	10C	17M	17N		
78M	107M	10C	17M	17N	68M	3S
79M	62M	32E	107M	10C	68M	3S
80M	17M	17N				
81M	17M	17N				
82M	107M	10C	17M	17N		
83M	107M	10C	17M	17N	68M	3S
84M	17M	17N				
85M	107M	10C	17M	17N		
86M	107M	10C	17M	17N		
87M	17M	17N	62M	32E	68M	3S
88M	17M	17N	107M	10C		
89M	17M	17N				
90M	17M	17N	62M	32E	68M	3S
91M	17M	17N	62M	32E	68M	3S
92M	107M	10C	17M	17N	68M	3S
93M	17M	17N				
94M	17M	17N				
95M	107M	10C	17M	17N		
96M	107M	10C	17M	17N		
97M	107M	10C	17M	17N		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.3B — DON 2013 peers at Southern group level (S) with meta level (M) equivalents

	Southern Peer Code (S) with Equivalent Meta Branch Code (M)					
Southern Group Branch Code	**Southern Peer 1 Code (S)**	**Equivalent Meta Code (M)**	**Southern Peer 2 Code (S)**	**Equivalent Meta Code (M)**	**Southern Peer 3 Code (S)**	**Equivalent Meta Code (M)**
1S	3S	68M	15S	80M		
2S	3S	68M	15S	80M		
3S	3S	68M				
4S	3S	68M	15S	80M		
5S	5S	70M				
6S	15S	80M	3S	68M		
7S	3S	68M	5S	70M		
8S	3S	68M	15S	80M		
9S	15S	80M	3S	68M		
10S	3S	68M	15S	80M		
11S	15S	80M	3S	68M		
12S	15S	80M	3S	68M		
13S	3S	68M	5S	70M		
14S	14S	79M				
15S	15S	80M				
16S	3S	68M	15S	80M		
17S	15S	80M	3S	68M		
18S	3S	68M	15S	80M		
19S	3S	68M	15S	80M		
20S	3S	68M	15S	80M		
21S	15S	80M	3S	68M		
22S	14S	79M				
23S	5S	70M	3S	68M		
24S	15S	80M	3S	68M		
25S	15S	80M	3S	68M		
26S	3S	68M	15S	80M		
27S	15S	80M	3S	68M		
28S	3S	68M	15S	80M		
29S	15S	80M	3S	68M		
30S	3S	68M	15S	80M		
31S	15S	80M	3S	68M		
32S	3S	68M	15S	80M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.4A — DON 2013 peers at meta level (M) with Central group (C) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Central Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
98M	17M	17N	107M	10C		
99M	107M	10C	17M	17N		
100M	17M	17N	62M	32E	68M	3S
101M	17M	17N				
102M	107M	10C	17M	17N		
103M	17M	17N				
104M	68M	3S				
105M	17M	17N				
106M	107M	10C	17M	17N		
107M	107M	10C				
108M	17M	17N	68M	3S	107M	10C
109M	62M	32E	17M	17N		
110M	107M	10C	17M	17N		
111M	107M	10C	17M	17N		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.4B — DON 2013 peers at Central group level (C) with meta level (M) equivalents

	Central Peer Code (C) with Equivalent Meta Branch Code (M)					
Central Group Branch Code	**Central Peer 1 Code (C)**	**Equivalent Meta Code (M)**	**Central Peer 2 Code (C)**	**Equivalent Meta Code (M)**	**Central Peer 3 Code (C)**	**Equivalent Meta Code (M)**
1C	13C	110M	10C	107M		
2C	13C	110M	10C	107M		
3C	13C	110M	10C	107M		
4C	13C	110M				
5C	13C	110M	10C	107M		
6C	13C	110M				
7C	10C	107M				
8C	13C	110M				
9C	13C	110M	10C	107M		
10C	10C	107M				
11C	13C	110M	10C	107M		
12C	13C	110M	10C	107M		
13C	13C	110M				
14C	13C	110M	10C	107M		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.5A — DON 2013 peers at meta level (M) with Western group (W) equivalents

	Meta Peer Code (M) with Equivalent Group Code					
Meta Branch Codes for Western Branches	**Meta Peer 1 Code (M)**	**Equivalent Group Code**	**Meta Peer 2 Code (M)**	**Equivalent Group Code**	**Meta Peer 3 Code (M)**	**Equivalent Group Code**
112M	17M	17N				
113M	17M	17N	68M	3S	107M	10C
114M	17M	17N	107M	10C	68M	3S
115M	17M	17N	107M	10C		
116M	17M	17N	62M	32E	68M	3S
117M	17M	17N	107M	10C	68M	3S
118M	62M	32E	17M	17N		
119M	62M	32E	17M	17N		
120M	17M	17N	107M	10C		
121M	62M	32E	17M	17N		

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 14.5B — DON 2013 peers at Western group level (W) with meta level (M) equivalents

	Western Peer Code (W) with Equivalent Meta Branch Code (M)					
Western Group Branch Code	**Western Peer 1 Code (W)**	**Equivalent Meta Code (M)**	**Western Peer 2 Code (W)**	**Equivalent Meta Code (M)**	**Western Peer 3 Code (W)**	**Equivalent Meta Code (M)**
1W	9W	120M				
2W	2W	113M				
3W	10W	121M	6W	117M	2W	113M
4W	9W	120M	2W	113M		
5W	9W	120M				
6W	6W	117M				
7W	7W	118M				
8W	8W	119M				
9W	9W	120M				
10W	10W	121M				

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 15: DON 2013 targets at meta level and equivalent state group levels (Chapter 6)

Appendix 15.1 — DON 2013 targets at meta level (M) and equivalent Northern group level (N)

Meta Branch Code (M)	Equivalent Northern Branch Code (N)	Target at Meta Level	Equivalent Target at Northern Group Level
1M	1N	136146	8620
2M	2N	121455	8620
3M	3N	136146	8620
4M	4N	123997	8620
5M	5N	99700	8620
6M	6N	136146	8620
7M	7N	99700	8620
8M	8N	136146	8620
9M	9N	123997	8620
10M	10N	99700	8620
11M	11N	136146	8620
12M	12N	75402	5466
13M	13N	136146	8620
14M	14N	136146	8620
15M	15N	94496	8620
16M	16N	68091	5713
17M	17N	136146	8620
18M	18N	136146	8620
19M	19N	136146	8620
20M	20N	77381	6583
21M	21N	136146	8620
22M	22N	46702	3101
23M	23N	33307	2510
24M	24N	136146	8620
25M	25N	33307	2510
26M	26N	114109	8620
27M	27N	136146	8620
28M	28N	75402	5466
29M	29N	84727	7262
30M	30N	121455	8620
Totals		**3262825**	**228252**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 15.2 — DON 2013 targets at meta level (M) and equivalent Eastern group level (E)

Meta Branch Code (M)	Equivalent Eastern Branch Code (E)	Target at Meta Level	Equivalent Target at Eastern Group Level
31M	1E	73924	24578
32M	2E	136146	35973
33M	3E	99418	28376
34M	4E	128800	33441
35M	5E	62690	17222
36M	6E	136146	35973
37M	7E	136146	37318
38M	8E	111848	33635
39M	9E	268M07	15169
40M	10E	136146	37318
41M	11E	75402	26067
42M	12E	62690	17222
43M	13E	70036	20900
44M	14E	63793	20900
45M	15E	136146	37318
46M	16E	38955	17497
47M	17E	136146	35973
48M	18E	136146	35973
49M	19E	51104	24429
50M	20E	36980	6187
51M	21E	87551	28991
52M	22E	58369	17222
53M	23E	62258	17222
54M	24E	99700	29258
55M	25E	14658	12841
56M	26E	75402	25225
57M	27E	61652	21409
58M	28E	98899	28592
59M	29E	111848	32301
60M	30E	14658	12841
61M	31E	83646	25844
62M	32E	2509	2509
63M	33E	136146	37318
64M	34E	87551	27241
65M	35E	70036	20900
Totals		**2920351**	**881183**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 15.3 — DON 2013 targets at meta level (M) and equivalent Southern group level (S)

Meta Branch Code (M)	Equivalent Southern Branch Code (S)	Target at Meta Level	Equivalent Target at Southern Group Level
66M	1S	136146	78925
67M	2S	136146	68348
68M	3S	33091	33091
69M	4S	87551	43668
70M	5S	15591	1843
71M	6S	58369	40142
72M	7S	21425	12259
73M	8S	136146	64822
74M	9S	136146	85535
75M	10S	62690	42346
76M	11S	62258	42346
77M	12S	77381	48516
78M	13S	31147	22675
79M	14S	21071	12592
80M	15S	136146	107130
81M	16S	136146	68348
82M	17S	70036	45431
83M	18S	62258	42346
84M	19S	136146	82450
85M	20S	55344	39261
86M	21S	77381	47194
87M	22S	30950	12592
88M	23S	33307	22675
89M	24S	136146	103604
90M	25S	48442	36617
91M	26S	109847	50719
92M	27S	99202	50719
93M	28S	136146	71873
94M	29S	136146	82450
95M	30S	121455	61296
96M	31S	114109	57771
97M	32S	55344	39261
Totals		**2709708**	**1618845**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 15.4 — DON 2013 targets at meta level (M) and equivalent Central group level (C)

Meta Branch Code (M)	Equivalent Central Branch Code (C)	Target at Meta Level	Equivalent Target at Central Group Level
98M	1C	92072	21198
99M	2C	77381	18319
100M	3C	109847	21918
101M	4C	136146	25516
102M	5C	33307	9683
103M	6C	136146	25516
104M	7C	33091	3925
105M	8C	136146	25516
106M	9C	99418	22637
107M	10C	3925	3925
108M	11C	73924	14721
109M	12C	63253	7524
110M	13C	114109	25516
111M	14C	92072	21198
Totals		**1200838**	**247110**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western

Appendix 15.5 — DON 2013 targets at meta level (M) and equivalent Western group level (W)

Meta Branch Code (M)	Equivalent Western Branch Code (W)	Target at Meta Level	Equivalent Target at Western Group Level
112M	1W	136146	21330
113M	2W	25314	10383
114M	3W	52536	15195
115M	4W	70036	19766
116M	5W	98899	21330
117M	6W	68091	18820
118M	7W	38955	4363
119M	8W	38955	9394
120M	9W	77381	21330
121M	10W	51104	13876
Totals		**657417**	**155787**

M = Meta; Groups are N = Northern; E = Eastern; S = Southern; C = Central; W = Western