Essays on Australian Income Inequality

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Certification

This thesis contains no material or work which has previously been submitted for the award of any other degree in any tertiary institution or university. To the best of my knowledge, this thesis contains no material previously published or written by another person, except where due reference has been made.

[redacted]

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Date

Statement of Authorship

I hereby certify that the work embodied in this thesis contains published papers of which I am a joint author. I have included as part of the thesis a written statement, endorsed by my supervisor, attesting to my contribution to the joint publication.

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Chapter 2

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Chapter 3

Kennedy, T., Rae, M., Sheridan, A., & Valadkhani, A. (2017). Reducing gender wage inequality increases economic prosperity for all: Insights from Australia. *Economic Analysis and Policy*, 55, 14-24. https://doi.org/10.1016/j.eap.2017.04.003

Chapter 4

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Abstract

This thesis contains three empirical studies exploring income inequality and its impact on economic growth and productivity in Australia. The inequality-output nexus is examined using national, sub-national and gender-specific data calculated from Australian Taxation Office (ATO) statistics and data published by the Australian Bureau of Statistics (ABS).

Chapter 2 calculates Gini coefficients for Australia as a whole and in each of the states and territories from 1942 to 2013. These newly created series reveal that although national and sub-national income inequality exhibit similar trends over time, there are important short-term variations across regions. State-level Gini coefficients are then used in panel regressions to estimate Australia's inequality-growth nexus. This study concludes that rising income inequality has negative implications for economic growth, while additional investment in education can boost output growth in the long-run. These results support the notion that policymakers should address rising income inequality by implementing measures that support and enhance human capital accumulation given the long-run economic and social benefits.

Following on from this finding, Chapter 3 examines how gender inequality affects productivity. To do this, gender wage gaps are calculated for all of Australia's states and territories using Average Weekly Earnings data published by the ABS from 1982 to 2013. These data are then used as explanatory variables in four different models estimating the

relationship between gender-based income inequality and productivity. Irrespective of the model chosen, it concludes that reducing gender income inequality has positive implications for economic growth that rival those associated with additional investment in human capital. This corroborates the conclusion of Chapter 2 and strengthens the case for policymakers to address rising inequality through additional investment in education.

Motivated by the findings of Chapters 2 and 3, Chapter 4 examines the long-run relationship between inequality and real per capita income using gender-specific Gini coefficients from 1942 to 2013. Using taxation statistics, this chapter derives Gini coefficients for men, women and all taxpayers separately, which are then used to estimate the inequality–growth nexus controlling for within-gender differences in inequality. It concludes that models which allow for differences in gender inequality offer more explanatory power than those models where such differences are overlooked.

This thesis argues that policymakers should not only concern themselves with income inequality for political and social reasons, but also because rising inequality has negative implications for economic growth. Rather than relying on redistributive income transfers which are potentially harmful to long-run productivity growth, this thesis proposes addressing inequality by implementing measures that promote human capital accumulation and economic mobility. Such policies may include greater funding for research and development or targeted investment in female education and training to help reduce gender-based occupational segregation.

Chapter 1

Introduction

1.1 International trends in income inequality

Piketty's (2014) *Capital in the Twenty-First Century* is arguably the most important study of income inequality since the seminal work of Kuznets (1955) and the logical starting point for any contemporary research on income inequality. Piketty (2014) collates data from various sources to show inequality trends for a number of economies including the United States (US), Canada, the United Kingdom (UK), France and Australia, among others. The research highlights two distinct themes in income inequality over the course of the past one hundred years. First, Piketty (2014) notes inequality began the Twentieth Century at elevated levels, with the top percentile earning a disproportionally large share of economy wide income. Inequality was particularly pronounced in the UK and France, where the share of the top 1 per cent of total income was close to 22 per cent and 21 per cent, respectively. The period from 1920 through to the 1940s coincided with a reduction in income inequality across most countries in Piketty's (2014) sample, an outcome corroborated by evidence from Canada (Saez and Veall, 2005), New Zealand (Atkinson and Leigh, 2005), the UK (Atkinson, 2005) and the US (Piketty and Saez, 2003). The shift toward a more egalitarian income distribution is often attributed to a decline in top-income shares following the Great Depression and the reduction of capital incomes during World War Two (WWII) (Atkinson et al., 2011). The Great Depression and WWII had non-trivial ramifications for income inequality. In the US, wage controls imposed by the National War Labor Board led to an equalisation of earned income and a narrower gap between top- and bottom-income earners (Piketty and Saez, 2003). Similar measures in Japan resulted in the share of total wages accruing to the top 5 per cent of earners falling from 19 per cent in 1939 to 9 per cent in 1944 (Atkinson et al., 2011). In Europe, destruction of businesses and physical capital during WWII contributed to sharp declines in capital incomes for top earners. Losses were particularly devastating in France where two-thirds of the capital stock was destroyed (Piketty, 2014). Most countries in Piketty's sample saw inequality drift lower in the decades following WWII, a development Piketty and Saez (2003) attribute to the proclivity of governments to impose more progressive taxation structures in the post-war world. This trend continued until the 1970s when many countries, including the UK, the US, Canada and Japan recorded their most egalitarian income distributions of the past century.

The second theme evident in Piketty's (2014) work is a broad-based upturn in income inequality from the 1980s. This reversal is prevalent across the US, Canada, the UK, Australia, Japan and Continental Europe with the respective income distributions becoming increasingly unequal in the past three decades. The rise in inequality is most striking in the United States where the share of total income earned by the top percentile rose from 8 per cent in 1980 to 18 per cent in 2012 (Piketty, 2014). There are various explanations for the rapid rise in inequality since the 1980s. First, Goldin and Katz (2007) argue that for most of the past three decades technological progress has persistently outpaced growth in human capital, driving a wedge between the incomes of high and low skilled workers. Second, progressive taxation policies introduced after WWII began to be unwound, led by sharp declines in top marginal tax rates (Saez and Veall, 2005; Piketty, 2014). This was particularly evident in Australia where the top marginal tax rate declined from 75 per cent in 1951 to 45 per cent in 2016 (Atkinson and Leigh, 2007). Global financial deregulation through the 1980s contributed to a surge in capital income growth which disproportionally benefited top income earners and exacerbated the already widening gap between the top and bottom of the income distribution (Atkinson and Leigh, 2007). Third, the increase in senior executive remuneration packages in recent decades has easily outpaced average wage growth. For example, Atkinson and Leigh (2007) note that in the early 2000s the typical remuneration for an Australian chief executive officer (CEO) was ninety-eight times the wage of the average worker. Although the number of CEOs is relatively small as a share of the total labour force, the magnitude of these wage gaps has a material influence on the share of income accrued by the top percentile.

Income inequality is a decisive issue for politicians and policymakers. Indeed, the recent rise in inequality is considered to be an influential factor behind growing support for the populist movement in the UK, Continental Europe and the US (Calhoun, 2016; Inglehart and Norris, 2016). With the income distribution of many advanced economies becoming increasingly unequal, the role of inequality in shaping social, political and economic outcomes will remain of utmost importance to policymakers.

This thesis addresses one of these dimensions by examining the relationship between income inequality and economic growth. The ensuing chapters explore this nexus from different perspectives using national, sub-national and gender-specific data. Irrespective of the methodology or inequality series used, this thesis finds that rising income inequality has negative implications for economic growth. This is an important conclusion and argues that policymakers should address rising inequality not only to improve social cohesion, but also to boost economic activity.

1.2 Income inequality in Australia

1.2.1 Sources of income inequality data

Before discussing trends in income inequality for Australia, it is worth highlighting the most common sources from which inequality data are derived; these include the Household Income Surveys (HIS), Household Expenditure Surveys (HES), Average Weekly Earnings (AWOTE), the Household, Income and Labour Dynamics in Australia (HILDA) Survey, the Census and taxation statistics. While a high-quality source, most ABS data are published infrequently and only provide periodic updates of inequality measures. For example, the HIS was conducted only five times prior to 1990 and is now collected on a biennial basis. The HES is only released every six years, while Census data only offers a snapshot of income inequality every five years. The infrequency of Census observations mean inequality in inter-survey years is undocumented, distorting the assessment of the evolution of income inequality (Piketty and Saez, 2003). The biannual AWOTE data from the early 1980s and the annual HILDA survey since 2001 have presented useful alternatives for documenting total household disposable income. However, limited comparable observations in these series have prevented any meaningful time series analysis on the trends and determinants of income inequality in Australia.

Compared with survey data from the HIS, HES, HILDA and the Census, taxation statistics exhibit three distinct advantages. First, taxation statistics allow the investigation of income inequality in Australia over a much longer, consecutive period. Second, these statistics remain the only source that provides detailed long-run information on income inequality across states and territories. Third, these statistics provide a more accurate indicator of top-income earners compared with other survey data that tend to under-sample this group (Leigh, 2005). For these reasons, with the exception of gender wage gaps which are calculated using AWOTE data, this thesis primarily uses taxation statistics to calculate income inequality.

It is worth pointing out that the use of taxation statistics encounters several limitations. First, unlike taxation statistics, surveys allow greater freedom of response and are better able to distinguish between different sources of income growth. Second, given that the tax unit in Australia is the individual, these statistics may not fully capture inequalities across households. Third, since not everyone files, or is required to file, a tax return, these statistics may not provide a complete picture of income distribution across the entire population (Leigh, 2005).

Despite these limitations the use of taxation statistics to examine income distribution in Australia has a long history, including earlier studies by Brown (1957), Saunders (1993), Lydall (1968), Harris (1970), Ternowetsky (1979), Hamilton and Saddler (1997) and Smith (2001), among others. More recently, Leigh (2005) uses taxation statistics to estimate income inequality for Australian adult males. Specifically, Leigh (2005) calculates Gini coefficients for Australian male taxpayers to be used as a proxy for household inequality during the period 1942–2002. Meanwhile, Atkinson and Leigh (2007) and Burkhauser et al. (2015) use taxation statistics to examine inequality for the top 10 per cent of the income distribution in Australia. This thesis differs from the extant literature in that it uses taxation statistics to calculate Gini coefficients not only for all taxpayers, but also for males and females separately. Furthermore, it also compiles Gini coefficients for all taxpayers at the state and territory level.

There is on-going debate as to whether inequality should be measured at the individual or household level. In one of the earliest attempts, Kuznets (1955) measures US inequality at the individual level, even though this requires some data transformation as US taxation statistics are published at the household level. In contrast, Piketty and Saez (2003) analyse inequality at the household level and stipulate that the choice of measurement unit is unlikely to exert any material effect on inequality estimates. Since Australian taxation statistics are lodged and reported for individuals, this thesis also reports income inequality at the individual level to preserve consistency. In short, this thesis represents the first systematic study on income inequality at national, sub-national and gender levels in Australia.

1.2.2 Trends in income inequality

Despite different methodologies and approaches, each of the sources discussed in section 1.2.1 indicate that income inequality in Australian has widened in recent decades. The long-run insight provided by Leigh (2005) and Atkinson and Leigh (2007) show that inequality has followed a U-shape curve since the early Twentieth Century; a conclusion shared by Piketty and Saez (2003) in their study of the US, as well as Piketty's (2014) recent work. Specifically, Atkinson and Leigh (2007) find that the share of income accruing to the top percentile moved lower from 1921 to 1945. The decline in inequality during the 1930s and early 1940s was particularly noteworthy and consistent with global trends associated with the Great Depression and WWII. Inequality spiked in the early 1950s following a surge in sheep farmers' incomes on the back of peak world wool prices (Jones, 1975). However, this spike proved short-lived as the normalisation in wool prices the following year saw inequality return to pre-boom levels. Between 1955 and 1980, Australia's income distribution became more equitable and the gap between the haves and have-nots persistently narrowed.

In the past three decades, Australian income inequality has increased. This experience was not unique to Australia as widening income differentials also featured prominently in many developed economies such as Canada (Saez and Veall, 2005), New Zealand (Atkinson and Leigh, 2005), the UK (Atkinson, 2005) and the US (Piketty and Saez, 2003). Inequality continued to widen through the 1990s and 2000s, with the income share of the top percentile rising to levels last seen in the 1950s (Atkinson and Leigh, 2007). Inequality temporarily declined in the 2008–09 period, partly reflecting a reduction in capital income for top earners following the Global Financial Crisis (ACOSS, 2015; Wilkins, 2015).

Today, Australia's inequality statistics are striking. Individuals in the top 20 per cent of the income distribution earn approximately five times the income of a person in the bottom 20 per cent (ABS, 2015, Cat. 6523; ACOSS, 2015). Even more concerning is that income gaps between high- and low-income earners are widening. Indeed, since the mid-1980s, real wage growth for the top 10 per cent of income earners has increased more than 70 per cent, but the same figure is only 14 per cent for the bottom 10 per cent of income earners (ACOSS, 2015). Along with the social and political costs associated with rising inequality, there are also economic consequences that need to be considered. This thesis seeks to address these economic consequences, with an explicit emphasis on the relationship between income inequality and economic growth.

1.2.3 Gender wage gaps

On average, women continue to earn less than men in all OECD economies (OECD, 2015a). The OECD data indicate that although the gender wage gap, defined as the difference between male and female income expressed as a percentage of male income, has narrowed in many countries over the past two decades, divergences remain striking. The largest wage gaps currently exist in Korea, Japan, Finland and Canada, while Belgium, Hungry, Italy and New Zealand are now reporting the smallest income discrepancy between genders.

In Australia, the gender wage gap narrowed from 1950 to 1980, in large part due to the introduction of legislation such as the *Equal Pay for Equal Work Act* in 1969 and the *Equal Pay for Work of Equal Value Act* in 1972 (Watson, 2010). The push for gender equality continued in the subsequent years, with the *Sex Discrimination Act* in 1984 contributing to a further reduction in gender-based income inequality.

However, progress stalled from the early 1990s and there is now evidence that Australia's gender wage gap is widening (OECD, 2015a; WGEA, 2016a). The literature offers four plausible explanations for the lack of progress in eliminating gender income inequality. First, direct discrimination in hiring behaviours, particularly at the senior executive level, has resulted in significant under representation of women in these positions. In Australia this has contributed to a situation where two-thirds of senior executives are men, while women are over-represented in the low-paid service sector (WGEA, 2016a). Second, indirect discrimination widens gender wage gaps through failing to offer adequate flexibility in working arrangements. Inflexible work arrangements are most restrictive for mothers who often assume the role of primary care giver for their children. In Australia, indirect discrimination contributes to 70 per cent of mothers working on a part-time basis, while only 6 per cent of fathers were in comparable positions (Charlesworth et al, 2011). Third, occupational segregation, defined as the extent to which men and women are distributed across different sectors, is prominent when one gender accounts for a disproportionately large share of a sector's workforce. In Australia occupational segregation is particularly pronounced in the mining and construction sectors where men comprise approximately 80 per cent of the workforce (WGEA, 2015). Finally, differences in education and work experience are influential in shaping wage outcomes. Although educational attainment is higher among women in Australia, gender differences in work experiences are striking as women comprise a larger share of part-time employment (Miller, 2005). Given part-time employment is typically associated with low-quality jobs, less upward mobility in career progression and fewer training and education opportunities, these factors may contribute to low growth in female earnings.

This thesis explores how gender wage gaps have evolved in Australia's states and territories over the course of the past three decades. Particular emphasis is placed on the effect that gender inequality has had on per capita income growth, potential drivers of these wage discrepancies and how policymakers can address income imbalances.

1.3 The income inequality–economic growth nexus

Economists remain divided over the effects, if any, income inequality exerts on economic growth. Proponents of a positive inequality–growth nexus advocate the following two transmission channels. First, greater concentration of income, and thus, widening income inequality, encourages saving and investment which in turn promotes economic growth. For example, Kaldor (1957) argues that since high-income individuals have a higher propensity to save, and given that saving equals investment, more unequal societies should experience a higher growth rate relative to those where aggregate savings are lower. Bourguignon (1981) formalised this hypothesis by showing that when savings is a convex function of income, output is shown to be larger in societies with an uneven distribution of income. Second, Mirrlees (1971) suggests higher inequality may invoke favourable behavioural responses and create incentives for individuals to exert more effort in an attempt to maximise utility. Such incentive-based approaches are consistent with the efficiency wage hypothesis where labour productivity rises with earning potential (Katz, 1986). Since wider income differentials are likely to attract more productive workers, the efficiency wage hypothesis can be used to explain differences in output per capita, and thus, income inequality across industries (Katz, 1986).

In contrast, the following theories are commonly cited to explain the negative inequality–growth relationship. First, Hibbs (1973) highlights the role of inequality on political instability, where a high concentration of economic resources encourages rent-seeking behaviours and the exploitation of political power. This fosters a general lack of trust in governments, creating civil unrest and disincentives to invest. This linkage is most prevalent in developing economies where democratic processes are fragile and power is more likely to be usurped. Second, access to credit markets can be a decisive factor in shaping the linkage. In societies where the income distribution is narrowly focused, most households lack the collateral required to borrow freely against future income in credit markets (Cingano, 2014). This binding constraint limits the ability of the poor to invest in human capital which in turn exacerbates income inequality. Third, the negative linkage can stem from governments responding to rising inequality by implementing redistributive policies and income transfers. Such policies are thought to lower long-run productivity by reducing the incentives to work among high- (reducing disposable income) and low- (means-testing creates incentives to favour welfare benefits over work) income earners (Okun, 1975; Perotti, 1996; Alesina and Rodrik, 1994; Persson and Tabellini, 1994).

Apart from these two distinctive transmission channels, there is a third view postulating a dynamic inequality–growth nexus. This view has its antecedent in the Kuznets curve whereby inequality initially increases during early stages of economic development, before declining as more individuals gain access to the nation's resources (Kuznets, 1955). Barro (2000) and Castello–Climent (2010) find support for a dynamic relationship and conclude that inequality is most harmful to GDP growth in low-income economies, with the negative effect dissipating, or turning positive, once income per capita exceeds a critical threshold. Against this backdrop, Naguib (2015, p. 34) suggests that sample selection plays an instrumental role when undertaking cross-country studies as the inequality–growth nexus "*operates in different ways in developed and developing economies.*"

The importance of sample section and potential for a dynamic nexus has contributed to a growing number of studies exploring the relationship between inequality and economic growth in a single-country setting (Barro, 2000). This thesis adds to these studies by using taxation statistics to examine long-run inequality trends in Australia and the subsequent effect on economic growth.

1.4 Empirical evidence on the inequality–growth nexus

The relationship between income inequality and economic growth carries important policy implications. For this reason, the extant literature is vast, with research strongly arguing both in favour and against redistributive policies. One reason for these conflicting viewpoints is that most studies have relied on cross-country data over a short time span, neglecting heterogeneity of data and measurement standards, aggregation problems and cultural and institutional differences, among others (Frank, 2009; Rooth and Stenberg, 2012). These drawbacks have resulted in increasing calls for studies exploring the relationship between inequality and economic growth using sub-national data. (De Dominicis et al., 2008; Naguib, 2015).

1.4.1 Cross-country studies

Some early studies on the inequality–growth nexus include Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996) and Deininger and Squire (1996), among others. In general, these studies explore the nexus through the lens of cross-country data over the 1960–1985 period and find overwhelming supporting evidence for a negative relationship. However, these studies have been criticized for mixing observations from developed and developing economies to ensure adequate sample sizes. Such an approach is deemed problematic given inequality is thought to affect growth in developed and developing economies differently (Barro, 2000; Castello-Climent, 2010; Naguib, 2015). Furthermore, studies in this genre only capture a snapshot at a point in time, neglecting the possibility of a dynamic inequality–growth nexus (Kuznets, 1955).

To improve on these early studies, more recent investigations have employed advanced panel data analysis (Forbes, 2000; Cingano, 2014; Naguib, 2015). The findings from these studies have remained mixed. For example, Forbes (2000) and Naguib (2015) find a positive inequality–growth nexus whereas Cingano (2014) reports a negative relationship. These mixed results indicate that data quality, cross-jurisdiction comparability, estimation techniques and other idiosyncratic factors may influence empirical results. This division in the literature makes a compelling case for further investigation of the inequality-growth nexus under a single-country setting as discussed in the following section.

1.4.2 Single-country studies

The use of a country's state-level or regional data possesses several advantages over cross-country statistics when exploring the inequality–growth nexus. First, data are collected under the same standards and methodologies that ensure comparability over a long-time horizon. Second, single-country studies help to minimize political, institutional and cultural differences that are common in cross-country studies (Barro 2000; Frank 2009). Last, but not least, large and unexpected flows of productive factors between states can magnify small disparities in initial conditions that influence inequality and growth (Partridge, 2005).

Since the 1990s, a small branch of literature has explored the inequality–growth nexus using sub-national data. For example, Frank (2009) uses individual tax filing data available from the US Internal Revenue Service to calculate annual inequality for 48 US states over the period 1945–2004. Meanwhile, Partridge (1997, 2005) and Panizza (2002) use panels spaced at a minimum of ten-year intervals, resulting in only a small number of observations per cross section. In general, these studies find support for a positive relationship between inequality and economic growth. In a detailed US-county level study, Fallah and Partridge (2007) conclude that this relationship is positive in metropolitan areas and negative in regional centres. In Europe, Perugini and Martino (2008), Rodriguez-Pose and Tselios (2008) and Rooth and Stenberg (2012) report a positive relationship between inequality and economic growth. In general, these studies attribute their findings to the effect that income inequality has on worker productivity and attracting skilled labour.

A compelling case can be made for studying the inequality-growth nexus in Australia. Annual taxation statistics, from which inequality estimates can be calculated, are available at both the national and state level from the early 1940s. The ABS also publish a variety of datasets measuring Australia's income distribution, some of which can be used to examine the more granular aspects of inequality such as gender wage gaps. As discussed in the following section, this thesis uses these datasets to explore the inequality–

growth nexus and contributes to the relatively small and nascent literature examining this relationship in a single-country setting.

1.5 Structure of the thesis

This thesis overcomes the data limitations outlined in section 1.4 by using statistics published by the ATO and ABS to calculate income inequality at the national and sub-national level in Australia. These inequality series are then used to analyse the relationship between income inequality and economic growth from three different perspectives. First, Chapter 2 calculates Gini coefficients at the national level, as well as for the states and territories from 1942 to 2013. State-based Gini coefficients are then used to estimate the relationship between income inequality and real output per capita. Second, taking AWOTE data published by the ABS, Chapter 3 calculates gender wage gaps for all Australian states and territories. These data are subsequently used to estimate the effect of gender-based income differentials on productivity. Third, Chapter 4 contributes to the literature by calculating long-run Gini coefficients for male, female and all taxpayers in Australia from 1942 to 2013. Chapter 4 then shows how using gender-specific Gini coefficients when modelling the inequality–growth nexus can improve the fit with actual data. To that end, this thesis highlights the shortcomings of using aggregate data when exploring trends in income inequality. Chapter 5 concludes.

1.5.1 Chapter 2

Chapter 2 explores the relationship between income inequality and output growth per capita in Australia for the period 1942 to 2013. It adds to the current body of literature in two important ways. First, using ATO taxation statistics, it estimates income inequality, measured by Gini coefficients, for all taxpayers from 1942 to 2013. It compliments Leigh (2005) by not only calculating Gini coefficients for male taxpayers, but also for their female counterparts. Second, it estimates the effects of inequality on growth for each state and territory in Australia. While Gini coefficients are available from 1942 the data on real output, human capital and physical capital stock by states and territories only become available after 1986, resulting in a truncated sample period. Even with this limitation, the ability to estimate the inequality–growth nexus in a single country avoids many of the problems identified in section 1.4.

Chapter 2 finds that national and state-based Gini coefficients have followed similar trends over time, spiking in the early 1950s on the back of rising wool prices, before correcting in subsequent years. Inequality maintained a downward trajectory until the late 1970s, at which point these trends reversed and moved higher. This is consistent with the work of Piketty (2014) who finds that inequality has increased in most developed economies since the early 1980s. The data reveal some interesting variation by region, with inequality in Victoria and New South Wales typically higher than that reported for the less populous states. Inequality has also increased sharply in Western Australia since the early 2000s and now rivals that of New South Wales.

These Gini coefficients are then used in state-based panel regressions estimating the inequality–growth nexus. Chapter 2 reports a negative and significant relationship between inequality and growth. Based on this result, it argues that minimizing income inequality not only improves social cohesion, but also boosts economic activity.

1.5.2 Chapter 3

Chapter 3 explores the inequality–growth nexus from a different perspective, examining the effect of gender income inequality on productivity. Gender wage gaps are calculated from AWOTE data for all of Australia's states and territories for the period 1986–2013. These data are then used to examine the effect of gender income inequality on output growth per capita.

Consistent with the existing literature, gender wage gaps are calculated as the average dollar value difference between male and female incomes expressed as a share of male income. The data reveal positive wage gaps in all states and territories, or in other words, average male income is consistently higher than that of females across Australia. Imbalances have become increasingly pronounced in Western Australia and Queensland where gender wage gaps in 2013 were recorded at 26 per cent and 22 per cent, respectively. Wage gaps in the more populous states of New South Wales and Victoria are narrower and more stable, though women, on average, continue to earn less than men.

The effect of gender income inequality on output per capita is calculated using four different approaches: (1) panel ordinary least squares (OLS) with fixed effects; (2) panel two-stage least squares (2SLS) with fixed effects; (3) fixed-effects generalised method of moments (GMM); and (4) random-effects GMM. Regardless of the estimation method, Chapter 3 concludes that widening gender wage gaps exert adverse effects on per capita output growth. Specifically, the results indicate that a 10 per cent narrowing of the gender wage gap can increase per capita output by 3 per cent. To put this into perspective, the economic benefit from reducing gender inequality rivals the positive spill-over associated with additional investment in human capital. This finding corroborates the conclusion of Chapter 2 and lends support to the notion that policymakers must address rising inequality through greater investment in human capital.

1.5.3 Chapter 4

For the first time, Chapter 4 uses gender-specific Gini coefficients to estimate the inequality–growth nexus for the period 1950 to 2013. Chapter 4 addresses concerns raised by Chantreuil and Lebon (2015) and Perrons (2015), among others, that gender differences in income have not been considered in a systematic manner in the existing literature. In contrast to Chapter 3, it focuses on the dynamics of the inequality-growth nexus through the lens of gender-specific Gini coefficients. This distinction is important because Gini coefficients estimate income dispersion within a sample, whereas gender wage gaps measure the income differential between the sexes. As such, these Gini coefficients represent inequality within the male and female sub-populations separately and provide no direct indication of inequality between genders.

Chapter 4 uses four separate models to explore the inequality-growth nexus: (1) a gender-specific threshold model with fixed effects; (2) a conventional threshold model; (3) a quadratic Kuznets type model; and (4) a cube function model. It finds that the gender-specific threshold approach fits the data better than the remaining models, supporting the view that gender differences need to be accounted for when examining the relationship between income inequality and output growth. Furthermore, it finds that the inequality–growth nexus is contingent on the level of per capita income, with the sign of the inequality coefficient turning from negative to positive once a critical threshold is reached. This result conflicts with the proposed inverted U-shaped Kuznets curve and instead offers support for the U-shaped curve espoused by Piketty (2014) and Leigh (2005, 2013).

Finally, Chapter 4 notes that inequality among men and women evolves differently based on broader economic performance. For example, since 1980 income inequality among men has increased at a faster rate than that of women for a given level of per capita income. This finding carries implications for future research as it suggests that studies reliant on aggregate Gini coefficients are likely to understate the degree of within-group inequality for men, while overstating within-group inequality for females. Future research should therefore incorporate gender-based inequality measures, wherever possible, to more appropriately capture inequality trends in the underlying income distribution.

1.5.4 Chapter 5

This thesis finds that national and state-based Gini coefficients have increased steadily since the early 1980s, reversing the downtrend of the preceding three decades. Gender wage gaps are also found to exist across all states and territories despite the introduction of legislation intended to address such discrepancies. Regardless of the inequality measure used, this thesis concludes that rising inequality has negative implications for subsequent economic growth.

These findings also suggest policymakers must be selective when deciding how to address rising income inequality. In Australia, the conventional practice has been to manage inequality through progressive taxation and redistributive income transfers, policies which potentially lower long-run productivity and distort incentives (Okun, 1975; Ichino et al., 2011). As an alternative, this thesis supports the notion that policymakers should address rising inequality through greater investment in human capital given the long-run benefits to both equality and efficiency.

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Chapter 2

Does income inequality hinder economic growth? New evidence using Australian taxation statistics

2.1 Introduction

The relationship between income inequality and economic growth carries important policy implications. If inequality enhances (hinders) economic growth, this would provide a strong argument against (in favour of) redistributive policies. However, the inequality–growth nexus remains open to debate. Proponents of a positive nexus argue that inequality creates incentives to work harder and accumulate savings necessary for investment (Cingano, 2014; Mirrlees, 1971; Shin, 2012). In contrast, negative relationships arise when inequality forces governments to invoke growth-distorting taxation polices, under-invest in human capital or contributes to financial and credit market imperfections (Agnello et al., 2012; Esarey et al., 2012; Lim and McNelis, 2016).

One reason for these conflicting viewpoints is that most studies have relied on cross-country data over a short time span, neglecting heterogeneity of data and measurement standards, aggregation problems and cultural and institutional differences, among others. For these reasons, there have been increasing calls to examine this nexus using sub-national data (De Dominicis et al., 2008; Naguib, 2015).

In response, a relatively small branch of the inequality-growth literature has emerged over the last fifteen years or so that uses sub-national state or regional data. For example, several studies have analysed panel data for US counties or states (Fallah and Partridge, 2007; Frank, 2009; Partridge, 1997, 2005) or regions in Europe (Asteriou et al., 2014; Perugini and Martino, 2008; Rodríguez-Pose and Tselios, 2010; Rooth and Stenberg, 2012). The issue, however, is that the lack of observations has meant that average inequality, often for ten-year intervals, is used as the dependent variable, creating short-and-wide panels with large-N and small-T (see e.g. Panizza, 2002; Partridge, 1997, 2005). Frank (2009) is one of the few studies to use a panel with annual data on inequality for 48 US states over the period 1945 to 2004.

State- or regional-level data has several advantages over cross-country aggregates when investigating the relationship between inequality and income. First, data are compiled using the same collection standards and methodologies. Second, within-country studies share the same political systems and institutions, which helps to minimise cultural differences inherent in cross-country studies (Barro, 2000; Frank, 2009). Third, large factor flows between states should magnify how relatively small disparities in initial conditions influence economic growth (Partridge, 2005). In addition, if the panel contains annual inequality measures for each state or region the inequality–growth relationship can be more reliably tracked over time compared with using data at periodic intervals that produce more of a snapshot in time.

Australia makes an interesting country to study the effect of income inequality on real economic growth. Despite being a country that prides itself on egalitarianism, it has become increasingly unequal in terms of both income and wealth distribution (Greenville et al., 2013; Leigh, 2005; Wilkins, 2014, 2015). In this sense, rising income inequality in Australia is representative of trends in Europe and the US (Piketty, 2014) and across the OECD more generally (see e.g. OECD, 2014). But Australia is also interesting in that the resources boom commencing from the late 1990s has benefited some regions more than others, contributing to growing disparities in income distribution across states and territories.

Until now concerns over data quality and the lack of long-term official inequality statistics have prevented a robust study of Australia's inequality–growth nexus (Leigh, 2005). This study contributes to the extant literature in three distinct ways. First, Chapter 2 constructs a national income inequality series for Australia by calculating Gini coefficients based on individual taxation statistics released by the Australian Taxation Office (ATO) for the period 1942–2013. This series is considerably longer than the biennial inequality statistics released by the ABS since 1995 (ABS 2015, Cat. 6523). This study differs from Leigh (2005) in that it uses data on all, rather than only male, taxpayers to calculate Gini coefficients for Australia. Second, Gini coefficients are calculated for all eight Australian states and territories (Victoria, New South Wales, ACT, Queensland, Northern Territory, Western Australia, South Australia and Tasmania).[1] This is the first attempt to provide disaggregated, long-run Gini coefficients for Australia and its states and territories.

Third, using these state- and territory-level Gini coefficients, Chapter 2 undertakes a state-based panel study of the inequality–growth nexus. While Gini coefficients are calculated from 1942 to 2013, state-level data on economic growth, human capital and fixed capital formation have only become systematically available from 1986. Hence, panel data analysis is restricted to a shorter time span.

Income inequality is of great importance to policymakers given the potential economic, social and political ramifications. This chapter explores one of these dimensions by examining Australian income inequality at the sub-national level and its relationship with economic growth. Additional insights into this nexus are invaluable in helping policymakers address rising inequality, particularly given the myriad ways inequality may affect growth (Forbes, 2000; Partridge, 2005). In general, it is found that inequality has widened in all Australian states and territories since the late-1970s. Beginning from the mid-1980s, inequality has exerted a negative, and delayed, impact on the economy. Whereas investment in both physical and human capital has positively influenced it. The positive relationship between human capital and economic growth is particularly important

[1] Taxation statistics were published annually in the *Report of the Commissioner of Taxation* from 1942 to 1999. Since 2000 the ATO has published taxation statistics on their website.

given evidence that additional investment in education and upskilling can also help to lower income inequality (Bénabou, 2002; Ostry et al., 2014).

While further investigation is required to determine what drives this nexus, these results still carry important policy implications. Specifically, it can be argued that an effective way for Australian policymakers to address rising inequality is through greater investment in human capital given the egalitarian and economic benefits. This would mark somewhat of a deviation from the conventional wisdom given the preference in Australia to address rising inequality through progressive taxation and transfers. Reducing income inequality through greater investment in human capital has the added benefit of avoiding the negative externalities associated with redistribution, such as diminishing economic incentives and lowering productivity (Alesina and Rodrik, 1994; Ichino et al., 2011; Partridge, 1997; Persson and Tabellini, 1994).

2.2 Measures of income inequality in Australia

There are five key official data sources for the study of income inequality in Australia; namely, the Household Income Surveys (HIS), the Household Expenditure Surveys (HES), the Household, Income and Labour Dynamics in Australia (HILDA) Survey, the Census and taxation statistics.[2] A major advantage of taxation statistics is that they allow one to

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[2] Taxation statistics are collected by the ATO, the HILDA survey is commissioned by the Department of Social Services and the remaining sources are surveyed by the ABS.

investigate inequality in Australia using annual data over a much longer period, particularly at the state- and territory-level. Furthermore, unlike survey-based data, taxation statistics capture a greater extent of high-income earners, and thus, provide a more accurate indicator of inequality among the top-end of the income distribution. Based on these grounds, Leigh (2005) uses taxation statistics to calculate Gini coefficients for Australian male taxpayers over the period 1942–2002. Meanwhile, Atkinson and Leigh (2007) and Burkhauser et al. (2015) rely on taxation statistics to estimate inequality for the top 10 per cent of the income distribution. This series differs from Leigh (2005) in that Gini coefficients are calculated for all taxpayers in Australia as well as for each state and territory.

However, taxation statistics also have limitations in estimating inequality. First, income-distribution surveys allow greater freedom of responses and are better able to distinguish between sources of income growth than taxation statistics. Survey data is also more likely to capture non-taxable income, which by definition is not included in the relevant taxation statistics. Second, given that the Australian tax unit is the individual, taxation statistics may not fully capture inequalities across households. Third, since not everyone files a tax return, taxation statistics may not provide a complete picture of income distribution across the population (Leigh, 2005). Using estimates of the size of the labour force published by the ABS, and ATO taxation statistics over the same period, this study finds that taxation statistics, on average, capture 87 per cent of the total labour force for the period 1978–2013.

2.3 Alternative views on the inequality–output nexus

In theory, inequality exerts a positive impact on income through two main channels. First, inequality encourages savings, and therefore investment, since the rich have a lower propensity to consume (Bourguignon, 1981; Kaldor, 1957). This is especially relevant for poorer countries as it allows at least part of the population to accumulate the minimum required to invest in education and entrepreneurship (Barro, 2000; Ostry et al., 2014). Second, higher inequality creates incentives for individuals to work harder and invest given the ability to earn higher wages (Katz, 1986; Mirrlees, 1971). Individuals are also incentivised to upskill by investing in human capital or switch to more productive industries, both of which lift economic growth (Cingano, 2014).

There are three channels through which a negative relationship might exist. First, Hibbs (1973) argues that a high concentration of economic resources can create incentives for rent-seeking behaviors, which lead to the exploitation of political power. This fosters a general lack of trust in government, giving rise to civil unrest and disincentives to invest. Second, financial and credit market imperfections reduce the ability of poorer individuals to borrow freely against future income in credit markets. This creates a binding constraint on the household sector and limits the ability of low-income earners to invest in either physical or human capital (Banerjee and Newman, 1991). This can be detrimental to an economy given under-investment in human capital is widely thought to have negative long-run consequences for economic growth, physical investment and economic mobility (Bénabou, 2002; Cingano, 2014; Ostry et al., 2014). Finally, there are political economy channels, through which voters may regard inequality beyond a critical threshold unacceptable, forcing governments to implement redistributive policies. In particular, if the median voter feels that their income is below the economy-wide average, they will vote in favour of policies that redistribute income and wealth from high- to low-income individuals (Esarey et al., 2012). Redistribution comes at a cost, however, with such policies thought to lower growth by misallocating resources and creating disincentives for both high-income (greater tax burden) and low-income (means-testing creates incentives to favour benefits over work) earners.

Using cross-sectional data from a variety of countries ranging from 1960 to 1985, Alesina and Rodrik (1994), Deininger and Squire (1996), Perotti (1996) and Persson and Tabellini (1994) find evidence of a negative relationship between inequality and growth. There are two notable drawbacks of these early studies. First, these cross-country studies are likely to capture only an average relationship that suffers from aggregation bias, which is amplified when the sample consists of developed and developing countries. This point is highlighted by Barro (2000), who finds that the nature of the inequality–growth nexus differs distinctively between developed and developing economies. Second, cross-sectional regressions only estimate this relationship at a point in time, providing no indication of how this relationship may change as an economy matures (Kuznets, 1955).

In order to improve on the early cross-country findings, more recent studies have employed panel data (see, e.g. Barro, 2000; Cingano, 2014; Forbes, 2000; Naguib, 2015). The findings from the panel studies are mixed. For instance, Cingano (2014) finds a negative relationship between income inequality and output growth, while Naguib (2015) finds that growth and inequality are positively related. These mixed results suggest sample selection is critical when uncovering this relationship in cross-country studies. Barro (2000) separates a sample of one-hundred countries over the period 1960 to 2000 into rich and poor categories. He finds that income inequality is detrimental to economic growth in poorer countries, while some degree of inequality proves to be beneficial for wealthier nations. Naguib (2015, p. 34) believes that a consensus is emerging whereby the relationship between inequality and growth *"operates in different ways in developed and developing economies."*

A small number of studies examine the inequality–growth nexus using panel data for US counties or states or regions in Europe. Findings are mixed. Some studies have found a positive association (e.g. Frank, 2009; Partridge, 2005), whereas others (e.g. Panizza, 2002) have found a negative relationship between inequality and growth. Overall, the mixed results for Europe and the US with sub-national data reflect the use of different estimation methods, different measures of income inequality and different sample periods.

2.4 Empirical methodology

2.4.1 Gini coefficients for Australian states and territories

Gini coefficients are calculated using annual taxation statistics included in the *Report of the Commissioner of Taxation* for the period 1942–1999 and the ATO website for the remaining period 2000–2013. Taxation statistics provide detailed information on taxable income, net tax, gender, location and income source, among others. Individuals are categorized into different taxable-income bands, with frequent changes in the number of bands between years. Following Leigh (2005), equation (2.1) is used to estimate the adjusted version of the Gini coefficient (G_i) for each of Australia's states and territories in any given year during the sample period.

$$G_i = \frac{N}{N-1}\left[1 - \sum_{i=1}^{N} P_i (S_i + S_{i-1})\right] \tag{2.1}$$

Where N is the number of income groups, P_i is the fraction of the population in group i and S_i is the share of total income in group i and all groups below, with $S_0 = 0$. Leigh (2005) notes that the grouping of income data into a relatively small number of bands may impose a non-negligible bias on the Gini coefficient estimates. To correct this and following Leigh (2005), Chapter 2 adopts the Deltas (2003) correction procedure in which the Gini coefficient is scaled by $N/(N-1)$ in equation (2.1). This adjustment technique reduces the bias owing to data grouping. Furthermore, the ATO included non-taxpayers, or those who pay net tax of zero, only for the decade from 2000 to 2010, creating a sharp temporary level shift in income inequality that renders estimated Gini coefficients non-comparable with the rest of the sample period. In order to account for this definitional bias, it is assumed that the average percentage of zero income tax-return lodgers remains the same throughout the sample period.

2.4.2 Aggregate versus male-only Gini coefficients

Income inequality has been examined at both the individual (Kuznets, 1955) and household level (Piketty, 2014). While there is debate as to which level is most appropriate, Piketty and Saez (2003) suggest that the implications of this choice are relatively minor given inequality estimates derived from individuals are likely to be very similar to those calculated at the household level. In Australia, calculating Gini coefficients for individuals requires less data transformation given tax returns are lodged by individuals, rather than households. The main drawback, though relatively minor, is that individual inequality estimates may not perfectly capture inequalities across households given within-household income transfers.

Since Australian taxation statistics are reported at the individual level, Gini coefficients reported in this thesis follow the work of Kuznets (1955) and are based on individual incomes, both male and female. The decision by Leigh (2005) to use male-only taxation statistics to calculate Australian Gini coefficients owes to the close correlation between male Gini coefficients and household Gini coefficients in the United States, even though Leigh (2005) acknowledges that this relationship may not hold true for Australia.

The omission of female income earners is problematic, particularly in recent decades given the rise in female labour force participation which has contributed to women becoming primary income earners in approximately one-quarter of dual income Australian households (Cassells et al., 2013; Greenville et al., 2013). To test whether male-only or both genders should be included when estimating inequality, this study separately regresses male-only Gini coefficients and aggregate Gini coefficients (male and female) on ABS household Gini coefficients for as many years as possible back to 1967 (first print) and finds no notable outperformance of either series. However, when the sample is shortened to the 1995–2013 period, which captures the increase in female labour-force participation and consistency in the ABS Gini coefficient methodology, the aggregate series returns a higher *t*-statistic. This analysis suggests that both genders need to be taken into account when calculating Gini coefficients.

2.4.3 Impact of non-lodgers on Gini coefficient estimates

Based on ABS labour force data from 1978 to 2013, taxation statistics capture an average of 87 per cent of Australia's total labour force. In order to determine the effect of non-lodgers on inequality estimates, Chapter 2 separately computes a series of Gini coefficients assimilating non-lodgers based on the ATO's *Review into the Non-Lodgement of Individual Income Tax Returns* (Inspector General of Taxation, 2009).[3] Individuals earning less than the tax-free threshold comprise 80 per cent of non-lodgement with the lowest

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[3] Non-lodgers are those individuals within the labour force that fail to lodge a tax return. The number of non-lodgers are calculated as the number of individuals within the labour force less the number of lodged taxation returns.

reportable income of zero, which provides an upper bound on calculated Gini coefficients.[4] Late submitters and tax evaders account for the remaining 20 per cent of non-lodgers, and given the ATO's finding that these individuals have incomes closely aligned with the reported distribution are incorporated accordingly. The inclusion of non-lodgers does not materially alter the path of income inequality at the national level; a conclusion which likely extends to the states and territories when considered separately.

2.4.4 Panel regression analysis

In the literature, technological advancements, the rate of change in physical stock of capital, and rising human capital are considered to be the main sources of economic growth (Cingano, 2014; Mankiw et al., 1992; Sequeira, 2008). That is $\dot{Y}_{it} = f\,(\alpha_{it}, \dot{I}_{it}, \dot{H}_{it})$. Based on the earlier review of the extant literature, inequality can either positively or negatively affect economic growth depending on the sign of γ in the following relationship:

$$\dot{Y}_{jt} = \alpha_j + \sum_{i=0}^{p} \beta_{ij} L^i \dot{I}_{jt} + \sum_{i=0}^{p} \eta_{ij} L^i \dot{H}_{jt} + \sum_{i=0}^{p} \gamma_{ij} L^i \dot{G}_{jt} + \varepsilon_{jt} \qquad (2.2)$$

Where $\dot{Y}_{jt} = \Delta Ln(Y_{it})$ is the change in the natural logarithm of real economic growth in state j at time t, a_j is the fixed or random effects (intercept terms) showing technological

[4] Since reported income cannot be negative, assigning zero income to this group ensures that these individuals are at the furthest point from the reported distribution. Given the Gini coefficient is a dispersion measure, this ensures an upper bound on inequality estimates.

differentials across states, $\dot{I}_{jt}$ is the growth rate of investment, $\dot{H}_{jt}$ is the growth rate of human capital, $\dot{G}_{jt}$ is the state-based Gini coefficient, L^i is a lag operator, whereby $L^i x_t = x_{t-i}$, and ε_{jt} is the stochastic residual term. As can be seen in equation (2.2), logarithmic changes in the Gini coefficient are added to examine the specific effect of inequality in each state on economic growth. This is necessary because all the four variables in equation (2.2) are stationary only after converting them to logarithmic changes. Time series properties of the panel are examined by using the ADF-Fisher χ^2 test (Maddala and Shaowen, 1999) and the *W* test (Im et al., 2003). All variables in equation (2.2) are I(0) only in the first log differences. Hence, this study uses a growth equation. The Schwarz information criterion (SIC) is used to determine the optimal lag length and the general-to-specific modelling strategy to estimate a parsimonious version of equation (2.2). The β_{ij} and η_{ij} coefficients are expected to be positive, but the sign on the coefficient of γ_{ij} is *ex ante* unknown. In order to capture heterogeneities among the eight state and territories in Australia, the intercept term is allowed to exhibit fixed or random effects depending on the outcome of the Hausman test.[5]

[5] Another alternative way of examining the effect of inequality is to construct a measure of total factor productivity (TFP) and then regress it on explanatory variables such as knowledge, innovation, patents, human capital and other factors including inequality (Madsen, 2014).

2.5 Data

2.5.1 Australian and state and territory Gini coefficients

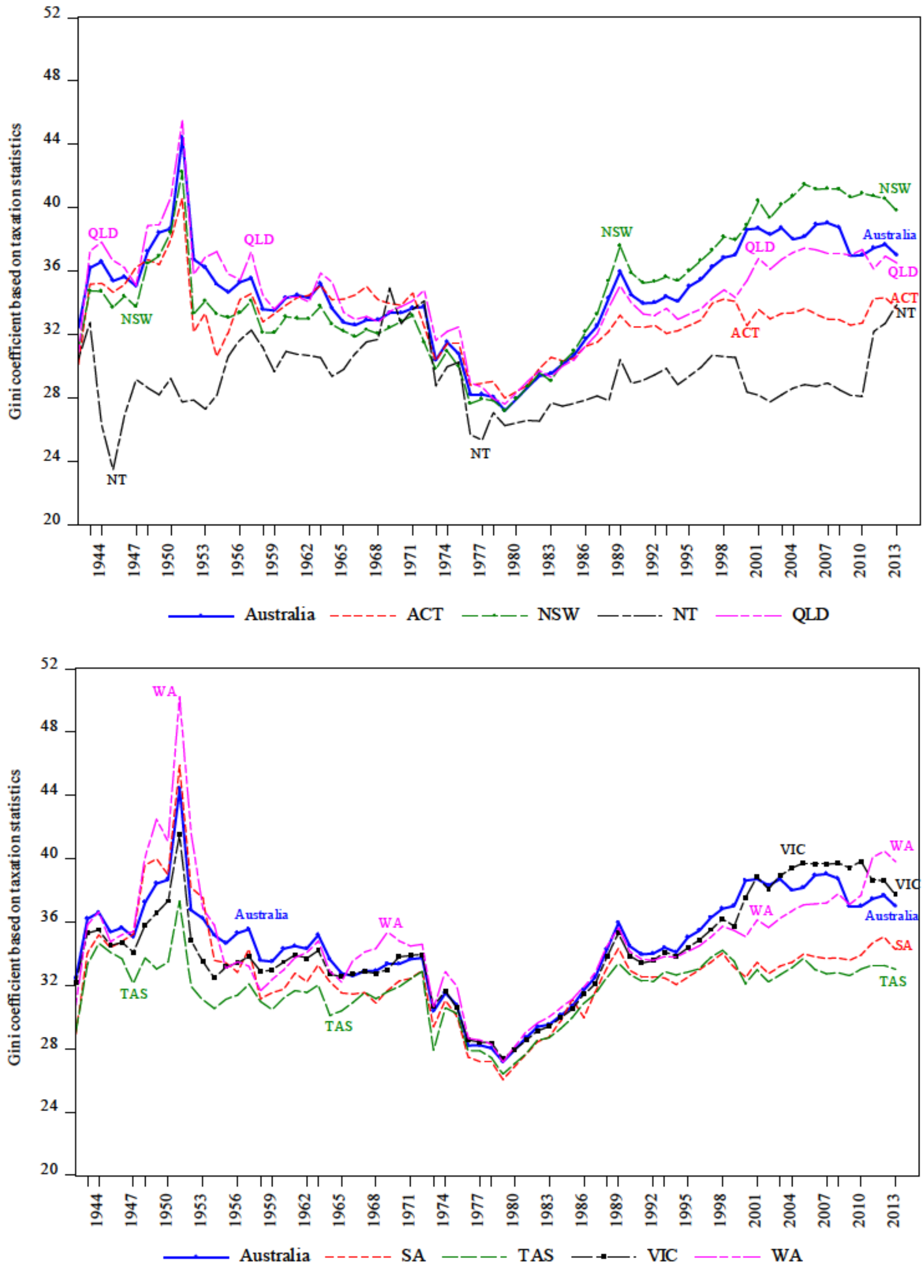
Figure 2-1 shows the computed state and territory Gini coefficients as well as the Gini coefficients for Australia as a whole during the period 1942–2013.[6] While Gini coefficients for Australia as a whole are not used in modelling the inequality–growth nexus below, they serve as an interesting point of comparison with those for the states and territories. Figure 2-1 depicts the inequality trends for Australia, which, not surprisingly, are very similar to Leigh's (2005) results for adult males only. The exclusion of women by Leigh (2005) means that Gini coefficients prior to 1980 are slightly lower than those calculated using taxation data for both genders. The two series have converged in recent decades, driven by rising female labour force participation and the partial narrowing of gender income differentials.

Casual observation of Figure 2-1 reveals a brief spike in inequality in the early 1950s, associated with the 1950–51 wool boom. Apart from this, income inequality fell in the 1950s and remained fairly stable in the 1960s. Inequality fell again in the early 1970s, before rising from the late 1970s. This trend is consistent with Atkinson and Leigh (2007), who report that top-income shares increased dramatically during the 1980s and 1990s.

[6] See Appendix Table 1A for the numerical value of these Gini coefficients.

Possible reasons for rising inequality in Australia include declining unionisation, a reduction in top marginal tax rates and the internationalization of the market for English-speaking Chief Executive Officers (CEOs) (Leigh, 2005).

Figure 2-1. Computed national, state and territory Gini coefficients based on taxation statistics, 1942-2013.



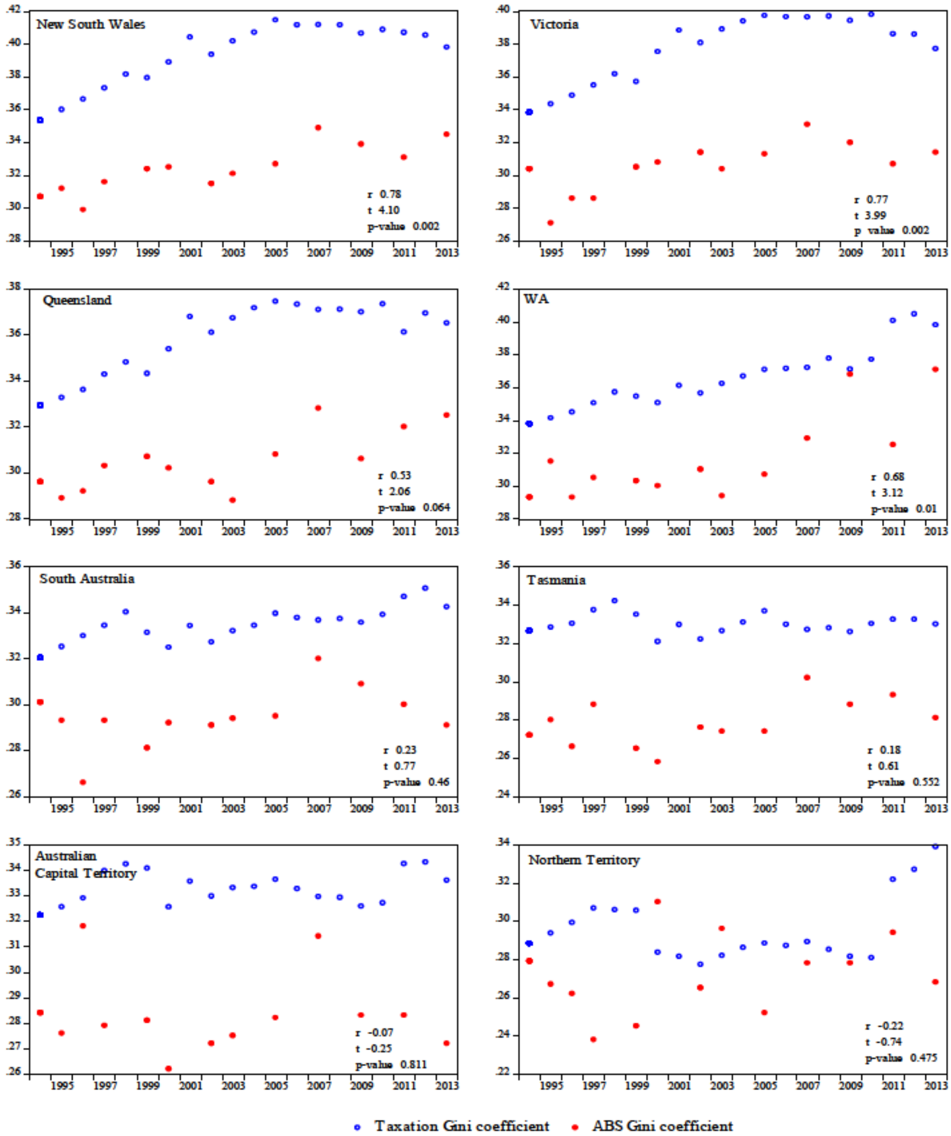
Each of the states and territories shared similar starting points in terms of the value of the Gini coefficient in 1942, but have exhibited different patterns since World War II. With the exception of the Northern Territory, inequality in the states and territories spiked to varying degrees during the wool boom, then declined through the 1950s, remained fairly stable in the 1960s and then declined again throughout the 1970s. Inequality across the states and territories has increased since the late 1970s. In general, these trends follow closely the overall pattern of the national Gini coefficient. Northern Territory, Tasmania and, to a lesser extent, the ACT consistently reported the lowest Gini coefficient in Australia over time. Putting aside the level of income, this trend suggests that the extent of income inequality was relatively smaller in the less populous states and territories. In other words, the larger the pie, the more uneven the distribution. During the post-global financial crisis period, the Gini coefficient was falling in New South Wales, Victoria and Queensland, but rising in the Northern Territory and Western Australia. Finally, and in relation to the preceding point, both the Northern Territory and Western Australia have registered the highest growth rate in the Gini coefficient since 2008; a sign of rapidly rising income inequality in both of these states/territories.

2.5.2 Compiled Gini coefficients versus ABS irregular Gini series

To assess the reliability of the state based inequality estimates, this study compares calculated Gini coefficients with those released by the ABS (2015, Cat. 6523.0 *Household Income and Wealth, Australia, 2013–14*) for the biennially available years in the post-1995 era, particularly for the largest four states (New South Wales, Victoria, Queensland and

Western Australia). Figure 2-2 indicates a strong relationship between this study's calculated Gini coefficients and those of the ABS. The insignificant positive correlation between these two series for the smaller states is not surprising given different survey methods, statistical coverage and definitional changes adopted by the ABS.

Figure 2-2. Taxation-based Gini coefficients versus the ABS biennially available Gini coefficients.



2.6 Panel regression results

Table 2-1 provides the descriptive statistics, variable definitions, measurement scales and sources of data used in estimating the inequality–income nexus. The data on real output (total final demand), human capital and fixed capital formation by states and territories can only be obtained or computed after 1986. Thus, while Gini coefficients are available for the period 1942–2013, the estimation sample is confined to the period 1986–2013. On average, the Gini coefficient falls within the range 0.294 (Northern Territory) and 0.382 (New South Wales). While this is for a shorter period, it is consistent with the general trend identified in Figure 2-1, where Northern Territory and New South Wales exhibited a more equal and unequal income distribution, respectively.

Table 2-1. Descriptive statistics by state, 1986-2013.

Description	ACT	NSW	NT	QLD	SA	TAS	VIC	WA
Gini coefficient G_{jt}								
Mean	0.330	0.382	0.294	0.352	0.332	0.340	0.366	0.358
SD	0.008	0.027	0.015	0.019	0.010	0.017	0.027	0.021
Source: Authors' computations using tax return data								
Real output (A$ Millions, Chain volume measures)								
Mean	586	17524	1115	13093	3709	1042	13263	9877
SD	284	5539	739	6984	1272	330	5476	6408
Source: ABS (2015, *Cat.* 5206.0, Table 25)								
Investment in physical capital (A$ Millions, Chain volume measures)								
Mean	8741	82968	3698	47619	17727	5281	61015	29184
SD	3405	21243	1626	19190	4610	1252	18377	12830
Source: Authors' calculations and ABS (2015, *Cat.* 5206.0, Table 25)								
Human stock capital (the number of people with university degrees, persons)								
Mean	88201	831704	14344	444356	198118	55450	744048	260519
SD	25777	268586	3667	147484	61764	15093	232318	85043
Sources: Authors' calculations, DETYA (2001) and http://docs.education.gov.au/node/34949								

Table 2-2. The panel unit root test results.

Variable	*IPS*		*ADF-Fisher*	
	W-stat	*p*-value	χ^2	*p*-value
$Ln(Y_{it})$	0.288	0.61	11.17	0.80
$\dot{Y}_{jt} = \Delta Ln(Y_{it})$	-7.96	0.00	80.87	0.00
$Ln(I_{jt})$	-0.50	0.31	16.90	0.39
$\dot{I}_{jt} = \Delta Ln(I_{jt})$	-2.75	0.00	43.66	0.00
$Ln(H_{jt})$	4.24	1.00	2.88	0.99
$\dot{H}_{jt} = \Delta Ln(H_{jt})$	-3.64	0.00	39.12	0.00
$Ln(G_{jt})$	-0.45	0.33	21.26	0.17
$\dot{G}_{jt} = \Delta Ln(G_{jt})$	-7.23	0.00	82.59	0.00

Notes: IPS denotes the panel unit root test proposed by Im et al. (2003).

Table 2-3. Estimated panel regression results using the general-to-specific modelling approach $\dot{Y}_{jt} = \alpha_j + \beta_{0j}\dot{I}_{jt} + \eta_{1j}\dot{H}_{it-1} + \gamma_{2j}\dot{G}_{it-2} + \varepsilon_{jt}$

	Model 1: GMM with random effects			Model 2: OLS with a common effect		
Variable	Coefficient	*t* ratio	*p*-value	Coefficient	*t* ratio	*p*-value
C	-0.063	-7.68	0.01	-0.068	-6.69	0.00
$\dot{I}_{jt}$	1.687	6.41	0.01	2.718	19.26	0.00
$\dot{H}_{it-1}$	1.265	3.82	0.01	0.291	1.84	0.07
$\dot{G}_{it-2}$	-0.255	-3.74	0.01	-0.276	-3.23	0.00
R^2	0.729			0.843		
Adjusted R^2	0.725			0.841		
DW	2.25			2.10		
Instrument rank[(a)]	5			-		
J-statistic[(b)]	1.692		0.193	-		
Hausman test[(c)]	χ2(3)=0.08		0.98	-		

Note: (a) The instruments are a constant, $\dot{Y}_{jt-1}$, $\dot{I}_{jt-1}$, $\dot{H}_{it-1}$, $\dot{G}_{it-2}$ and $\dot{G}_{it-2}$. (b) The null hypothesis in this test indicates that over-identifying restrictions are valid. (c) This test compares the fixed and random effects estimates of coefficients and indicates that the random effects are uncorrelated with the explanatory variables.

According to Table 2-2, both the panel ADF-Fisher χ^2 test and the W unit root test suggest that the growth rates of all the four variables are I(0). Given possible simultaneities arising from the instantaneous interactions between the dependent and independent variables, equation (2.2) is estimated using generalized method of moments (GMM) with random effects (Model 1) and OLS with a common effect (Model 2). The GMM instruments are listed in Table 2-3, which includes the first lag of the four variables appearing in equation (2.2). Given the use of annual growth rate data in the estimation process, the use of lags higher than two years cannot be justified. In this regard, validity of the proposed instruments is tested using the Sargan-Hansen's j test. As shown at the bottom of Table 2-3, the null hypothesis of the over-identifying restrictions is statistically valid and cannot be rejected at any conventional level. The use of the random-effects model is also justified based on the Hausman test reported at the bottom of Table 2-3, consistent with the null hypothesis that there is no misspecification.

For Model 1, the coefficients on investment growth in both physical and human capital remain positive and statistically significant at the 1 per cent level. Table 2-3 indicates that the effect of inequality on growth is negative and highly significant at the 1 per cent level, suggesting that falling income inequality can substantially boost economic growth. On average, an additional 10 per cent rise in the growth of inequality can bring about a 2.55 per cent fall in real output growth. In terms of magnitude and relative importance, the estimate of γ in Model 1 is about 15 per cent of the other two determinants of economic growth (i.e. β and η).

In terms of Model 2, all estimates exhibit the expected sign and enter equation (2.2) significantly. For example, the coefficient on the main variable of interest, γ, remains negative at the 1 per cent significance level, indicating a negative inequality–growth nexus across the Australian states and territories. Specifically, an additional 10 per cent increase in the growth of inequality reduces the growth rate by 2.76 per cent, all things being equal. The estimate of γ in Model 2 is about 95 per cent of η, which may partly reflect the catalytic role of human capital accumulation in widening income inequality.

On average, the results in Table 2-3 support the view that physical capital exerts the largest impact on economic growth across eight states and territories. Specifically, according to the results of the preferred model (Model 1), a 1 per cent increase in investment raises output by 1.7 per cent, all things being equal, indicative of increasing returns to scale. Meanwhile, a 1 per cent increase in human capital lifts real output by 1.3 per cent. These results are consistent with the *a priori* expectations. While policies aimed at increasing physical capital can immediately boost economic growth, the impact of a rise in human capital, or a fall in inequality, on the Australian economy appear to be statistically significant, but with one and two years delay, respectively (see the estimated coefficients of the current and lagged variables in Table 2-3.)

Irrespective of whether the other characteristics of states and territories are allowed to be time variant through the use of a random-effect model (Model 1) or held constant (Model 2), the coefficients in Table 2-3 are still highly significant and robust in terms of signs. Overall, it is concluded that while less inequality, as well as more physical and human capital formation, can stimulate economic growth, instantaneous variations mainly stem from changes in physical capital.

2.7 Discussion and conclusion

Income distribution has become increasingly unequal in Australia over time. The greater concentration of income among fewer people has come at a cost, with Chapter 2 finding a statistically significant negative relationship between inequality and economic growth. This suggests that the persistent rise in inequality in recent decades may have contributed to lower subsequent income growth. Persson and Tabellini (1994) and Alesina and Rodrik (1994) drew similar conclusions in their respective studies, highlighting that as inequality increases, so does the pressure for governments to use taxes and transfer payments to redistribute income, which, in turn, impedes economic incentives.

Chapter 2 argues that such a political process may also be contributing to Australia's inequality nexus for two reasons. First, Australia has a highly redistributive tax system, with personal income tax and transfers from high- to low-income earners considerably more progressive than the OECD average (Joumard et al., 2012). According to ACOSS (2015, p. 25), *"various income, asset and employment tests mean that as a proportion of overall transfer payments, Australia redistributes more income to the bottom 20 per cent than virtually any other OECD country."* Second, Australian average individual income is consistently higher than the median across the sample period, which *"motivates more redistribution through the political process"* (Barro 2000, p. 6). To the extent that redistributive income policies have disincentive effects on worker effort and lower productivity, one would expect such policies to have a detrimental impact on Australian per capita income (Alesina and Rodrik, 1994; Greenville et al., 2013).

These findings imply policymakers should not only concern themselves with inequality for political and social reasons, but also because rising income inequality has negative implications for economic growth. This study raises an interesting set of challenges for policymakers. On the one hand, lowering income inequality is beneficial for economic growth, not to mention the positive social implications of higher average living standards and more equitable welfare outcomes (Greenville et al., 2013). The conventional wisdom in Australia has been to address rising inequality through income transfers, which are thought to have distortionary effects and lower productivity (Ichino et al., 2011). The results, however, imply that policymakers should address such imbalances by implementing measures that support human capital accumulation, particularly given the long-run economic and social benefits (Sequeira 2008). Measures to promote human capital accumulation may include greater funding for research and development or targeted investment in female education to help reduce gender-based occupational segregation.[7]

Further investigation is required to determine whether the hypothesis that political

[7] These measures are consistent with Sen's (1997) capability approach to human capital.

channels are influencing Australia's inequality-growth relationship holds true. An obvious starting point would be to model this nexus using an approach similar to that outlined by Persson and Tabellini (1994) and Partridge (1997). These studies are specifically designed to examine the influence of government redistribution on inequality and economic growth. Correctly identifying the factors shaping this nexus will undoubtedly help in the development of measures best suited to reducing inequality. For example, if Australia's inequality-growth nexus is found to be closely linked with credit market imperfections, then financial reforms and removing excessive regulation may prove more effective in reducing inequality (Agnello et al., 2012). There is also scope for future research to explore how inequality at a more granular level impacts economic activity. Chapter 3 partly addresses this topic by exploring how gender income differentials have influenced Australian labour productivity in the past three decades.

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I, the PhD candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated in the *Statement of Originality*.

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Chapter 3

Reducing gender wage inequality increases economic prosperity for all: Insights from Australia

3.1 Introduction

Four decades on from when laws aimed at tackling gender income inequality were introduced, men continue to earn significantly more than women in Australia. Despite more than 40 years of international policy attention to the continued inequality experienced by women in the paid workplace, income inequality persists (Pettit and Hook, 2012; Rubery, 2015). On average, women earn less than men in all OECD countries (OECD, 2015a).

Although Australian female labour force participation rates have increased from 48.2 per cent in June 1986 to 58.8 per cent in 2016 (ABS, 2016), the overall gender pay gap for full-time employment remains high at 19.1 per cent (WGEA, 2016a). Gender inequality is multidimensional. It is not sufficient to increase female labour market participation rates to achieve gender pay equality. In their analysis of 21 countries, Pettit and Hook (2012) demonstrate how policies that facilitate inclusion of women in the labour market often compromise greater gender equality in other areas, such as wage inequality caused by occupational segregation. For example, using the 2004 and 2011 British Workplace Employment Relations Surveys, Davies et al. (2015, p.537) found that *"there is no evidence that gender segregation is significantly less in high-performance workplaces than in workplaces taking a more traditional route."*

As Todd and Preston (2012) report from their analysis, women's increasing participation rates in the labour market have not redressed the occupational segregation that has dogged the Australian labour force, which continues to see women's employment in traditionally feminized (and lower paid) occupations and in less than full-time roles. One of the main reasons behind the persistence of the gender wage gap is the limited success in efforts to change masculinist organizational cultures, attitudes and behaviours, such that women are still overrepresented in undervalued industries and occupations (Todd and Preston, 2012; Peetz, 2015).

While it is no doubt critical to discover why, how and where pay discrimination continues, Chapter 3 argues that it is equally important to diverge from this valuable literature to address a consequential question that arises from this field of research: how do gendered wages influence society's per capita income? If eliminating gender inequality unequivocally lifts productivity and hence the standard of living in a society, policymakers should then come under greater public scrutiny as to why men and women are not paid the same. Therefore, Chapter 3 seeks to understand what impact wage disparity has on the productivity of the economy, proxied by per capita income.

Exploring the effect of the gender wage gap on GDP has been problematic because most of the literature has focused on covering a large number of dissimilar countries over a short time span. Such studies encounter myriad problems, including data heterogeneity, incomparable measurement standards, and political and cultural differences (De Dominicis, 2008). Booth (2016) finds cultural factors to be particularly important in explaining gender differences in economic preferences and performance, while Cooray and Potrafke (2011) and Cooray (2012) similarly conclude that culture and religion are influential in explaining gender inequality in education. In this regard, single-country studies are advantageous in that data are compiled using the same collection standards and methodologies, with the same statistical agency often responsible for collecting data across the entire sample period. Single-country studies also eliminate most of the social, political, cultural and institutional intricacies that are notoriously difficult to control in multi-country investigations (Frank, 2009).

Given this backdrop, the availability of high quality time series data makes Australia a particularly interesting case to examine the effects of gender wage inequality on GDP. The purpose of this research is, for the first time, to undertake a single-country study of the gendered wage-income nexus in Australia using panel data for all eight states and territories during the period 1986 to 2013. The aim of this chapter is to provide empirical evidence of the effect gender inequality has on per capita income in order to inform future policy considerations in tackling wage disparity. Australian gender income inequality is now considerably above the OECD average of 15.5 per cent in 2013, which is a stark turnaround from the early 2000s, when the gender wage gap was narrower than most OECD countries. In 2013, the OECD ranked Australia as the 11th most unequal nation based on income inequality between genders, worse than the United States, United Kingdom and Germany (OECD, 2015a).

3.2 Changing policy approaches to redressing gender income inequality

Women's unequal labour representation and gender pay inequality have attracted public policy attention for the past 40 years. Early arguments for the need to redress gender inequality were framed within a social justice perspective. Proponents of this approach argued for the importance of any benefits being more equally shared across society. In Australia, the *Equal Pay for Equal Work* decision of 1969 and the *Equal Pay for Work of Equal Value* decision of 1972 were the first steps taken to close Australia's gender wage gap (Watson, 2010). However, these equal pay cases only had limited success in narrowing gender wage gaps given they failed to address other structural drivers of wage inequality, such as gender-based occupational segregation (Borland, 1999; Watson, 2010).

Continued human rights and social justice activism throughout the 1970s led to anti-discrimination[8] and affirmative action legislation[9] being enacted in the 1980s. The

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[8] The relevant legislation includes the *Sex Discrimination Act 1984* which prohibits discrimination on the grounds of sex, marital status, pregnancy and family responsibilities, and the *Human Rights and Equal Opportunity Commission Act 1986* which prohibits discrimination in employment on the basis of race, colour, sex, religion, political opinion, national extraction, or social origin, age, criminal record, sexual

combination of legislation, prohibiting discrimination on the basis of sex and prompting private sector firms with more than 100 employees and the public sector to be proactive in enabling equality, was designed to support a more balanced sharing of benefits across society. However, a lack of traction on the social justice argument with employers saw the momentum for change slow by the early 1990s (Strachan et al., 2007). This was not unique to Australia (Kirton and Greene, 2010; Rubery, 2015).

Throughout the 1990s, in a climate of growing neo-liberalism, claims for the efficacy of the free market gained increasing influence on public policy (Hancock, 1999). In this context, the business case for increasing women's participation rates gathered momentum. Proponents of the business case purport that increasing women's participation in the workplace contributes to organizational performance with the focus clearly being on the benefits to the firm (Kramar, 1998). A common argument for the business case is that employing women widens the labour pool and, by including their different perspectives, firms can better meet market needs (Thomas and Ely, 1996). By the mid-2000s, the business case held more credence among employers and governments than the social justice case (Kirton and Greene, 2010), and the discourse of those advocating for gender equality was most commonly framed in the utilitarian terms of improving corporate

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preference, physical or intellectual disability, impairment (including HIV infection) and trade union activity; and various State anti-discrimination Acts.

[9] *Affirmative Action (Equal Opportunity for Women) Act 1986*, which was changed to the *Equal Opportunity for Women in the Workplace Act 1999* and then to the *Workplace Gender Equality Act 2012*.

performance.

Research into the impact on firm performance of increasing women's representation on corporate boards and workgroup diversity has, however, produced mixed findings (Pletzer et al., 2015; van Dijk et al., 2012). As Eagly (2016) demonstrates, this hasn't stopped 'passionate advocates' of the business case from making optimistic generalizations about the impact of women's inclusion on corporate boards or within workgroups more generally, and in so doing, compromising the science-policy relationship. Her argument for the importance of keeping scientific knowledge at the forefront to inform evidence-based gender equality policy is a timely contribution to the debate.

3.3 Gender wage equality and the economy

There is a wide divergence of views on what influence a gender wage pay gap has on the economy. While one school of thought argues that gender equality contributes to the economy, a few contrary studies contest this view. In an important study, Seguino (2000) finds gender income inequality is beneficial to growth in the early stages of economic development. This finding is based on a set of 20 semi-industrialised countries with observations ranging from 1975–1995. However, Schober and Winter-Ebmer (2011) attempt to replicate Seguino's study using a different dataset and find a gender wage gap is negatively related to economic growth. The fact that different datasets can result in conflicting conclusions highlight the importance of data quality and consistency in cross-country studies. This reinforces the argument that cross-country studies suffer from aggregation bias, and fail to take into account country-specific factors, such as equal pay legislation, which directly influences income differentials between genders.

On the other side of the debate, gender income inequality is thought to lower real output through at least two channels. First, since an individual's effort is closely related to their wage rate, gender income inequality discourages the lower paid gender from exerting maximum effort (Mirrlees, 1971; Katz, 1986). This theory is closely associated with the efficiency wage hypothesis, which links individual effort to their real wage rate. Moreover, men are not incentivized to exert maximum effort since income is awarded on a gendered basis rather than any talent or merit.

Second, glaring wage disparities between genders reduces the opportunity costs of the lower paid gender not working. When women are paid less than men for an identical job, female labour force participation will decline, in turn lowering real GDP per capita (Cavalcanti and Tavares, 2016). They find a 50 per cent rise in the gender wage gap results in a 35 per cent fall in income per capita in the long-run. Research by Birch (2005) determines that an increase in the wage rate is associated with increased female labour force participation, while a widening gender wage gap reduces the supply of female labour.

In the Australian context, Cassells et al. (2009) find a narrow gender wage gap would have a considerable positive impact on economic growth. This is one of the few single-country studies exploring the gender inequality–growth nexus at the national level.

Using limited time series observations (1990–2008) they find eliminating the entire wage gap would contribute an additional A$93 billion, or 8.5 per cent of GDP. The literature notes four main drivers behind Australia's gender wage gap. First, direct discrimination in hiring behaviours has limited the number of women in managerial positions (Borland, 1999; Baron and Cobb-Clark, 2010; Watson, 2010). In 2011, two-thirds of total hours worked in managerial positions were by men, while lower paid positions in community and personal services sectors were biased toward a larger share of female employment (Todd and Preston, 2012). This so-called 'glass ceiling' often encountered by women is most common in the private sector where organization culture, attitudes and behaviours adversely affect women's employment prospects (Kee, 2006; Peetz, 2015; Booth, 2016). An example of this dichotomy is evident between Australia's private and public sectors. Collective bargaining agreements, legislation and other instruments are more common in the public sector and have contributed to lower gender wage inequality, while private sector incomes are more likely to be determined by corporate culture, leading to larger income differentials (Peetz, 2015).

Second, indirect discrimination reduces female labour force participation and contributes to a widening in the gender wage gap (Wooden, 1999). Indirect discrimination takes many forms, including the failure of employers to offer adequate flexibility in working arrangements. Charlesworth et al. (2011) find workplace inflexibility is most negative for women given mothers most often assume the role of primary caregiver for their children. This pushes women into lower-paying, less secure forms of employment, with 70 per cent of mothers working part-time in 2011. In contrast, only 6 per cent of fathers held part-time positions (Charlesworth et al., 2011) as the gendered culture in which they live and work reinforces the ‘naturalness’ of men’s full-time presence in the workplace (Sheridan, 2004).

Third, occupational segregation, defined as the extent to which men and women are distributed across different occupations, can also widen the wage disparity when job types with a higher proportion of women are paid less than traditionally ‘male’ jobs (Miller, 1994). Occupational segregation is particularly pronounced in Australia’s mining and construction sectors, with men accounting for more than 80 per cent of the workforce in these industries (WGEA, 2015). In contrast, Peetz (2015) argues traditionally ‘female’ orientated industries, such as childcare, elderly care and nursing have continually been undervalued by society, preventing the gender wage gap from narrowing. Moreover, the exclusion of unpaid housework from most estimates of occupational segregation understates the overall gender division given women undertake a greater share of unpaid housework in comparison to men (ABS, 2009).

Finally, the increase in gender income inequality may be owing to differences in education and work experiences. While education is an unlikely driver given average educational attainment in Australia is higher for women (Miller, 2005), there are glaring discrepancies between work experiences. In their study of gender pay gaps of German professionals with higher education qualifications, Leuze and Straub (2016) distinguish between female typical tasks (reproductive and care related work) and female typical working arrangements (part-time work). They conclude that while there is some impact on the type of work being done, it is the latter factor impacting most on the gender pay gap. In Australia, too, women are still more likely to work in a part-time capacity. This drives a wedge in the gender wage gap since part-time employment is associated with lower quality jobs, limited access to training and fewer promotion and career opportunities (Sheridan, 2004; Todd and Preston, 2012). Booth (2016) argues that such gender differences in employment preferences owes to the culture inherent in Australian workplaces which ingrain the normalcy of women working in part-time capacities. Differences in work experience are influential in creating a 'sticky floor', a scenario where both genders are appointed to the same pay scale, but women are appointed at the bottom and men further up the scale (Kee, 2006).

3.4 Data on gender wage inequality

The Australian Bureau of Statistics (ABS, 2015a) provides the most widely cited gender inequality data in Australia. The average weekly ordinary time earnings (AWOTE) release provides a comprehensive and frequent update on individual incomes by gender, and is the preferred source of inequality data used by Australia's WGEA.[10] The AWOTE series is released on a semi-annual basis, with the ABS publishing ordinary time weekly cash

[10] Other sources from which gender inequality can be derived include the Survey of Income and Housing (SIH), Employee Earnings and Hours (EEH), Census data, the Household, Income and Labour Dynamics in Australia Survey (HILDA) and data published by the Workplace Gender Equality Agency (WGEA).

earnings disaggregated by gender since 1982. The main advantage of AWOTE is the breadth of coverage and frequency, with data on incomes segregated by gender published at the national, state and industry level twice each year. It should be noted that the ABS implemented a new survey methodology in September 1981, with average income data collected after this date not strictly comparable to the pre-1981 time series (ABS, 2015a). The ABS selects approximately 5,500 employer units to complete each survey.

Table 3-1. Definitions and sources of the data employed

Description	ACT	NSW	NT	QLD	SA	TAS	VIC	WA
Gender pay gap (as a percentage of the men's wage)								
Mean	16.04	16.18	15.59	16.96	12.89	14.40	15.48	22.11
SD	3.83	1.52	2.03	1.82	2.59	2.72	1.71	2.68
Source: ABS (2015a)								
Real output (A$ Millions, Chain volume measures)								
Mean	8409	72806	19077	31616	31706	11104	28563	48576
SD	3299	24383	39954	17369	27396	9271	20027	31368
Source: ABS (2015, *Cat.* 5206.0, Table 25)								
Labour force (thousand persons)								
Mean	177	3151	99	1799	746	226	2423	986
SD	25	355	17	383	60	16	305	190
Source: ABS (2015, *Cat.* 5202.0, Table 12)								
Physical stock of capital (A$ Millions, Chain volume measures)								
Mean	17909	230054	66309	101380	110039	37531	89306	157892
SD	4423	84006	138921	52536	102290	31437	60705	101783
Source: Authors' calculations and ABS (2015, *Cat.* 5206.0, Table 25)								
Human stock capital (the number of people with university degrees, persons)								
Mean	88201	831704	14344	444356	198118	55450	744048	260519
SD	25777	268586	3667	147484	61764	15093	232318	85043
Sources: Authors' calculations, DETYA (2001) and http://docs.education.gov.au/node/34949								

Australian states and territories:
- ACT=Australian Capital Territory
- NSW=New South Wales
- NT=Northern Territory
- QLD=Queensland
- SA=South Australia
- TAS=Tasmania
- VIC=Victoria
- WA=Western Australia

After sourcing the annual income for men and women from the ABS (2015a), the gender gap is defined as the difference between the two incomes expressed as a ratio of male income. Table 3-1 shows the sources, definitions and measurement scales of the other four variables; real output, labour force, real stock of physical capital and human capital. Since there is no published data on the stock of physical and human capital for Australian states and territories, they are computed based on the assumptions discussed below.

First assume K_{it} (the stock of capital in state *i* at time *t*) is approximated by:

$$K_{it} = K_{it-1}(1-\delta) + I_{it} \tag{3.1}$$

where I_{it} is gross fixed capital formation and δ denotes the depreciation of the stock of capital. Given state real output data were available in 1985, K_{it} was approximated assuming an initial incremental capital-output ratio (ICOR) of 3. Equation (3.1) is then utilised to generate real capital stock for the rest of the sample period (1986–2013), given a depreciation rate of 3.3 per cent assuming zero scrap value after a thirty-year useful life, i.e. (100-0)/30. The estimated ICOR during the entire sample period averaged across all eight states was 3.22, which was quite close to the lower band of the accepted range between 3 and 5 (Balassa, 1978, p. 108).

Since state level data on human capital are also unavailable, equation (3.2) is used to approximate the total number of Australians with university degrees (H_t) at any given point in time:

$$H_t = H_{t-1}(1-\delta) + CC_t \tag{3.2}$$

where CC_t denotes the total number of university course completions in any given year. Similar to physical assets, it is assumed graduates typically work for 30 years and then retire. The use of the linear depreciation (retirement) rate is then calculated to be $\delta = (100-0)/30 \text{ years} = 3.33\%$. In order to use the law of motion, the number of working-age people with university degrees in the first year of the sample 1985 is required. To this end, the latest Penn World Table version 8.1 (Feenstra et al., 2013) is utilised to obtain changes in total human capital between 1985 and 1986. Subsequently it is observed that Australia had a stock of 51.5 and 52.37 million years of schooling in 1985 and 1986, respectively. This means H_{1986} was 1.017 (52.37/51.5) larger than H_{1985}. Given equation (3.2), H_{1986} can be calculated by:

$$H_{1986} = \frac{H_{1985}}{1.017}(1-0.033) + 77,781 \Rightarrow H_{1986} = 1,582,066$$

where once again $H_{1986} = H_{1985}/1.017$ and CC_t in 1986 was 77,781 (DETYA, 2001). Once the stock of human capital has been calculated for the base year (1985), CC_t can be substituted into equation (3.3) to estimate aggregate human capital from 1987 to 2013. Equation (3.3) calculates how the number of working-age Australians with university degrees (H_t) are distributed across eight states and territories utilising actual course completion data during the sample period:

$$H_{it} = \frac{CC_{it}}{\sum_{i=1}^{8} CC_{it}} H_t \tag{3.3}$$

The assumption is not counter-intuitive because the distribution of human capital across states and territories is thought to closely follow that of course completions.

Using annual time series data during 1986-2013, Table 3-1 provides the mean and standard deviation for the five variables across all eight states and territories in Australia. In terms of the size of the labour force, New South Wales (NSW, 3.151 million), Victoria (VIC, 2.423 million) and Queensland (QLD, 1.799 million) have the highest average numbers of full-time equivalent employees. Therefore, when the variables are measured in per capita terms, the smaller states in most cases show relatively higher averages and standard deviations. The results for the gender wage gap in Table 3-1 reveal that wage disparities on average have been largest in Western Australia (WA, 22.11 per cent) and QLD (16.96 per cent). This is consistent with the WGEA (2015) study where occupational segregation was found to be highest in these states owing to a disproportionate number of men employed in the high paying construction and mining sectors (WGEA, 2015). The lowest average wage gap exists in South Australia (SA, 12.89 per cent) and Tasmania (TAS, 14.40 per cent), albeit the gaps are still quite sizable.

Figure 3-1. Wage gap as a percentage of male income across eight Australian states and territories.

For a detailed account of the inequality trend, Figure 3-1 plots how the gender wage gap has changed over time for each individual state and territory. In order of magnitude, the worst performing states in which the gap has persistently been on the rise since early 2000 are WA, QLD, the Northern Territory (NT) and SA. The rise of inequality in these states, particularly WA and QLD, is representative of occupational segregation, with men comprising 84 per cent of the workforce in the mining sector where income growth in recent decades has often outpaced the national average (WGEA, 2016a). These observations are a major cause for concern as they constitute 38 per cent of Australia's workforce (see Table 3-1). In the two most populous states (NSW and VIC), the gender wage gap follows a mean reverting pattern and remains stagnant over time. On the plus side, the Australian Capital Territory (ACT) and TAS, which have relatively large public sectors, have conspicuously narrowed income inequality during the period 1986-2014. Notwithstanding this promising trend, these small states make up only 4.2 per cent of the total labour force during the sample.

3.5 Research methodology

Consistent with the existing literature, the gender wage gap is defined as the difference between male and female incomes expressed as a percentage of male income:

$$GAP_{it} = (M_{it} - F_{it}) / M_{it} \quad (3.4)$$

where GAP_{it} denotes the gender wage gap at year t and state (or territory) i, M_{it} and F_{it} are the male and female annual average incomes, respectively. To determine the long-run impact of gender inequality on real output per capita, it is important to control for other factors influencing the dependent variable. The major determinants of GDP within the Cobb-Douglas production function are labour, physical capital and human capital (Romer, 1990; Valadkhani, 2003). After expressing output per unit of labour and augmenting the resulting relationship with the gender wage gap variable, the equation can be stated:

$$Ln(Y_{it} / L_{it}) = \alpha_i + \beta Ln(K_{it} / L_{it}) + \mu Ln(HC_{it} / L_{it}) + \lambda Ln(GAP_{it}) + \varepsilon_{it} \quad (3.5)$$

where Y_{it} is real output (income) at year t and state (or territory) i, L_{it} is labour force, K_{it} is real physical stock of capital, HC_{it} is human capital, ε_{it} is the residual term and i is the number of states and territories in Australia. It is theoretically expected that coefficients β and μ will be positive, indicating that in the long-run an increase in per capita physical capital and human capital will boost labour productivity.[11] The sign for λ is expected to be negative, whereby a widening gender wage gap lowers labour productivity and hence aggregate income across states. However, given the sign of the coefficient λ is not known *a priori* because the literature is split on the effect of the gender gap, there is less conviction on this issue for now. The common intercept and fixed/random effect coefficients are respectively shown by α and α_i. The latter can capture the effects of other time-invariant

[11] The ABS (2015c) notes that conceptual and methodology issues have meant that interstate differences in industry composition are difficult to measure. As a result, each state's industry breakdown is primarily derived from a top-down model where the national total is disaggregated by industry using fixed shares, rather than the ABS's preferred bottom-up approach. Such difficulties in allocating productive activity across states may contribute to why productivity in some regions such as the ACT is materially greater than that recorded in other states and territories.

state-specific socio-economic characteristics.

At an empirical level, one can only specify and estimate equation (3.5) when there is at least one cointegrating vector linking the dependent variable to the independent variables. Before conducting cointegration tests, it is important to determine the order of integration of all the variables. To verify the consistency and robustness of the results, three different panel unit root tests are used: Levin, Lin and Chu (LLC, 2002); Im et al. (2003); and Augmented Dickey Fuller-Fisher (Maddala and Wu, 1999). The LLC test allows a common unit root process, whereas the other two tests assume individual unit root processes across states and territories. The results in Table 3-2 show that according to the LLC test, all four variables contain a unit root. However, the results from the Im et al. (2003) W and ADF-Fisher χ^2 tests reach the same inferences except for the gender wage gap variable which is found to be I(0). Based on the LLC test, this study proceeds by assuming that all variables are I(1) or integrated of order 1.

Table 3-2. Panel unit root test results.

		LLCt	W	ADF-Fisher χ^2
$Ln(Y_{it}/L_{it})$	Stat.	2.07	2.06	11.3
	p-value	0.98	0.98	0.79
$\Delta Ln(Y_{it}/L_{it})$	Stat.	-9.32	-6.12	66.46
	p-value	0.00	0.00	0.00
$Ln(K_{it}/L_{it})$	Stat.	3.53	1.04	18.93
	p-value	0.99	0.85	0.27
$\Delta Ln(K_{it}/L_{it})$	Stat.	-11.09	-8.55	98.30
	p-value	0.00	0.00	0.00
$Ln(HC_{it}/L_{it})$	Stat.	11.09	7.52	1.92
	p-value	1.00	1.00	1.00
$\Delta Ln(HC_{it}/L_{it})$	Stat.	-3.17	-6.50	69.94
	p-value	0.00	0.00	0.00
$Ln(GAP_{it})$	Stat.	0.38	-2.4	31.43
	p-value	0.65	0.01	0.01
$\Delta Ln(GAP_{it})$	Stat.	-17.90	-15.73	183.6
	p-value	0.00	0.00	0.00

Note: The LLC test assumes a common unit-root process, whereas the other three tests allow individual unit root processes.

Table 3-3. The results of various panel cointegration tests.

Residual tests	Null hypothesis	Statistic	p-value	Statistic	p-value
	No cointegration	Non-weighted		Weighted	
Pedroni:					
Panel PP		-1.62	0.05	-2.08	0.02
Panel ADF		-1.70	0.04	-2.21	0.01
Kao	No cointegration	-7.32	0.00		
Johansen-Fisher unrestricted rank tests	Hypothesized number of CEs	Trace test		Maximum eigenvalue test	
		Statistic	p-value	Statistic	p-value
JF	No cointegration	59.36	0.00	59.89	0.00
JF	At most 1	13.43	0.64	12.38	0.72
JF	At most 2	9.58	0.89	9.23	0.90
JF	At most 3	15.06	0.52	15.06	0.52

Notes: Johansen-Fisher=JF. Chapter 3 used 232 panel observations in the above tests. The optimal lag length was chosen based on the Schwarz information criterion.

After ensuring that all variables contain a unit root, the focus turns to the number of cointegrating vector(s). Once again to check the robustness of the results, four well-established panel cointegration tests are performed: Phillips–Perron (Pedroni, 1999, 2004); Dickey Fuller-Fisher (Pedroni, 1999, 2004); Kao (1999); and Johansen-Fisher unrestricted rank (Maddala and Wu 1999). According to the three residual-based tests appearing on the top of Table 3-3, the null hypothesis of no cointegration is rejected at the 5 per cent level of significance or better. Furthermore, both the maximum eigenvalue and trace versions of the Johansen-Fisher test reject the null of no cointegration at the 1 per cent level of significance. However, the null hypothesis of "at most 1" cannot be rejected at any conventional level.

Irrespective of which test is taken into consideration, there is statistical evidence of at least one long-run cointegrating vector linking labour productivity to its three determinants as formulated in equation (3.5). Therefore, one can safely conclude that labour productivity is cointegrated with all three variables appearing on the right hand side of equation (3.5). This means that there is a significant long-run relationship between per capita output, the gender wage gap and the other two conventional determinants of productivity namely (K_{it} / L_{it}) and (HC_{it} / L_{it}).

Given the divergence of empirical results in the gender gap literature, it is critical to use different models in order to make robust inferences regarding the sign and statistical significance of β, μ and λ. To this end, the parameters of the first cointegrating vector (i.e. equation using panel ordinary least squares (POLS=Model 1) are estimated with fixed effects:

$$\text{POLS estimators}=\left(\sum_{i=1}^{M}\mathbf{X}_i'\mathbf{Q}\mathbf{X}_i\right)^{-1}\left(\sum_{i=1}^{M}\mathbf{X}_i'\mathbf{Q}\mathbf{Y}_i\right) \tag{3.6}$$

where $\mathbf{Q}$ denotes the fixed effects transformation operator defined as $\mathbf{Q{=}I_{MT}} - \mathbf{P}$ with $\mathbf{P{=}I_M} \otimes \Im_\mathbf{T}$. In equation (3.5) a simultaneity problem may arise from the instantaneous interactions between dependent and independent variables. The reverse causation occurs because states with higher per capita income are also more likely to have better educated citizens or a larger physical stock of capital. In other words, the variables on the right-hand side of equation (3.5) could also simultaneously be influenced by per capita income. In order to address both the simultaneity problem and cross-sectional dependence, panel two-stage least squares (P2SLS=Model 2) with fixed effects are used to estimate the coefficients of equation (3.5) as follows:

$$\text{P2SLS estimates}=\left(\sum_{i=1}^{M}\mathbf{X}_i'\hat{\mathbf{\Omega}}^{-\frac{1}{2}}\mathbf{P}_{\mathbf{Z}_i^*}\hat{\mathbf{\Omega}}^{-\frac{1}{2}}\mathbf{X}_i\right)^{-1}\left(\sum_{i=1}^{M}\mathbf{X}_i'\hat{\mathbf{\Omega}}^{-\frac{1}{2}}\mathbf{P}_{\mathbf{Z}_i^*}\hat{\mathbf{\Omega}}^{-\frac{1}{2}}\mathbf{Y}_i\right) \tag{3.7}$$

where $\mathbf{\Omega}$ is the cross-sectional residual variance-covariance matrix and $\mathbf{Z}_i^* = \hat{\mathbf{\Omega}}^{-\frac{1}{2}}\mathbf{Q}\mathbf{Z}_i$, $\mathbf{P}_{\mathbf{Z}_i^*} = \mathbf{Z}_i^*(\mathbf{Z}_i'^*\mathbf{Z}_i^*)^{-1}\mathbf{Z}_i'^*$ denotes the orthogonal projection matrix onto the $\mathbf{Z}_i^*$, and $\boldsymbol{Z}$ contains a number of instruments (Wooldridge, 2010). In the presence of cross-sectional heteroskedasticity, the diagonal version of $\mathbf{\Omega}$ provides feasible estimators whereby observations with a higher variance are assigned with a smaller weight.

To check the sensitivity of the results to different estimation methods, the fixed-effect version (Model 3) of generalized method of moments (GMM) and the random-effect version of GMM method are also applied.[12] It should be noted the estimation methods were carefully selected to address the problems of cross-sectional dependence and simultaneity arising from the instantaneous interactions between the dependent and independent variables. If consistent results are obtained from all of the above four methods, this should leave no doubt in the minds of sceptics as to the long-run negative impact of a rising gender wage gap on the Australian economy.

The use of the above estimation methods results in obtaining four different models as shown in Table 3-4. All four estimated models perform very well in terms of goodness-of-fit statistics. The coefficients of determination (R^2s) are all approximately 0.99 regardless of estimation method. The resulting residual series are integrated of order zero, I(0), as the null of non-stationarity is strongly rejected at the 1 per cent level of significance. One can thus argue that the residuals are well-behaved.

Irrespective of estimation method, all coefficients for per capita stock of physical capital (β) and human capital (μ) are positive and statistically significant at the 9 per cent level or better. The estimated long-run elasticities in Table 3-4 show that a hypothetical 10 per cent increase in physical and human capital raises labour productivity between 10.00-

[12] Given the use of annual time series data, the first lags of the dependent and independent variables are used as instruments.

10.20 per cent and 0.60–1.30 per cent, respectively depending on which model is considered. The positive coefficient of μ across all four models is consistent with the expectation that additional investment in education raises labour force productivity.

Table 3-4. Long run impact of the wage gap on real per capita output.

Variable	Estimation method	*Intercept*	$Ln(K_{it}/L_{it})$	$Ln(HC_{it}/L_{it})$	$Ln(GAP_{it})$	Fixed Effects	Adj. R^2	LLC test on residuals
Model 1:	POLS							
Coefficient		-1.203	1.003	0.071	-0.126	Figure 3-2	0.992	
t ratio		-4.40	127.69	1.88	-3.11			-5.37
p-value		0.00	0.00	0.06	0.00			0.00
Model 2:	P2SLS							
Coefficient		-0.824	1.015	0.079	-0.300	Figure 3-2	0.991	
t ratio		-2.34	104.88	1.99	-4.54			-7.85
p-value		0.02	0.00	0.05	0.00			0.00
Model 3:	Fixed-effect GLS						0.994	
Coefficient		-0.747	1.020	0.060	-0.297	Figure 3-2		
t ratio		-2.52	123.98	1.69	-4.67			-8.00
p-value		0.01	0.00	0.09	0.00			0.00
Model 4:	Random-effect GLS					Figure 3-2	0.987	
Coefficient		-1.207	1.019	0.125	-0.258			
t ratio		-3.69	107.65	3.37	-4.12			-3.22
p-value		0.00	0.00	0.00	0.00			0.00

Note: (a) This estimation method assumes the first stage long-run coefficients to be homogeneous. (b) This method allows the first stage long-run coefficients to be heterogeneous.

Fixed-effects are used in Models 1-3 and random-effects in Model 4 to account for structural differences between the states and territories, denoted by α_i rather than α. The following correlation matrix shows that the estimated time variant fixed and random effects associated with Models 1-4 are highly correlated:

Table 3-5. Correlation matrix for time variant fixed and random effects associated with Models 1-4.

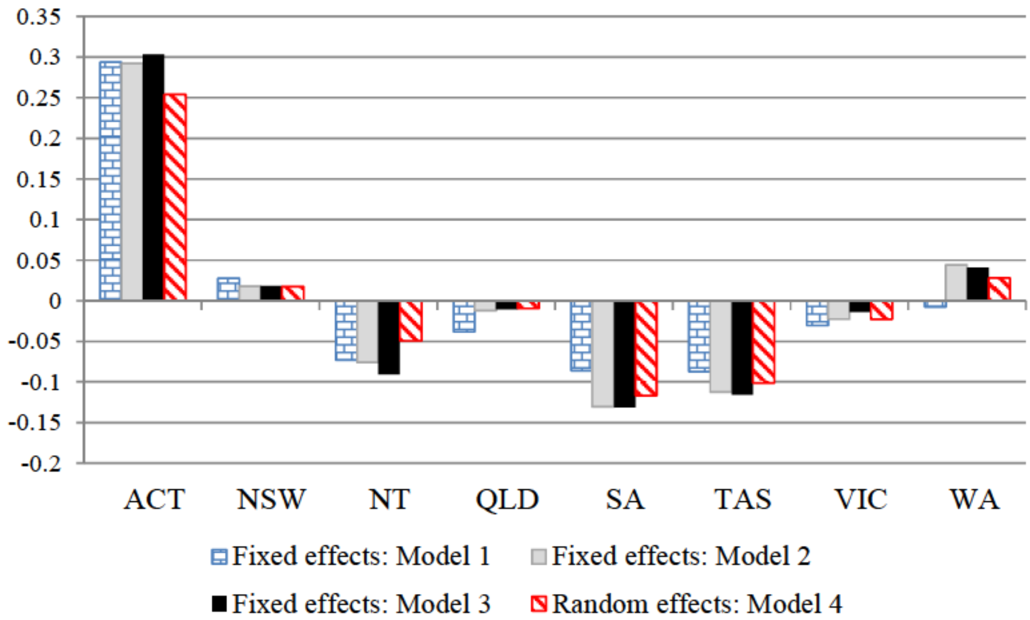
	Model 1	Model 2	Model 3	Model 4
Model 1	1.000	0.975	0.977	0.976
Model 2	0.975	1.000	0.999	0.998
Model 3	0.977	0.999	1.000	0.995
Model 4	0.976	0.998	0.995	1.000

The estimated fixed/random effects are plotted in alphabetical order of the states and territories in Figure 3-2. After controlling the long-run impacts of all the three major contributing factors in equation (3.5), the estimated fixed/random effect coefficients, *ceteris paribus*, show the effects of other determinants of real per capita output. For ACT, NSW and WA all the estimated effects from the four models are consistently positive, whereas TAS and SA have the largest negative effects.

Regarding the focus of this chapter, the estimated long-run elasticities (λ) associated with the gender wage gap are statistically and consistently significant at the 1 per cent level in all four models presented in Table 3-4. The signs on the gender wage gap are negative, so one can then conclude that the higher the gap, the lower per capita output. The magnitude of λ in Models 2, 3 and 4 is at least twice as large as the elasticity found in Model 1, suggesting that once the simultaneity problem and cross-sectional dependence are addressed, the impact of narrower gender wage gaps on productivity are enhanced.

These results indicate that a 10 per cent narrowing of the gap increases per capita output in the long-run within a range between a minimum of 1.3 per cent (Model 1) and a maximum of 3 per cent (Model 2). To put this in perspective, in all four models the long-run impact of reducing the gender gap is not less than the positive spillover effects associated with improving human capital. This finding can be substantiated by comparing the magnitudes of μ with λ in Table 3-4. It is worth acknowledging that while additional investment in female education can increase human capital and therefore help to minimize gender income differentials (Jahan and Alauddin, 1996; Hossain and Tisdell, 2005), the results indicate that policies targeted toward directly narrowing existing wage gaps are worthwhile in their own regard. Therefore, it can be argued that eliminating the gender gap has a substantially desirable effect on the Australian economy so ‘gender wage gap sceptics’ cannot economically afford to ignore such an important social issue any longer. This evidence provides a means to reinvigorate the business case for gender pay equality, through extending the social justice basis to recognise the opportunities for labour productivity gains.

Figure 3-2. Estimated fixed and random effects in Table 3-4.



3.6 Conclusion

Using average earnings data published by the ABS, Chapter 3 finds gender wage gaps exist in all of Australia's states and territories, with women consistently earning less than men. It is particularly concerning that gender wage gaps have increased in some states during the past decade, most notably the mining orientated economies of Western Australia and Queensland. Gender wage gaps in the more populous states of New South Wales and Victoria have proven more stable, though even here, women in the labour force remain at a considerable earnings disadvantage. Discrimination, occupational segregation and differing work experiences are likely to be the main drivers preventing a convergence in male and female incomes.

While the introduction of equal pay legislation in the late 1960s and early 1970s helped to address direct discrimination, imbalances in gender representation across occupations and industries are still striking (WGEA, 2015). Kee (2006) and Booth (2016) suggest that these imbalances may result from cultural factors influencing both education and employment preferences. Reducing occupational segregation has the advantage of increasing female labour force participation and the pool of talent available to employers (Thomas and Ely, 1996; Birch, 2005), which in turn encourages worker effort, spurs innovation and enhances productivity (Mirrlees, 1971). Rather than allowing advocates to shape the policy arena with, at best, partial information and little regard for research findings, Eagly (2016) argues for the need to ensure thoughtful consideration of social science in shaping policy efforts.

The main contribution of this chapter is to provide an empirical insight into the role gender wage gaps have had on labour productivity. Gender inequality is found to adversely affect per capita output in the long-run, with each model consistently reporting a negative, highly significant, coefficient (λ) for the gender wage gap. Chapter 3 also finds that reducing the wage gap by 10 per cent can boost labour productivity by up to 3 per cent in the long-run. This research has important policy implications and argues that correcting imbalances in gender income inequality should be a higher priority for policymakers given the benefits to both equity and efficiency.

These findings are consistent with those of Chapter 2 where it was determined that rising inequality is unequivocally negative for economic growth. The following section combines elements of Chapters 2 and 3 by demonstrating how modelling the inequality-growth nexus using gender-specific Gini coefficients improves the fit with the actual data relative to models where gender differences in inequality are overlooked.

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I, the PhD candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated in the *Statement of Originality*.

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Chapter 4

Refitting the Kuznets curve using a gender-specific threshold model

4.1 Introduction

The distribution of income, and its effect on per capita GDP, has become much debated since the publication of Thomas Piketty's (2014) *Capital in the Twenty-First Century.* For example, in the period since the publication of this volume, two of the mainstream economics journals have published symposia discussing its contents: the *American Economic Review* in its May 2015 issue and the *Journal of Economic Perspectives* in its winter 2015 issue. In addition, an entire book (Pressman, 2016) and several standalone review articles (see e.g. Milanovic, 2014; King, 2016) have been devoted to discussing Piketty's (2014) ideas. Piketty's (2014) volume has been regarded as a continuation of Kuznets' (1955) research on the long-term evolution of income inequality (Pressman, 2016). Kuznets (1955) stated that with the rise of real per capita GDP, inequality first increases and then subsides forming an inverted U-shaped curve. Piketty (2014) dismisses the Kuznets curve, arguing that over the last 150 years income inequality follows a U-shaped curve, in which high-income inequality at the beginning of the twentieth century declined to reach a minimum in the mid-twentieth century, before rising again toward the end of the twentieth century.

At a theoretical level, most studies suggest that the Kuznets curve is a plausible depiction of the relationship between GDP per capita and income inequality given the shift in labour from the agricultural to manufacturing sectors, the development of a modern financial sector and technological progress that accompanies economic development (see Barro, 2000 for a review of the theoretical arguments). The empirical literature, however, is divided as to whether the relationship between inequality and per capita income is U-shaped, inverted U-shaped or non-existent (see e.g. Anand and Kanbur, 1993; Fields, 2001; Tsakloglou, 1988).

One criticism that has been made of Piketty's (2014) analysis is his failure to take sufficient account of the gender differences in income inequality. This point has been put most forcefully in a critique by Perrons (2014, p.668) who suggests that *"more attention to the gendered nature of inequality would enrich [Piketty's] analysis in two main ways. First, by showing the ways in which inequality is experienced differently depending not only on class, but also on other aspects of identity including gender, and second, by attending in more depth to the processes through which inequalities are produced and legitimated"*.

This criticism, or limitation, is not restricted to Piketty's (2014) analysis. More generally, despite growing interest in income inequality and its effect on per capita GDP, little attention has been given to the role of gender differences in this relationship (Chantreuil and Lebon, 2015). Again, to quote Perrons (2015, p.209) on this point: *"The burgeoning literature on growing economic inequality pays little, or no, attention to the enduring and universal question of gender inequality."* There is a large literature on the gender wage gap. This literature suggests that after declining rapidly in the 1970s and 1980s, it narrowed only slightly in the 1990s and that convergence in the gender wage gap stalled altogether through the mid-2000s (Cha and Weeden, 2014). One would expect that the gender wage gap would have an important impact on income distribution between, and within, households, with implications for incentives to work (female labour supply). Yet, with few exceptions (see, e.g. Gallego-Granados and Geyer, 2014, 2015), there is very little research on the distributional or behavioral effects of the wage gap, let alone the implications of gender differences in income inequality for the relationship between income inequality and per capita GDP.

To get a true handle on the relationship between income inequality and per capita GDP, one has to take account of gender differences in income inequality. To illustrate this argument, Chapter 4 examines the relationship between income inequality and per capita GDP using a long time series for Australia, paying particular attention to within-gender differences in income inequality. The first step is to compute gender-specific Gini coefficients based on taxation statistics released by the Australian Taxation Office (ATO) for the period 1950 to 2013. Both series are considerably longer in duration than inequality statistics published by the Australian Bureau of Statistics (ABS), and differ from Leigh

(2005) who only calculates Gini coefficients for adult males. Second, male and female Gini coefficients are treated as a panel with dimensions n = 2 and t = 64 and test four models: (1) a gender-specific threshold model with fixed effects; (2) a conventional threshold regression; (3) a quadratic Kuznets type model; and (4) a cube curve. Chapter 4 finds that the gender-specific threshold model with fixed effects fits the actual data much better than the other three models. This result suggests that failure to account for gender differences may mask the effects of variation in gender income inequality on per capita GDP over time, leading to false inferences.

Australia makes an interesting case in which to examine the effect of income inequality on per capita GDP. Leigh (2005, 2013) suggests that income inequality in Australia over the course of the twentieth century resembles Piketty's (2014) U-shape, rather than the Kuznets curve. Most agree that income inequality in Australia has risen over the last three decades (ACOSS 2015; Atkinson and Leigh, 2007; Fenna and Tapper, 2015; Leigh, 2005, 2013; Wilkins, 2014, 2015). In this respect, trends in income inequality in Australia have been similar to the OECD as a whole (Piketty, 2014). Based on the World Top Incomes Database, the top 1 per cent income share has increased from 6.8 per cent to 10 per cent in the OECD and from 4.8 per cent to 10 per cent in Australia over the period 1982–2007 (Islam and Madsen, 2015). The main reasons for growing income inequality in Australia have been globalization and technological progress, falling unionisation rates and tax rates becoming less progressive (Gaston and Rajaguru, 2009; Leigh, 2013). The gender wage gap in Australia is also broadly reflective of the OECD.

The OECD (2012) reports that the gender wage gap for full time employees in OECD countries in 2010 was 16 per cent, while for Australia the comparable figure was 12 per cent.[13] While earlier studies reached mixed findings, the most recent research suggests that occupational segregation is an important reason for the gender wage gap in Australia (Coelli, 2014).

There are several advantages with using single-country panel data. One reason for the lack of consensus on the relationship between income inequality and per capita income is that most previous studies have used cross-country data derived from a large number of incomparable countries over a short time span. There are myriad problems with such an approach, including data heterogeneity, definitional, cultural and institutional differences. One advantage of single-country panel data when compared with cross-country approaches is that the data are compiled using the same collection standards and methodologies, facilitating between and within gender comparisons over time (Kim, 2003; Naguib, 2015). A second advantage is that gender-specific Gini coefficients compiled within a single country are subject to the same legislative changes and political systems, which eliminates much of the institutional and cultural differences inherent in cross-country studies. By way of comparison, cross-country studies largely fail to capture structural differences between nations, including gender-based occupational segregation and labour-market flexibility.

[13] While the OECD (2012) suggests the gender wage gap in Australia is a little less than the OECD average, other research suggests that the gender wage gap in Australia has barely shifted since the 1990s, stuck between 15 per cent and 17 per cent (NATSEM, 2009; Young, 2013) which is almost identical to the OECD average.

These sorts of factors are much less likely to contribute to omitted variables bias across genders than across countries.

4.2 Theoretical framework

In order to examine the relationship between income inequality and per capita GDP, in addition to considering gender differences in income inequality, the effect of income inequality on GDP should be allowed to vary with changes in income (Partridge, 1997; Savvides and Stengos, 2000). To consider both of these issues within a single framework Chapter 4 proposes the following gender-specific threshold panel regression for a single country:

$$Ln(G_{it}) = \varepsilon_{it} + \begin{cases} \alpha_{i1} + \beta_{i1} Ln(Y_t), \text{ if } Ln(Y_t) < \gamma \\ \alpha_{i2} + \beta_{i2} Ln(Y_t), \text{ if } Ln(Y_t) \geq \gamma \end{cases}, \; i = 1 \text{ (male)}, i{=}2 \text{ (female)} \tag{4.1}$$

where Y_t denotes real per capita income, α_{i1} and α_{i2} are gender-specific intercept terms (i.e. fixed effects) and the magnitude and sign of the slope coefficients (β_{i1} and β_{i2}) depend on the optimal threshold parameter (γ). Equation (4.1) can also be written as:

$$Ln(G_{it}) = \sum_{j=1}^{2} 1_j[Ln(Y_t), \gamma] \cdot \left[\alpha_{ij} + \beta_{ij} Ln(Y_t)\right] + \varepsilon_{it} \tag{4.2}$$

where $1(\cdot)$ is the indicator function, which is equal to one if the condition in the first square parentheses is satisfied and zero otherwise and ε_{it} is the residual term. As can be seen, both the intercept and slope coefficients are allowed to exhibit one shift from regime 1 (α_{i1},

β_{i1}) to regime 2 (α_{i2}, β_{i2}) across both genders (i = 1,2) depending on the value taken by the optimal threshold parameter. Assuming a 20 per cent trimming region, a lower bound γ^l and an upper bound γ^u are then determined for the threshold parameter. Within the specified range for γ, the residual sum of squares (RSS) are minimized with respect to the three sets of parameters:

$$S(\alpha_{ij}, \beta_{ij}, \gamma) = \sum_{t=1}^{T} \sum_{i=1}^{2} \left\{ Ln(G_{it}) - \sum_{j=1}^{2} 1_j [Ln(Y_t), \gamma] \cdot \left[\alpha_{ij} + \beta_{ij} Ln(Y_t) \right] \right\}^2 \tag{4.3}$$

A small increment such as 0.001 is then added to the lower bound (i.e. γ^l + 0.001), after which RSS are re-estimated. In the next iteration γ^l + 0.002 is used and the RSS is recorded. This iterative grid search ends when the upper bound γ^u is reached. That is:

$$\hat{\gamma} = \underset{\gamma \in [\gamma^l, \gamma^u]}{\arg\min} \ \text{RSS}(\gamma) \tag{4.4}$$

Once γ is set, the sample is divided into two sub-samples as shown in equation (4.1). Given that the total sample size is 128 (2 × 64 years), only one shift in all coefficients is considered to ensure that there are at least 50 observations per sub-sample. In order to test gender differences, Model 2 (equation 4.5) specifies that the slope coefficients for both genders are forced to be equal, but still varying across the two regimes:

$$Ln(G_{it}) = \sum_{j=1}^{2} 1_j [Ln(Y_t), \gamma] \cdot \left[\alpha_j + \beta_j Ln(Y_t) \right] + \varepsilon_{it} \tag{4.5}$$

Compared with equation (4.2), the subscript *i* has now been removed from equation (4.5). Similar to Model 1, the parameters of Model 2 are estimated by minimizing the RSS in the grid.

Following a number of studies in the literature (e.g. Bleaney and Nishiyama, 2004; Desbordes and Verardi, 2012), Chapter 4 also estimates a quadratic equation (Model 3) as follows:

$$Ln(G_{it}) = a + bLn(Y_t) + cLn(Y_t^2) + \varepsilon_{it} \quad (4.6)$$

If $b > 0$ and $c < 0$ there is support for the Kuznets curve hypothesis. In addition, a cube equation (Model 4) is estimated, in which the magnitude and sign of the coefficients are *ex ante* unknown and remain to be determined empirically.

$$Ln(G_{it}) = a + bLn(Y_t) + cLn(Y_t^2) + dLn(Y_t^3) + \varepsilon_{it} \quad (4.7)$$

4.3 Deriving Gini coefficients from taxation statistics

Gini coefficients are derived from annual taxation statistics included in the Report of the Commissioner of Taxation during 1950–1999 and the ATO website for the remaining years (2000–2013). Although the ATO has published taxation records dating back to 1942, the income distribution disaggregated by gender is only available from 1950 onwards. Taxation statistics sort individuals into ascending bands based on taxable income, with the number of bands varying in successive years. To account for any bias arising from data grouping, Gini coefficient are scaled by *N/(N-1)*, in which *N* denotes the number of income bands. This adjustment was first proposed by Deltas (2003) and adopted by Leigh (2005).

Following Leigh (2005), equation (4.8) is then used to calculate the adjusted Gini coefficient (G_i) for each gender in any given year:

$$G_j = \frac{N}{N-1}\left[1-\sum_{j=1}^{N} P_j (S_j + S_{j-1})\right] \tag{4.8}$$

where N is the number of income groups, P_j is the fraction of the population in group j and S_j is the share of total income in group j and all groups below, with $S_0 = 0$. An assumption is made that the average percentage of zero income tax-return lodgers remains the same over time.

A major advantage of taxation statistics is that they facilitate examination of income inequality in Australia using annual data over a much longer period than other sources. Another advantage is that they provide a more accurate indicator of top incomes compared with surveys that tend to under-sample high earners (Leigh, 2005). However, taxation statistics also have limitations in terms of estimating income inequality. First, income-distribution surveys allow greater freedom of responses and are better able to distinguish between sources of income growth (i.e. labour/capital split) than taxation statistics. Second, in countries, such as Australia, in which the tax unit is the individual, taxation statistics may not fully capture inequalities across households. Third, not everyone files a tax return, meaning taxation statistics potentially do not provide a complete picture of income distribution across the population (Leigh, 2005). This said, they are still fairly comprehensive. Using estimates of the size of the labour force published by the ABS from 1978 to 2013 and ATO taxation statistics over the same period, it can be concluded that taxation statistics, on average, capture 87 per cent of the total labour force. Hereafter, individuals in the labour force that did not submit an income tax return are referred to as non-lodgers.

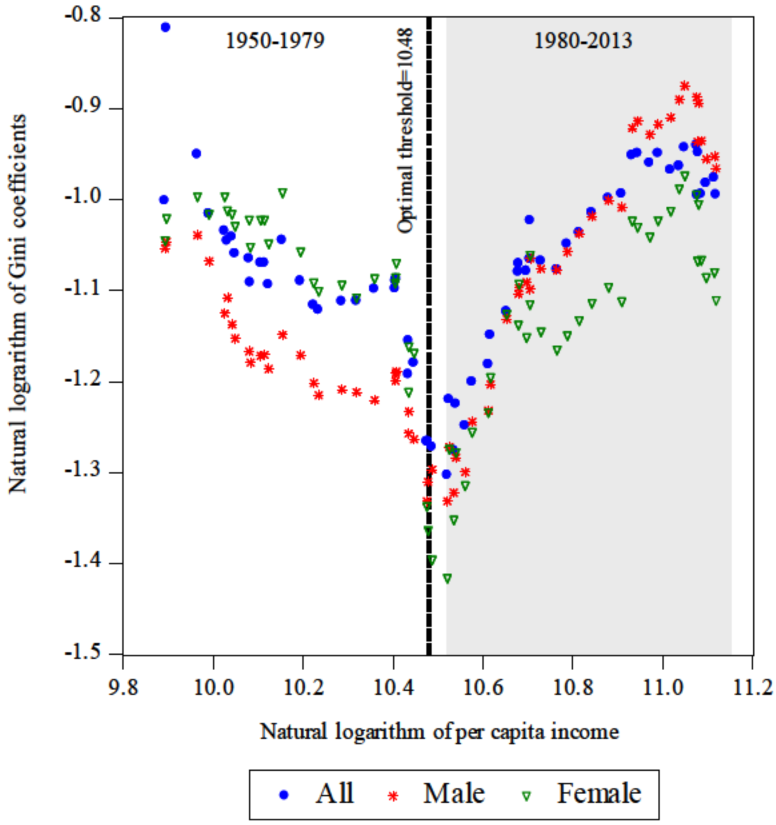
To gauge the impact non-lodgers have on income inequality, an alternate Gini coefficient series is computed based on assumptions regarding the income distribution of non-lodgers. Due to data limitations, Gini coefficients are only able to be calculated at the aggregate level rather than by gender. Income assumptions are based on the findings published in the ATO's Review into the Non-Lodgment of Individual Income Tax Returns (Inspector General of Taxation, 2009). The ATO's *Review into Non-Lodgment of Tax Returns* finds that individuals with income below the taxable threshold account for 80 per cent of non-lodgement, with the remainder comprised of a mix of late submitters and tax evaders. The income distribution of late submitters and tax evaders is thought to closely match that of tax-return lodgers, meaning that these individuals can be incorporated into the calculations by assigning incomes based on the reported income distribution.

Individuals below the tax-free threshold are assumed to earn zero income, which provides an approximation of the upper bound on the Gini coefficient.[14] Following this approach it can be concluded that the inclusion of non-lodgers does not significantly alter the path of inequality over time, with the findings most likely extending to gender-specific Gini coefficients.

Figure 4-1 shows the computed Gini coefficients by gender as well as the total Gini coefficient from 1950 to 2013. Income inequality is found to have widened both within and across gender groups since 1979. Female Gini coefficients are higher for a given level of GDP per capita than that of men until 1979, from which point the inverse is true. The three computed Gini series in Figure 4-1 resemble a U or V shape, similar to that proposed by Piketty (2014) and Leigh (2005; 2013) in the Australian context rather than the inverted U curve as suggested by Kuznets (1955).

[14] Based on taxation statistics for tax-return lodgers, the lowest reportable income for an individual below the tax-free threshold is zero. Hence, assigning zero earnings ensures this sub-group is at the furthest point from the existing income distribution, providing an upper bound on calculated Gini coefficients.

Figure 4-1. Relationship between Gini coefficients by gender and real per capita income, 1950-2013.



Sources: The Authors' calculations, ABS (2016) and Australian Taxation Office (various years).

4.4 Findings for the relationship between inequality and per capita GDP

The relationship between inequality and real per capita income is examined using 128 panel observations (64 years and two genders) and the following four models: (1) a gender-specific threshold model with fixed effects; (2) a conventional threshold regression; (3) a quadratic Kuznets type model; and (4) a cube curve. Table 4-1 presents the results of Models 1-2 using OLS estimation methods. To address the possible simultaneity problem and check the robustness of the results, Models 1 and 2 are also estimated using two-stage least square (2SLS) as shown in Table 4-2, where $Ln(G_{it-1})$ and $Ln(Y_{it-1})$ are instruments. Tables 4-1 and 4-2 show that the OLS and 2SLS estimators are very similar in terms of sign and magnitude, and hence the inferences remain the same. The results also changed very little when $Ln(G_{it-1})$, $Ln(G_{it-2})$, $Ln(Y_{it-1})$ and $Ln(Y_{it-2})$ are used as instruments.[15]

Based on Table 4-1, prior to 1980, Models 1-2 suggest that up to a certain threshold ($Ln(Y_t)$<10.5 in Model 1 and $Ln(Y_t) < 10.6$ in Model 2) there is an inverse relationship between inequality and per capita income. In the post 1980 period this relationship became positive, whereby β_{21} is significantly greater than β_{12}. This means when $Ln(Y_t) \geq \gamma$, an equal rise in per capita income increases the Gini coefficient among men (β_{21}=0.67) more than that among women (β_{22}=0.48). However, given the results in Table 4-1 such differences are statistically insignificant when $Ln(Y_t)$<10.6 because the null hypothesis $\beta_{11}=\beta_{12}$ could not be rejected at any conventional level. Based on the Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn criterion (HQC) the estimated Model 1 outperforms Model 2.

According to Figure 4-2, Models 2, 3 and 4 in Tables 4-1 and 4-3 miss most of female (triangle) and male (hollow circle) actual observations at the extreme upper and lower ends of the fitted lines (curves). The results for Models 3-4 shown in Table 4-3 are consistent with Piketty's (2014) U-shape relationship rather than the inverted U curve

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[15] These results are available from the authors on request.

proposed by Kuznets (1955). None of the coefficients for Model 4 in Table 4-3 are statistically significant at the 5 per cent level. The Theil accuracy coefficients for Models 1 to 4 in Tables 4-1 and 4-3 are 0.023, 0.032, 0.042 and 0.035, respectively. The bias proportion and variance proportions in all four models are quite low, suggesting the absence of systematic errors and the ability to capture variability in the observed data. As shown in Table 4-4, the same conclusion is reached based on the correlation coefficient, root mean squared error, mean absolute error, and mean absolute per cent error.

Table 4-1. Estimated models 1 and 2 using OLS.

Identifier	Model 1			Model 2		
	Coefficient	*t* ratio	*p*-value	Coefficient	*t* ratio	*p*-value
	$Ln(Y_t) < 10.476$, *n*=52			$Ln(Y_t) < 10.618$, *n*=72		
α_1	–	–	–	3.071732	8.03	0.00
α_{11}	1.9475	5.41	0.00	–	–	–
α_{12}	1.5858	4.41	0.00	–	–	–
β_1				-0.4125	-11.09	0.00
β_{11}	-0.3058	-8.65	0.00	–	–	–
β_{12}	-0.2601	-7.36	0.00			
	$Ln(Y_t) \geq 10.476$, *n*=76			$Ln(Y_t) \geq 10.618$, *n*=56		
α_2				-5.0415	-9.24	0.00
α_{21}	-8.2801	-17.96	0.00	–	–	–
α_{22}	-6.3730	-13.83	0.00	–	–	–
β_2				0.3673	7.34	0.00
β_{21}	0.6671	15.63	0.00	–	–	–
β_{22}	0.4841	11.34	0.00	–	–	–
Adj R^2	0.840			0.701		
LLC *t* test[(a)]		0.70	0.76	1.045	-0.22	0.41
AIC	-3.179			-2.582		
SIC	-3.001			-2.493		
HQC	-3.107			-2.546		
Null hypotheses:						
$\alpha_{11}= \alpha_{12}$	F(1,120)=0.51		0.48			
$\alpha_{22}= \alpha_{22}$	F(1,120)=8.56		0.00			
$\beta_{11}=\beta_{12}$	F(1,120)=0.84		0.36			
$\beta_{21}=\beta_{12}$	F(1,120)=9.20		0.00			
$\alpha_1= \alpha_2$				F(1,124)=143.3		0.00
$\beta_1=\beta_2$				F(1,124)=156.3		0.00

Note: (a) The Levin, Lin and Chu (LLC, 2002) test results indicate that the residuals are stationary.

Table 4-2. Estimated models 1 and 2 using 2SLS.

Identifier	Model 1			Model 2		
	Coefficient	*t* ratio	*p*-value	Coefficient	*t* ratio	*p*-value
	$Ln(Y_t) < 10.466$, n=50			$Ln(Y_t) < 10.631$, n=70		
α_1	–	–	–	3.0671	7.63	0.00
α_{11}	1.7461	4.54	0.00	–	–	–
α_{12}	1.5962	4.15	0.00	–	–	–
β_1				-0.4120	-10.55	0.00
β_{11}	-0.2863	-7.59	0.00	–	–	–
β_{12}	-0.2612	-6.92	0.00			
	$Ln(Y_t) \geq 10.466$, n=76			$Ln(Y_t) \geq 10.631$, n=56		
α_2				-4.9522	-9.05	0.00
α_{21}	-8.2407	-17.29	0.00	–	–	–
α_{22}	-6.3432	-13.31	0.00	–	–	–
β_2				0.3591	7.15	0.00
β_{21}	0.6635	15.03	0.00	–	–	–
β_{22}	0.4813	10.91	0.00	–	–	–
Adj R^2	0.830			0.697		
LLC *t* test[(a)]		0.70	0.76	1.045	-0.22	0.41
AIC	-3.111			-2.561		
SIC	-2.930			-2.471		
HQC	-3.037			-2.525		

Table 4-3. Estimated models 3 and 4 using OLS.

Identifier	Model 3			Model 4		
	Coefficient	*t* ratio	*p*-value	Coefficient	*t* ratio	*p*-value
a	71.242	11.02	0.00	437.484	1.88	0.06
b	-13.848	-11.27	0.00	-118.349	-1.78	0.08
c	0.662	11.36	0.00	10.594	1.68	0.10
d				-0.314	-1.57	0.12
Adj R^2	0.544			0.550		
LLC *t* test[(a)]		0.79	0.79		0.47	0.68
AIC	-2.167			-2.171		
SIC	-2.100			-2.082		
HQC	-2.140			-2.135		

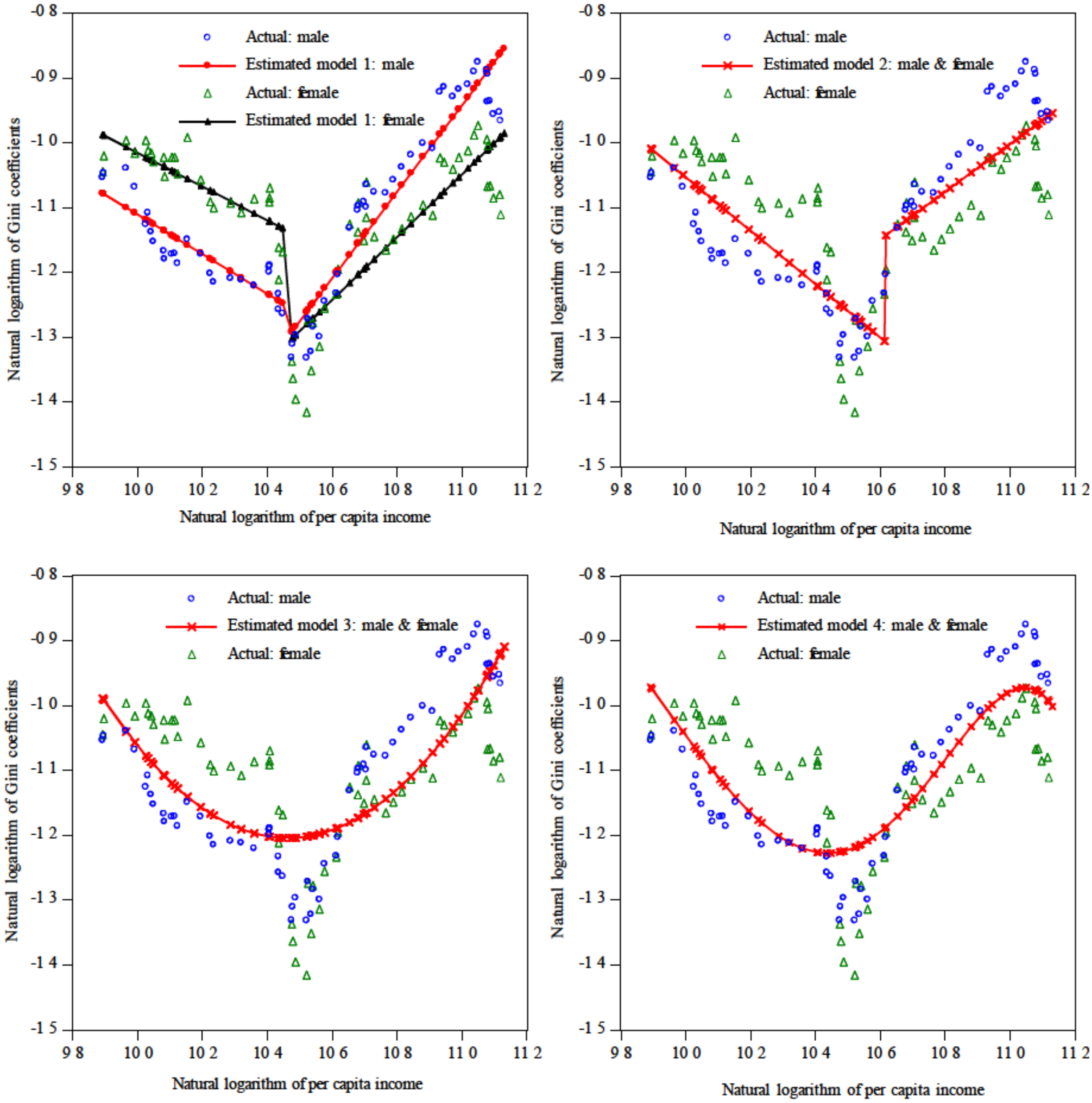
Note: (a) The Levin, Lin and Chu (LLC, 2002) test results indicate that the residuals are stationary.

Table 4-4. Tracking performance of the estimated four models in Table 1.

Description	Model 1	Model 2	Model 3	Model 4
Correlation coefficient	0.92	0.83	0.74	0.75
Root mean squared error	0.015	0.021	0.028	0.023
Mean absolute error	0.012	0.018	0.023	0.020
Mean absolute percent error	3.625	5.304	7.169	6.157
Theil inequality coefficient:	0.023	0.032	0.042	0.035
Bias Proportion	0.000	0.001	0.000	0.000
Variance Proportion	0.016	0.084	0.178	0.110
Covariance Proportion	0.984	0.915	0.822	0.890

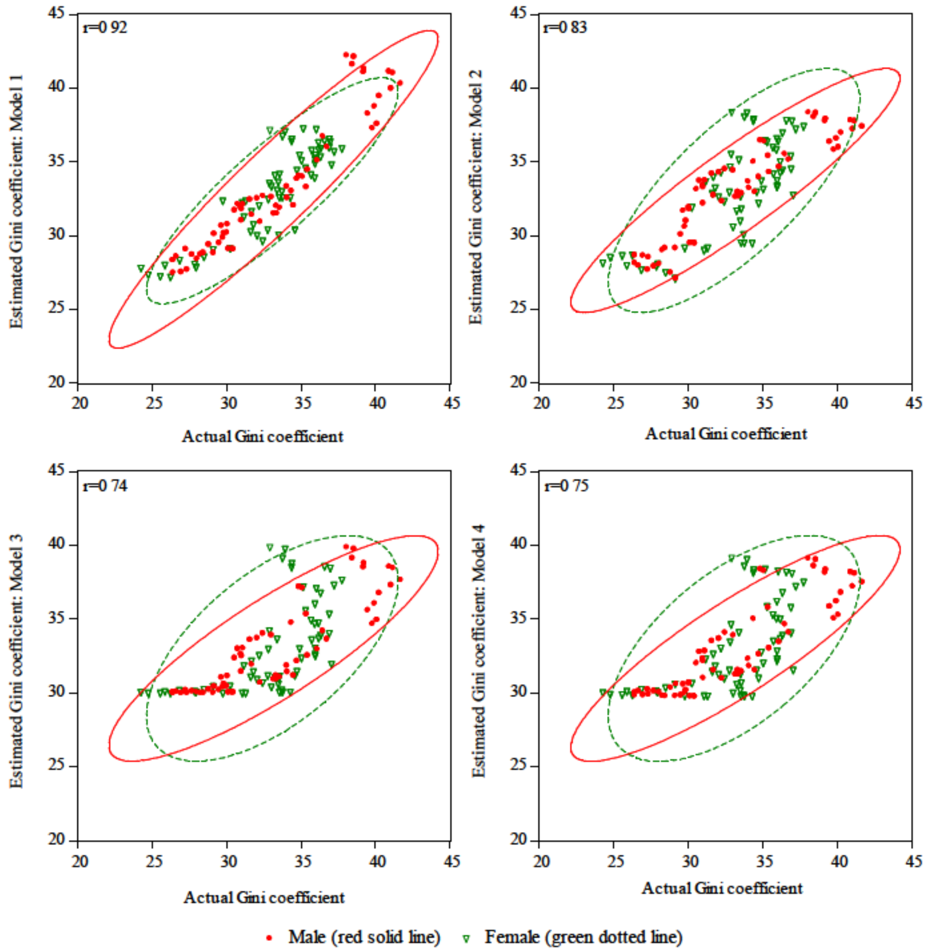
One can thus argue that Model 1 fits the actual data better than the other three models. Figure 4-3 shows the estimated Gini coefficients resulting from the four models together with the corresponding 95 per cent confidence ellipses. As can be seen, except for Model 1, none of the other three models can generate a narrow (reliable) confidence interval for female Gini coefficients. This finding lends support to Perrons (2015) criticisms of Piketty (2014) and the income inequality literature more generally, with gender based Gini coefficients offering a more accurate representation of underlying aspects of income inequality.

Figure 4-2. Tracking performance of the estimated four models.



As shown in Figures 4-2 and 4-3, the gender-specific threshold model with fixed effects is found to fit the actual data much better than the other three models. Indeed, the failure of Models 2-4 to consider gender differences causes the estimated average observation to differ materially from actual upper (male) and lower (female) historical data. Therefore, while these models capture the mean values relatively accurately, aggregate Gini coefficients often understate the degree of inequality within the male group, while at the same time overstating within group inequality for females. This suggests one set of coefficients does not fit all insofar as the use of aggregate and constant coefficients may mask the variation within, and between, gender income inequality over time.

Figure 4-3. Estimated Gini coefficients and the corresponding 95 per cent confidence ellipses.



Tables 4-1 and 4-2 highlight that the inclusion of gender-specific Gini coefficients improve the model's explanatory power and hence the significance of the identifiers. The decision to use gender-specific or aggregate Gini coefficients also has implications for examining the link between income inequality and real per capita income. As shown in Figure 4-2, while the models are consistent with Piketty's (2014) claim that there is a U-shaped relationship between income inequality and per capita income, the inclusion of gender-specific Gini coefficients in Model 1 highlights important sensitivities masked in the other models. Chapter 4 finds that when $Ln(Y_t) \geq 10.5$, an equivalent rise in real per capita income has a greater impact on income inequality among men (β_{21} = 0.67) than among women (β_{22} = 0.48).

This outcome is consistent with the conclusions of Atkinson and Leigh (2007), who find that the increase in real per capita GDP in recent decades has coincided with a rapid rise in CEO and executive compensation in Australia, with the latter a key driver of widening income inequality. Given that women comprise only 15 per cent of total CEO positions in Australia (WGEA, 2016a), the surge in executive salaries offers some insight into why income inequality is more pronounced among men when $Ln(Y_t) \geq 10.5$.

4.5 Conclusion

Taxation statistics published by the ATO provide an insight into Australia's gender-based income distribution, and allow us to calculate Gini coefficients for men and women separately from 1950 to 2013. Using these gender-specific Gini coefficients it is possible to ascertain the effect that gender differences in income inequality have had on real per capita GDP. This is an area of income inequality research that has been considered by Piketty (2014) and others (Perrons, 2014, 2015). The performance of the models is summarized in Table 4-4, with the gender–specific approach of Model 1 offering more explanatory power than those models in which gender differences are overlooked.

The results offer support for those who argue that the Kuznets curve is not an accurate representation of the relationship between income inequality and per capita income. Instead, the findings are consistent with the position espoused by Piketty (2014), and Leigh (2005; 2013) in the Australian context, that the relationship between real per capita GDP and income inequality is U-shaped. Indeed, incorporating gender-specific Gini coefficients makes the model a better fit for the actual data, in the sense that it more accurately captures observations at the extreme upper and lower ends of the fitted lines (curves).

This research is the first attempt at exploring the effects of income inequality on real per capita GDP using gender-specific Gini coefficients. The results suggest incorporating gender differences in income inequality improves the model's fit with the actual data and enhance the coefficient of determination. As such, this research has implications for future studies in that it suggests that gender-specific Gini coefficients should be used to measure income inequality, whenever possible, to get a more accurate representation of the true relationship between real per capita income and income inequality.

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University of New England

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(To appear at the end of each thesis chapter submitted as an article/paper)

I, the PhD candidate and the candidate's Principal Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated in the *Statement of Originality*.

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Chapter 5

Conclusion

5.1 Main findings

This thesis contributes to the literature by examining Australia's inequality–growth nexus using national, sub-national and gender-specific data. While the advantages of single-country studies are well documented, a lack of consistent long-term inequality observations has meant such studies are relatively few in number. Instead, most of the literature focuses on cross-country samples over short time horizons, an approach fraught with a myriad of issues.

There were two notable drawbacks in undertaking this study. First, although advantageous to other available data sources, there are limitations in using taxation statistics to calculate income inequality. These include the omission of late submitters and tax evaders, as well as less freedom of response compared to survey data. Second, state- and territory-level output data is only available from the mid-1980s onwards. Therefore, while inequality estimates can be calculated dating back to 1942, regression estimates are restricted to a much shorter time horizon. The application of panel data helps to overcome this issue and ensures an adequate number of observations.

Despite these shortcomings, the published papers included in this thesis help to shed light on the relationship between income inequality and output growth. Chapter 2 adds to the literature in two important ways. First, using ATO taxation statistics, this thesis calculates Gini coefficients for all Australian taxpayers at both the national and sub-national level. The national series reveals that inequality spiked higher in the early 1950s following the surge in Australia's terms of trade. Inequality narrowed in subsequent years and maintained a downward trajectory before bottoming out in the 1970s. Australia's income distribution has grown increasingly unequal ever since, with the national Gini coefficient now at the highest level since the mid-Twentieth Century. As highlighted by Leigh (2005) and Goldin and Katz (2007), possible drivers of rising income inequality include declining unionisation, falling top marginal tax rates, greater premiums for skilled workers and the internationalisation of the market for senior management.

Income inequality within Australia's states and territories follow similar trends overtime. With the exception of the Northern Territory, Gini coefficients in all jurisdictions spiked during the wool boom of the early 1950s before declining in the following two decades. Since then, inequality has increased across all eight states and territories. Tasmania and the North Territory have consistently reported the lowest Gini coefficients, while Gini coefficients in New South Wales and Victoria are often above the national aggregate[16]. In other words, the larger the share of the pie, the less equal the distribution.

Second, using state and territory Gini coefficients Chapter 2 pursues a panel data approach to examine the relationship between inequality and real GDP growth. Estimators show that coefficients on physical and human capital remain positive and statistically significant at the 1 per cent level, an outcome consistent with the stated *a priori* expectations. The long-run effect of inequality on output is negative and also significant at the 1 per cent level. Regardless of the estimation technique, the absolute size of the inequality coefficient is found to rival those for human and physical capital.

The findings of Chapter 2 indicate policymakers should concern themselves with inequality not only for social and political reasons, but also because a more equitable income distribution can spur economic growth. Rather than address rising inequality through income transfers, Chapter 2 argues policymakers should pursue policies that promote human capital accumulation. Such measures may include greater funding for research and development or targeted investment in female education to help reduce gender-based occupational segregation.

[16] It is possible non-lodgers have a larger effect on Gini coefficients in less populated states, resulting in slightly biased inequality estimates for Tasmania and the Northern Territory relative to other jurisdictions. However, this thesis finds little empirical evidence supporting the idea that the percentage of non-lodgers is considerably greater in Australia's less densely populated states. Nevertheless, various robust tests have been used to minimize any potential bias.

While an important finding, Chapter 2 is limited in that the econometric approach does not offer an explanation into what factors have shaped Australia's inequality-growth nexus. As such, there is scope for future research to build on these findings and investigate whether there is merit in the hypothesis that political channels are influential in the Australian context. Correctly identifying the drivers of this relationship will assist in the development of measures best suited to reducing inequality and minimizing negative externalities.

Chapter 3 approaches the relationship between inequality and growth from a different perspective, instead focusing on how gender wage gaps affect productivity. Chapter 3 makes the following contributions to the literature. First, it calculates gender wage gaps for all of Australia's states and territories for the period 1986 to 2013. Positive gender wage gaps are found to exist in all Australian states and territories, or in other words, men continue to earn more than women. There are some interesting developments across regions, with wage gaps narrowing in New South Wales, Victoria, Tasmania and the Australian Capital Territory during the course of the past two decades. Strikingly, gender inequality has become increasingly pronounced in Western Australia and Queensland, which is likely the result of occupational segregation associated with the resources boom.

Second, these series are then used to estimate the long-run relationship between gender wage gaps and labour productivity. To check the sensitivity of the regressions to different econometric techniques, four estimation methods are applied: (1) panel ordinary least squares with fixed effects; (2) panel two stage least squares with fixed effects; (3) fixed effects versions of generalized method of moments (GMM) and; (4) the random effects version of GMM.

Irrespective of the estimation method, gender wage gaps are found to have a negative and significant effect on productivity. Specifically, the results indicate that narrowing the gender wage gap by 10 per cent can increase long-run per capita output by up to 3 per cent. This is meaningful and implies the benefits from reducing gender wage imbalances may rival those of additional investment in education and human capital accumulation, a similar conclusion to that drawn in Chapter 2.

Although the introduction of legislation since the 1960s has helped to minimize gender wage inequality, segregation across occupations and industries remains striking. Chapter 3 advocates the need for greater emphasis on addressing occupational segregation through the creation of more flexible work arrangements, targeted investment in female education and greater awareness of non-traditional career paths (Thomas and Ely, 1996; Jaumotte, 2003; Birch, 2005; Perales, 2013). One shortcoming of the analysis undertaken in Chapter 3 is that wage gaps are calculated at the aggregate level and overlook potentially important discrepancies between sectors. This provides an opportunity for future research to investigate how gender wage gaps have evolved at the industry level and the related implications for productivity.

Chapter 4 incorporates elements of the prior two chapters and explores how

Australia's inequality-growth nexus has evolved over time taking into account within-gender variation in inequality. For the first time using taxation statistics, Chapter 4 calculates gender-specific Gini coefficients for every year from 1950 to 2013. These series are then used to examine the relationship between inequality and growth.

Gini coefficients for both men and women moved persistently lower during the period 1950 to 1979, though female Gini coefficients were consistently higher for a given level of GDP than that of men. The inverse is true from 1980 onward, when inequality for both genders started to move higher, led by an increasingly unequal distribution among men. The three series (male, female and total) resemble a U-shape distribution similar to that proposed by Leigh (2005; 2013) and Piketty (2014), rather than the inverted U-shape advocated by Kuznets (1955).

Four methods are used to model the relationship between inequality and real GDP per capita: (1) a gender-specific threshold model with fixed effects; (2) a conventional threshold regression; (3) a quadratic Kuznets type model; and (4) a cubic curve. The threshold approach of Models 1 and 2 suggest that up to a certain point, there is an inverse relationship between income inequality and output per capita. This relationship turned positive in the post-1980 period and the coefficient for the male Gini coefficient is significantly larger than the female counterpart. This means that since 1980, male income inequality has increased at a faster rate than that of women for a given level of per capita GDP. Models 3 and 4 are also consistent with Piketty's idea of a U-shaped relationship between these variables.

An important finding of Chapter 4 is that the inclusion of gender-specific Gini coefficients when modelling the inequality-growth nexus offers more explanatory power relative to models where such differences are overlooked. This is highlighted in Figure 4-2, where the gender-specific approach of Model 1 returns a much better fit with the actual data than Models 1-3. Irrespective of which model is chosen, Chapter 4 provides empirical support of Piketty's U- shaped relationship between inequality and real output per capita.

Chapter 4 advocates the use of gender-based income statistics over aggregate data when exploring the inequality-growth nexus. There is also the potential for future research to take this analysis further and delve into the granular detail provided in taxation statistics in an effort to better understand income inequality, with the ATO providing data on important demographic factors such as age and location, among others.

5.2 Policy implications

The findings of this thesis indicate policymakers should concern themselves with inequality not only to improve social cohesion, but also because ensuring a more equitable income distribution can spur economic growth. The conventional practice in Australia has been to address rising inequality through progressive income taxation and redistributive income transfers, policies which may have unintended distortionary effects and lower productivity (Okun, 1975; Ichino et al., 2011).

Rather than address rising inequality through income transfers, the findings presented in this thesis argue that policymakers should pursue policies that promote human capital accumulation. Human capital helps to lower inequality through improving economic mobility and reducing the wages premium for skilled labour (Goldin and Katz, 2007). Additional investment in human capital not only helps to lower inequality, but is also beneficial for longer-run per capita income growth as highlighted in the results of Chapters 2 and 3. Policies conducive to human capital accumulation may include targeted investment in education across sectors experiencing skill shortages, as well as greater investment in research and development.

The fact women, on average, continue to earn less than men across all states and territories indicates legislation intended to eliminate gender income inequality has proven ineffective. To correct such imbalances, policymakers must place greater emphasis on identifying and addressing the causes of gender income differentials, such as occupational segregation and indirect discrimination. These measures may include the introduction of programs that encourage women to pursue non-traditional career paths, greater investment in re-training across sectors where gender imbalances are most pronounced and the implementation of programs supporting the mobility of women in industry.

5.3 Directions for future research

There is scope for future research to use the Gini coefficients and gender wage gap series calculated in this thesis to examine other dimensions of Australia's inequality–growth nexus. In particular, there is the need to better understand the channels through which rising inequality affects economic activity. Following the conclusion of Chapter 2, an obvious starting point would be to model this nexus using a similar methodology to Persson and Tabellini (1994) and Partridge (1997). These studies are specifically designed to examine the influence of government redistribution on inequality and economic growth. Correctly identifying the factors shaping this nexus will undoubtedly help in the development of measures best suited to reducing inequality.

Further research is also required to identify the factors responsible for Australia's gender wage gap. Better understanding of how potential drivers such as discrimination, occupational segregation and differences in educational and work preferences influence wage outcomes would facilitate the implementation of policies better targeted at effectively addressing these wage discrepancies. For example, if occupational segregation is found to be a determining factor, then the policy response can focus on measures targeted toward increasing female participation rates in under-represented sectors.

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Appendices

Table 1A. Computed Gini coefficients using taxation statistics.

Year	Australia	ACT	NSW	NT	QLD	SA	TAS	VIC	WA
1942	0.3243	0.3010	0.3109	0.3044	0.3088	0.2891	0.2903	0.3214	0.3072
1943	0.3621	0.3515	0.3474	0.3273	0.3725	0.3403	0.3333	0.3530	0.3582
1944	0.3659	0.3521	0.3472	0.2631	0.3781	0.3518	0.3464	0.3550	0.3663
1945	0.3537	0.3465	0.3370	0.2345	0.3664	0.3438	0.3408	0.3452	0.3474
1946	0.3563	0.3514	0.3440	0.2688	0.3620	0.3478	0.3366	0.3470	0.3520
1947	0.3505	0.3622	0.3373	0.2913	0.3510	0.3523	0.3212	0.3408	0.3539
1948	0.3724	0.3671	0.3646	0.2861	0.3886	0.3958	0.3373	0.3578	0.4004
1949	0.3843	0.3639	0.3693	0.2817	0.3890	0.4000	0.3303	0.3655	0.4248
1950	0.3867	0.3794	0.3842	0.2920	0.4057	0.3899	0.3347	0.3732	0.4112
1951	0.4443	0.4060	0.4225	0.2773	0.4547	0.4590	0.3733	0.4155	0.5022
1952	0.3674	0.3215	0.3328	0.2784	0.3578	0.3816	0.3195	0.3483	0.4166
1953	0.3622	0.3331	0.3409	0.2727	0.3686	0.3750	0.3106	0.3350	0.3686
1954	0.3516	0.3059	0.3327	0.2812	0.3723	0.3358	0.3053	0.3247	0.3580
1955	0.3465	0.3212	0.3305	0.3061	0.3581	0.3341	0.3113	0.3317	0.3309
1956	0.3530	0.3420	0.3334	0.3164	0.3543	0.3282	0.3137	0.3340	0.3349
1957	0.3554	0.3457	0.3411	0.3225	0.3719	0.3429	0.3208	0.3380	0.3319
1958	0.3358	0.3279	0.3210	0.3116	0.3444	0.3114	0.3097	0.3287	0.3166
1959	0.3350	0.3330	0.3208	0.2963	0.3359	0.3154	0.3045	0.3297	0.3235
1960	0.3431	0.3385	0.3311	0.3091	0.3435	0.3173	0.3119	0.3347	0.3296
1961	0.3447	0.3433	0.3300	0.3073	0.3436	0.3276	0.3167	0.3391	0.3374
1962	0.3431	0.3446	0.3296	0.3066	0.3404	0.3221	0.3154	0.3370	0.3407
1963	0.3518	0.3509	0.3377	0.3051	0.3585	0.3327	0.3203	0.3420	0.3479
1964	0.3363	0.3419	0.3262	0.2935	0.3528	0.3220	0.3008	0.3271	0.3288
1965	0.3276	0.3421	0.3220	0.2979	0.3339	0.3150	0.3038	0.3254	0.3219
1966	0.3259	0.3449	0.3184	0.3077	0.3294	0.3144	0.3092	0.3274	0.3353
1967	0.3289	0.3502	0.3227	0.3152	0.3313	0.3154	0.3154	0.3286	0.3410
1968	0.3290	0.3419	0.3204	0.3168	0.3277	0.3087	0.3115	0.3275	0.3432
1969	0.3334	0.3393	0.3242	0.3491	0.3344	0.3166	0.3160	0.3298	0.3536
1970	0.3335	0.3383	0.3282	0.3267	0.3375	0.3226	0.3191	0.3380	0.3480
1971	0.3365	0.3459	0.3318	0.3358	0.3412	0.3242	0.3240	0.3388	0.3447
1972	0.3372	0.3247	0.3149	0.3411	0.3481	0.3292	0.3287	0.3393	0.3460
1973	0.3037	0.3035	0.2980	0.2876	0.3161	0.2938	0.2792	0.3069	0.3057
1974	0.3150	0.3139	0.3093	0.2995	0.3218	0.3103	0.3056	0.3164	0.3286
1975	0.3074	0.3142	0.2997	0.3024	0.3246	0.3004	0.3022	0.3059	0.3193
1976	0.2819	0.2879	0.2762	0.2567	0.2893	0.2744	0.2787	0.2852	0.2865
1977	0.2820	0.2890	0.2790	0.2529	0.2865	0.2717	0.2786	0.2841	0.2853
1978	0.2803	0.2901	0.2779	0.2705	0.2791	0.2717	0.2741	0.2836	0.2826
1979	0.2717	0.2798	0.2716	0.2624	0.2759	0.2605	0.2640	0.2735	0.2716
1980	0.2792	0.2839	0.2791	0.2640	0.2833	0.2685	0.2705	0.2793	0.2810
1981	0.2869	0.2880	0.2867	0.2657	0.2907	0.2765	0.2769	0.2852	0.2904
1982	0.2938	0.2985	0.2954	0.2652	0.2970	0.2843	0.2852	0.2912	0.2962
1983	0.2952	0.3055	0.2904	0.2766	0.2928	0.2872	0.2869	0.2940	0.3000
1984	0.3010	0.3030	0.3020	0.2746	0.2998	0.2975	0.2928	0.2994	0.3059

1985	0.3069	0.3048	0.3094	0.2763	0.3040	0.3113	0.2997	0.3048	0.3113
1986	0.3170	0.3124	0.3215	0.2785	0.3125	0.2995	0.3087	0.3144	0.3189
1987	0.3253	0.3149	0.3325	0.2810	0.3203	0.3158	0.3146	0.3210	0.3282
1988	0.3428	0.3218	0.3534	0.2780	0.3367	0.3311	0.3249	0.3380	0.3445
1989	0.3594	0.3320	0.3759	0.3040	0.3506	0.3434	0.3338	0.3530	0.3562
1990	0.3446	0.3243	0.3586	0.2889	0.3395	0.3292	0.3266	0.3381	0.3412
1991	0.3396	0.3242	0.3523	0.2908	0.3327	0.3252	0.3227	0.3341	0.3363
1992	0.3400	0.3255	0.3532	0.2946	0.3320	0.3249	0.3223	0.3356	0.3357
1993	0.3438	0.3205	0.3562	0.2985	0.3363	0.3246	0.3286	0.3409	0.3382
1994	0.3407	0.3222	0.3537	0.2881	0.3293	0.3204	0.3265	0.3384	0.3377
1995	0.3503	0.3256	0.3601	0.2936	0.3327	0.3252	0.3284	0.3436	0.3414
1996	0.3546	0.3289	0.3665	0.2991	0.3361	0.3299	0.3304	0.3487	0.3450
1997	0.3626	0.3396	0.3732	0.3067	0.3428	0.3345	0.3375	0.3550	0.3505
1998	0.3684	0.3422	0.3815	0.3058	0.3481	0.3403	0.3422	0.3617	0.3572
1999	0.3701	0.3406	0.3795	0.3055	0.3432	0.3313	0.3351	0.3572	0.3546
2000	0.3861	0.3255	0.3890	0.2835	0.3538	0.3249	0.3209	0.3754	0.3505
2001	0.3870	0.3356	0.4042	0.2814	0.3679	0.3344	0.3298	0.3884	0.3611
2002	0.3830	0.3297	0.3936	0.2772	0.3611	0.3272	0.3222	0.3808	0.3566
2003	0.3871	0.3331	0.4018	0.2818	0.3674	0.3321	0.3266	0.3891	0.3624
2004	0.3800	0.3334	0.4072	0.2860	0.3717	0.3344	0.3310	0.3940	0.3669
2005	0.3816	0.3363	0.4147	0.2883	0.3746	0.3397	0.3370	0.3974	0.3708
2006	0.3894	0.3326	0.4117	0.2871	0.3733	0.3378	0.3299	0.3966	0.3715
2007	0.3904	0.3295	0.4119	0.2892	0.3710	0.3368	0.3272	0.3965	0.3720
2008	0.3875	0.3292	0.4116	0.2851	0.3711	0.3373	0.3280	0.3970	0.3777
2009	0.3696	0.3257	0.4065	0.2814	0.3699	0.3357	0.3260	0.3943	0.3710
2010	0.3699	0.3271	0.4089	0.2807	0.3735	0.3391	0.3303	0.3982	0.3770
2011	0.3746	0.3424	0.4072	0.3217	0.3613	0.3469	0.3325	0.3862	0.4007
2012	0.3767	0.3431	0.4055	0.3269	0.3694	0.3507	0.3325	0.3861	0.4048
2013	0.3699	0.3360	0.3981	0.3387	0.3651	0.3426	0.3301	0.3772	0.3980

Source: Authors’ calculations using taxation statistics.

Table 2A. Female and male Gini coefficients derived from taxation statistics

Year	Gini coefficients [(a)]			Real per capita GDP [(b)]	Year	Gini coefficients			Real per capita GDP ($)
	Female	Male	Total			Female	Male	Total	
1950	0.369	0.3537	0.3867		1982	0.2786	0.277	0.2939	9456
1951	0.3604	0.3512	0.4443		1983	0.2796	0.2804	0.2953	9314
1952	0.3517	0.3487	0.3674		1984	0.2849	0.2882	0.301	9802
1953	0.3619	0.3438	0.3622		1985	0.2912	0.2918	0.3069	10164
1954	0.3634	0.3303	0.3516		1986	0.3025	0.3003	0.317	10212
1955	0.3572	0.3159	0.3465		1987	0.3243	0.3227	0.3253	10584
1956	0.3619	0.3207	0.353		1988	0.3352	0.3338	0.3428	10878
1957	0.3691	0.3246	0.3554		1989	0.3461	0.345	0.3594	11156
1958	0.3491	0.3076	0.3358		1990	0.3278	0.3334	0.3447	11149
1959	0.3504	0.3055	0.335	6237	1991	0.3205	0.3317	0.3397	10863
1960	0.3597	0.3098	0.3431	6123	1992	0.3162	0.336	0.34	11064
1961	0.3597	0.3113	0.3447	5968	1993	0.3181	0.341	0.3438	11423
1962	0.3597	0.3102	0.3431	6174	1994	0.3117	0.3405	0.3407	11834
1963	0.3706	0.3171	0.3518	6424	1995	0.3169	0.3475	0.3503	12115
1964	0.3473	0.3101	0.3363	6692	1996	0.322	0.3544	0.3547	12441
1965	0.3357	0.3007	0.3276	6888	1997	0.3282	0.3612	0.3626	12789
1966	0.3326	0.2968	0.3259	6962	1998	0.334	0.3676	0.3684	13283
1967	0.3349	0.2985	0.3289	7334	1999	0.3288	0.3648	0.3701	13676
1968	0.3302	0.2978	0.329	7578	2000	0.3593	0.398	0.3861	13993
1969	0.3373	0.2951	0.3334	7888	2001	0.3568	0.4011	0.387	14164
1970	0.3356	0.3014	0.3335	8264	2002	0.3531	0.3951	0.383	14561
1971	0.3377	0.3039	0.3365	8266	2003	0.3595	0.3996	0.3871	14828
1972	0.343	0.3046	0.3372	8278	2004	0.3633	0.4026	0.38	15244
1973	0.2977	0.2845	0.3037	8509	2005	0.3723	0.4107	0.3816	15542
1974	0.3129	0.2914	0.315	8511	2006	0.3776	0.4169	0.3894	15737
1975	0.3107	0.2828	0.3074	8614	2007	0.3697	0.4118	0.3904	16158
1976	0.2625	0.2642	0.2819	8860	2008	0.3659	0.4091	0.3875	16220
1977	0.2557	0.2697	0.282	8889	2009	0.3438	0.392	0.3696	16190
1978	0.2476	0.2735	0.2803	8967	2010	0.3441	0.3924	0.37	16324
1979	0.2426	0.2641	0.2717	9277	2011	0.3377	0.3846	0.3746	16504
1980	0.2587	0.2666	0.2792	9407	2012	0.3394	0.3857	0.3767	16810
1981	0.2686	0.2727	0.2869	9647	2013	0.3292	0.3808	0.3699	16869

Source: (a) Authors' calculations using taxation statistics; (b) ABS (2016).