University of New South Wales

School of Economics

Honours Thesis

Dissecting Labour Shares using BLADE

An empirical investigation into the trends and drivers of Australian labour shares

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Author:
Nalini Agarwal
Student ID: z5017091

Supervisor:
Professor Kevin Fox

Bachelor of Economics (Econometrics) with Distinction (Honours)
and
Bachelor of Laws

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Declaration

I hereby declare that the content of this thesis is my own work and that, to the best of my knowledge, it contains no material that has been published or written by another person or persons, except where due acknowledgement has been made. This thesis has not been submitted for award of any other degree or diploma at the University of New South Wales or any other educational institution.

Nalini

Nalini Agarwal
22nd November, 2019

Disclaimer: The findings and views expressed here are those of the author and no one else. They should not be attributed to the Australian Bureau of Statistics, Australian Treasury or units thereof. All errors are my own.

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Last, but not least, I'd like to dedicate this thesis to my beautiful niece, Siya. Your smiling (and crying) face gave me the courage and strength to push to the finish line.

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List of Abbreviations

Abbreviation	Full Term
3SD	Three Standard Deviation
ABS	Australian Bureau of Statistics
ABS National Accounts	Australian System of National Account
ANZSIC	Australia and New Zealand Standard Industrial Classification
ATO	Australian Taxation Office
BLADE	Business Longitudinal Analytical Data Environment
DF	Diewert and Fox
FTE	Full Time Equivalent
GDP	Gross Domestic Product
FIS	Financial and Insurance Services
FISIM	Financial Intermediation Services Indirectly Measured
ICT	Information and Communication Technology
MP	Melitz and Polanec
OECD	Organisation for Economic Co-operation and Development
RBA	Reserve Bank of Australia
SISCA	Standard Institutional Sector Classification of Australia
TOLO	Type of Legal Organisation
UNSW	University of New South Wales

Abstract

This thesis investigates labour share trends and drivers in Australia using a novel firm level panel dataset from the Australian Bureau of Statistic's Business Longitudinal Analytical Data Environment (BLADE). While a large body of work has documented labour share trends and drivers internationally, this thesis fills a knowledge gap in Australia's systemic understanding of income shares. Firm level data confirms that the aggregate labour share of income in Australia has fallen by 3% between 2001-02 and 2016-17. Excluding the Financial and Insurance Services sector, the labour share trend has remained stable overall. This thesis assesses whether this trend is due to measurement issues with labour share or underlying heterogeneity in firm level labour shares, and finds evidence for both. Net labour shares have declined, and there has been an increase in high labour share firms along with a reallocation of value added towards such firms over this period. Furthermore, four key theories for the trends in labour share are tested, and reduced form empirical evidence finds that competition, measured through concentration and mark-ups, are driving labour share trends. This thesis develops a novel empirical framework that adapts the Diewert and Fox (2010) productivity decomposition method and applies it labour shares to examine competition dynamics. The findings suggest that within-industry changes in competition are driving labour share trends in Australia, not reallocation of value added to productive firms. These results overturn the Autor, Dorn, Katz, Patterson, and Van Reenen (2019) superstar model that has been the focus of much recent attention in the literature. The reasons why this may be the case are explored both theoretically and empirically. Lastly, the research makes a significant contribution by policy debate on labour shares and similar issues like declining business dynamism, and stagnating wage growth by defining and providing new perspectives on the presence of 'fading superstar' industries in Australia.

Chapter 1
Introduction

There has been a recent decline in the share of total income accruing to workers in the form of wages and salaries, that is, the labour share of income. Dao, Das, Koczan, and Lian (2017) show that thirty advanced economies (representing two thirds of the global gross domestic product) have experienced a decline in labour share of income since 1990. This is further supported by Karabarbounis and Neiman (2013) who found evidence for a global decline and La Cava (2019) who demonstrates this trend in Australia since 1980.

This decline in labour share of income suggests that productivity growth does not translate to real wage growth,[1] reflecting broader economic and social concerns for stagnating wage growth and income inequality between capital owners and workers (Armstrong and Porter, 2007; Pak and Schwellnus, 2019; Piketty and Zucman, 2014). It also suggests a loss of consumer purchasing power needed to support economic growth and inflation (Bassanini and Manfredi, 2012; Manyika, Mischke, Bughin, Woetzel, Krishnan, and Cudre, 2019). If this trend is pervasive and long-lasting, this overturns a key stylised fact about constant income shares used in economic theory (Kaldor, 1957). Hence, it is important to measure labour share of income accurately and understand its drivers.[2]

The literature canvassing labour shares within Australia has been limited, focused at the aggregate level and assessing potential drivers of labour share (McKenzie, 2018; Peetz, 2018; Stanford, 2018).[3] The Reserve Bank of Australia and the Australian Treasury have expressed interest in labour shares as well as ancillary issues due to its policy implications (La Cava, 2019; Trott and Vance, 2018; Weir, 2018).[4] They agree that there is a need to look at the underlying structural factors affecting wage growth and productivity (Andrews, Deutscher, Hambur, and Hansell, 2019; Bishop and Cassidy, 2019; Campbell, Nguyen, Sibelle, and Soriano, 2019), although this has not been directed at labour shares (Weir, 2018). Consequently, there is a lack of systematic evidence on the trends and drivers of the labour share in Australia.

[1] Kehrig and Vincent (2017) and Schwellnus, Kappeler, and Pionnier (2017) both document a decoupling of productivity growth and real wages leading to declining labour shares.

[2] There is a growing body of work assessing measurement issues, including how to split capital income and labour income for business owners, whether to include depreciation of capital or housing returns into value added. Furthermore, there is extensive literature examining the causes of labour share decline with no consensus on the primary driver. These theories include capital-biased technological changes, globalisation and international trade, reduced bargaining power and unionisation, labour productivity dispersion and competition drivers. Other explanations for labour share decline include corporate tax cuts, rise in intangible capitals and an increase in the cost of housing.

[3] Manyika et al. (2019); Peetz (2018); Stanford (2018) for example give an overview of potential drivers affecting labour share, focusing on unionisation and the shift towards capital.

[4] For example, Weir (2018) provides several working explanations for the decline in labour share.

Accordingly, this thesis uses a novel micro-dataset, Business Longitudinal Analytical Dataset Environment (BLADE), provided by the Australian Bureau of Statistics (ABS). Comprising of highly confidential firm level data, this thesis analyses the data to bridge the gap in our understanding of the trends and drivers of Australian labour shares. This environment pools Administrative Tax Office (ATO) data for 99% of firms in Australia between 2001-02 and 2016-17, enabling the study of firm level labour share dynamics and macroeconomic level aggregated analysis.

This thesis undertakes an immense task of (1) measuring labour share in its decomposed form, and (2) assessing its drivers, such analysis which is often conducted separately in literature. However, with BLADE becoming available for use by approved UNSW students this year,[5] the opportunity to conduct such research became possible for the first time. This thesis takes advantage of this access to BLADE to answer research questions on trends and drivers of labour shares.

As a result, this thesis combines three key strands emerging from the labour share literature. First, it reflects the work of several authors who find that labour share stabilises once measurement issues are accounted for.[6] Second, this thesis assesses several models put forward in the literature to explain the decline in labour share using reduced form empirical regressions.[7] This reflects the Barkai (2016) model and recent work by Gutierrez and Piton (2019) with microeconomic data. Lastly, this thesis theoretically and empirically assesses the presence of superstar firms in Australia by proposing a novel empirical strategy. This builds on the work of Autor, Dorn, Katz, Patterson, and Van Reenen (2017); Autor et al. (2019) and Barkai (2016), adapting the Diewert and Fox (2010) dynamic productivity decomposition to labour shares and incorporating insights about competition.[8]

The empirical contribution of this thesis is six-fold. First, labour shares are constructed using firm level data and aggregated to the macroeconomic level to provide insight. Given the complexity and size of the data set, this is a non-trivial task with many measurement and conceptual issues needing to be addressed. Furthermore, this is the first time that the labour share for the non-corporate sector will be been measured, as Australian macroeconomic data does not separate income into the corporate and non-

[5] Access was arranged under the banner of the Economic Data Analysis Network (EDAN) project on "Parametric and Non-parametric Techniques for Firm Level Productivity Analysis: Feasibility applications using BLADE" and the project on "Market Concentration". Thanks to Professor Kevin Fox, Dan Andrews and Australian Bureau of Statistics for this arrangement, opportunity and access.

[6] This includes Bridgman (2018); Elsby, Hobijn, and Sahin (2013); Gutierrez and Piton (2019); Gutiérrez and Philippon (2017); Rognlie (2016).

[7] These model include (i) capital-biased technological changes (Karabarbounis and Neiman, 2013; Schwellnus et al., 2017), (ii) globalisation and international trade (Dao et al., 2017; Elsby et al., 2013), (iii) reduced bargaining power and unionisation (Piketty and Zucman, 2014)(e.g.Bental and Demougin), (iv) labour productivity dispersion (Gouin-Bonenfant, 2018), and (v) competition drivers (Autor et al., 2019; Barkai, 2016; De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016; Schwellnus et al., 2017). The last is the focus on this thesis.

[8] De Loecker and Eeckhout (2017), Edmond, Midrigan, and Xu (2018) and Covarrubias, Gutierrez, and Philippon (2019) provide insight into the measurement of competition and different competition models.

corporate sector.[9] The preliminary results in Chapter 3 show that labour share of income over the past sixteen years has fallen by 3 per cent. Excluding the Financial and Insurance Services (FIS) Division, the trend has remained stable overall. Second, this thesis assesses the long-term trend for measurement issues and heterogeneity at the firm level. Chapter 4 finds that net labour shares (gross labour shares sans depreciation) display a noticeable decline before and after the mining boom and to-date have not recovered to pre-mining boom levels. Third, it also develops several key facts about firm level labour share dynamics in Australia, including that trends in labour share are driven by an increase in the number of high labour share firms, but also the reallocation of value added to high labour share firms.

Fourth, this thesis explores several explanations for the decline in the labour share put forward by literature in Chapter 5.[10] Through reduced form empirical regressions, competition, measured through mark-ups and concentration, is identified as a key driver of labour share trends. Chapter 7 further presents results which suggest that concentration affects within-industry changes in labour share, particularly after 2007 and by non-primary industries. This is distinct from the evidence of reallocation that Autor et al. (2019) provides and represents the fifth contribution. Lastly, this thesis introduces a new perspective on competition dynamics in Australia, defining 'fading superstars' as four-digit industries where labour share has declined due to a reallocation of value added away from high productivity, low labour share firms.

This thesis also makes three original theoretical contributions, which are examined in Chapter 6. First, this thesis adapts the Diewert and Fox (2010) ("DF") productivity dynamic decomposition method to decompose labour shares; this new method reveals whether reallocation or within-industry effects dominate and does so in a way which is shown to be superior to alternatives in literature. Second, this thesis proposes a new empirical framework applying the adapted DF method to the identification strategy and econometric specification of Autor et al. (2017, 2019) to understand labour share components and how they respond to competition. Lastly, it reconciles the new empirical framework with the model of Autor et al. (2017, 2019) both theoretically and empirically. Overall, this thesis overturns the Autor et al. model using a new framework applied to Australian data and questions the robustness of their findings through empirical findings.

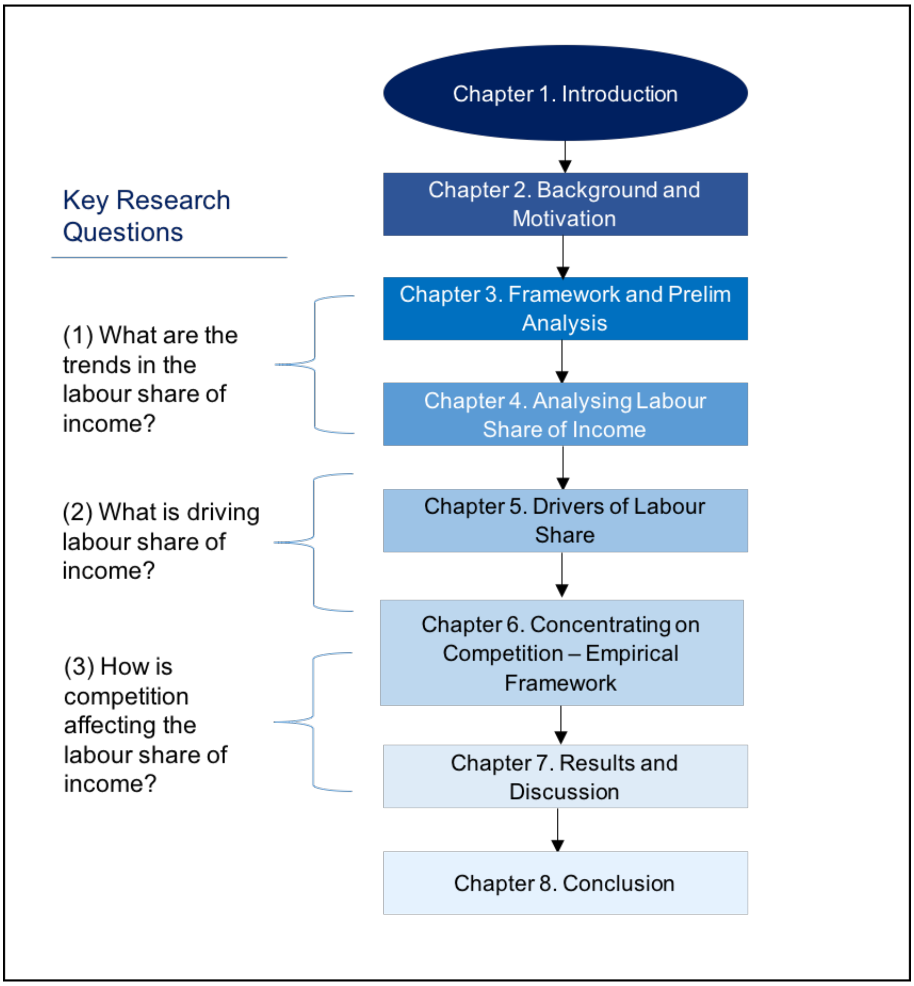
The structure of the thesis is outlined in Figure 1.1. In particular, Chapter 3 and Chapter 4 constructs firm level labour shares and examines labour share trends at the macroeconomic level for the first time. Then, Chapter 5 canvasses four key theories in the literature to

[9] Trott and Vance (2018) note that this is a key limitation when they assess the measurement of labour share in Australia

[10] This includes the reallocation of resources towards low-labour share and highly productive firms (Autor et al., 2017, 2019; Schwellnus et al., 2017; Van Reenen, 2018); increase in rent-seeking behavior (Barkai, 2016; De Loecker and Eeckhout, 2017; Gutiérrez and Philippon, 2017); growing labour productivity dispersion (Gouin-Bonenfant, 2018)); and, fall in the price of capital and increased capital–labour substitution (Karabarbounis and Neiman, 2013).

find that competition is the most significant driver of labour share trends. This is the most comprehensive assessment done in Australia thus far. Lastly, Chapter 6 and Chapter 7 develops a new empirical framework to evaluate the role of competition on the labour share, and finds that changes in concentration have a within-industry effect. [11]

Figure (1.1) Structure of Thesis

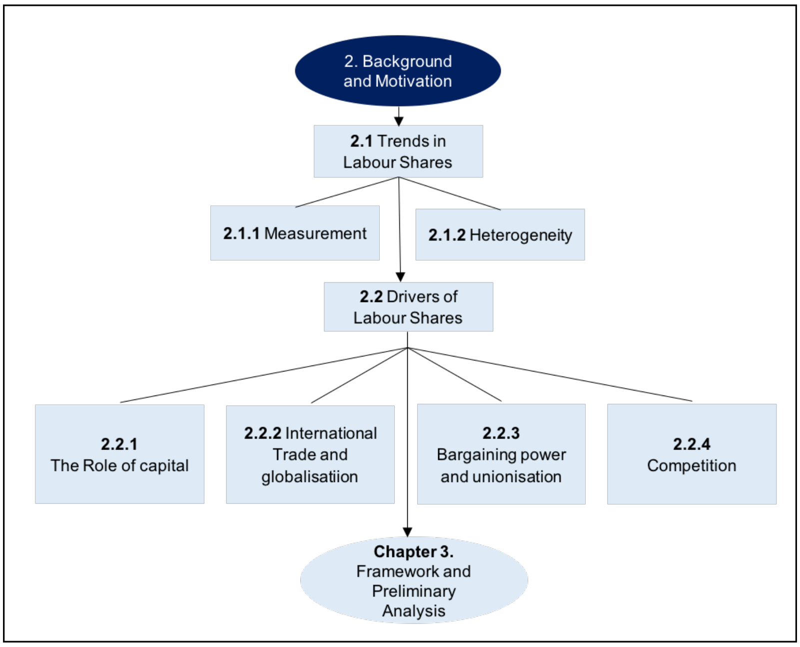


[11] Appendices provide detailed information on: the dataset BLADE (Appendix A), the construction of variables (Appendix B), results for concentration and mark-ups (Appendix C), Chapter 6 regression tables (Appendix D), and Chapter 7 regression tables (Appendix E).

Chapter 2
Background and Motivation

Labour shares provide a valuable starting point for understanding the distinction between workers and capital owners, and is an important determinant of personal income distribution (Atkinson, 2009). The decline in labour share of income in the last decade coincides with periods of stagnating wage growth and declining productivity (Dao et al., 2017), suggesting that real labour compensation is declining and workers are worse off (Kehrig and Vincent, 2017; Schwellnus et al., 2017). It also coincides with the increase in capital and profit shares, reflects more rent-seeking behavior (Barkai, 2016; Gutiérrez and Philippon, 2017) and a worsening divide between high and low income earners (Piketty and Zucman, 2014). The latter, in particular, could endanger social cohesion and slow down economic growth (Bassanini and Manfredi, 2012; Piketty and Zucman, 2014). This background motivates two key research questions: What are the trends in the labour share of income? What are the drivers? The literature in relation to these questions is discussed in Section 2.1 and Section 2.1.2 (See Figure 2.1).

Figure (2.1) Chapter 2 Overview - Background and Motivation



2.1 Trends in Labour Shares

Two key issues have emerged in relation to the trends of labour share. First, several papers have emphasised that the long-term trend in labour share depends on its measurement. Second, there is also the concern that long-term trends in labour share conceal underlying heterogeneity in firm level dynamics.

2.1.1 Measurement of Labour Shares

The trend in labour shares can be underestimated if the wages of self-employed individuals are excluded from payroll estimations of wages (Gollin, 2002; Gutierrez and Piton, 2019) or if it is imputed incorrectly (Elsby et al., 2013; Gutierrez and Piton, 2019). For example, looking at multiple countries, Gutierrez and Piton (2019) give evidence that the decline in labour share is removed once individuals who were self-employed in the corporate and the non-corporate sector are accounted for. Moreover, while it is common to impute payroll wages for self-employed, the hypothesis of equal average compensation is not normally confirmed (Cho, Hwang, and Schreyer, 2017) and it can lead to an implausible division of mixed income for self-employed, leading to an overestimation or underestimation of the labour share (Elsby et al., 2013). The literature has suggested many improvements to the measurement of self-employed income (e.g. Elsby et al., 2013; Gollin, 2002; Guerriero and Sen, 2012), which all lift the trend in declining income shares.

The labour share can also be underestimated if value added includes depreciation of capital stock or returns to housing as a form of income. Gutierrez and Piton (2019) and Gutierrez (2018) found that the decline in labour share in the USA is entirely driven by the real estate sector and returns to housing, as the value of housing capital has increased over the past years. Similarly, Rognlie (2016), Bridgman (2018) and Cho et al. (2017) show that income shares measured net of depreciation have remained stable. They argue that net labour shares are a preferred method of labour share estimation, as it is a better measure of inter-household income distribution from a welfare perspective. In comparison, most papers use gross labour shares as it reflects the ultimate command over resources that accrues to labour versus capital (Elsby et al., 2013; Karabarbounis and Neiman, 2013). Bridgman (2018) compares gross and net labour shares and finds that taking account of depreciation reduces the extent of decline for the United States, several European nations and Canada. Japan is an exception, where accounting for depreciation actually reverses and increases the downward trend in labour shares. Rognlie (2016) similarly finds that net labour shares are at their historical average.

Only a few academic papers have assessed measurement issues of Australia's labour share.[12] Trott and Vance (2018), for example, find that once depreciation and imputed housing return are considered, the trend in labour shares till 2015-16 reflects its historic averages. Trott and Vance (2018) explain that it is difficult to measure the effect of self-employment

[12] Piketty and Zucman (2014) makes adjustment to Australia's labour share, but only till 2011.

in Australia as National Accounts does not split income between the corporate sector and the household sector and so there has been a limited assessment of this measurement issue in Australia. Otherwise, most analysis has happened at the aggregate level using National Account Data as firm level data was previously not available for use e.g. La Cava (2019) and Weir (2018).

2.1.2 Heterogeneity in Labour Shares

While measurement is important, there is still a consensus that the fall is 'real and significant' (Autor et al., 2017, 2019). It is common across multiple countries suggesting that there are common factors, other than measurement at play. There is also growing recognition that the key factors affecting the long-term trend in labour share are within industry changes, rather than between industry (Andrews et al., 2019; Autor et al., 2017; Kehrig and Vincent, 2017; Weir, 2018). Labour share heterogeneity across industries and firms are two key stylised facts emerging in the literature.

First, labour share decline at the aggregate level veils substantial movements in labour share at the industry level. Dao et al. (2017) document that the aggregate decline in global labour shares conceals that the sharpest decline has been felt by manufacturing and transportation in advanced countries, and then agriculture in developing and emerging economies. Looking specifically at advanced economies, within the United States, Elsby et al. (2013) find that relative stability of labour share in the 1980s is disguised by substantial yet directionally offsetting labour share movements at the industry level. The second stylised fact is that, within industries, the distribution of labour shares has shifted and skewed towards firms with higher value add. Several studies in other jurisdictions have given evidence of reallocation of output to firms with lower labour shares, including Kehrig and Vincent (2017) and Autor et al. (2017) in the United States, Gouin-Bonenfant (2018) in Canada, and Berkowitz, Ma, and Nishioka (2017) for China (none for Australia). Separately, Kehrig and Vincent (2017) have found that while aggregate labour share has fallen, the median labour share has increased.

2.2 Drivers of Labour Shares

Despite extensive literature examining the theories of labour share decline, there is no consensus on its cause. Although Weir (2018) and La Cava (2019) have recently provided a useful analysis of the different theories on labour share and how they can relate in Australia, there is no conclusive or systematic assessment of them.[13]

2.2.1 The Role of Capital

Karabarbounis and Neiman (2013) estimate that the decline in equipment prices in advanced and developing countries explain around 50% of the decline in the global labour

[13] La Cava (2019) goes through each of the factors in a lot of detail, providing correlative analysis only using aggregated data

share. This analysis highlights that capital is a substitute for labour, with an elasticity in the range of 1.2 – 1.5. Using cross-country industry-level data, Schwellnus et al. (2017) found that technology driven declines in the relative investment price of capital accounts for about two-thirds of the aggregate labour share decline in countries within the Organisation of Economic and Co-operative Development ("OECD"). Most results, however, find that the elasticity of substitution of capital for labour is less than one (Antras, 2004; Chirinko, 2008; Oberfield and Raval, 2014). This makes the finding that the declining capital cost and decline in labour share seem less probable, or less likely to be a driver in labour share dynamics. Similarly, Autor et al. (2017) find a minimum role for capital when using firm level data in USA and Gutierrez (2018) finds no evidence at all.

Autor and Salomons (2018) emphasises the role of automation, where the displacement of labour from production takes the form of reduced labour income share. Eden and Gaggl (2015a,b) and Acemoglu and Restrepo (2018) find that the rapid advancement of ICT technology and robots, respectively, has accelerated automation of routine tasks and thus induces firms to disproportionately displace labour where the exposure to automation is larger. Using cross country data, Dao et al. (2017) show that labour share decline has been steepest in countries and industries that are more specialised in routine work, consistent with the theory of labour displacement. Autor and Salomons (2018), however, show that while labour-displacing technology is consistent with the decline in labour share in the 1980s, the recent acceleration in labour share decline in the 2000s is left somewhat unexplained by technological displacement and could actually be labour productivity enhancing where more labour tasks are created as a result of new technologies.

2.2.2 International Trade and Globalisation

Trade and globalisation have a similar effect on labour share as increases in capital intensity (Acemoglu and Restrepo, 2018). Traditional theory predicts that trade integration will lead capital-abundant advanced economies to specialise in the production of capital-intensive goods, triggering resource reallocation across sectors that lowers the labour share of income. Industry evidence of the United States by Elsby et al. (2013) shows that offshoring of the most labour-intensive stages of production to developing countries and increased import competition from emerging economies led to worker displacement and an increase in capital intensity. This also effects downstream customers and upstream suppliers due to the world. Dao et al. (2017) too identified that participation in global supply chains had a negative and significant effect on labour shares in emerging countries (although it was limited for advanced economies). These theories, however, do not explain the decline in labour share in labour-intensive emerging economies like China and India, which (Elsby et al., 2013) theory would dictate have an increase in labour share Karabarbounis and Neiman (2013).

As a small open economy, trade has a large impact on Australia's economy. Parham (2013) gave evidence that the large increase in terms of trade during the mining boom was responsible for a 4 per cent point decline in labour share. This, however, is at odds with a recent study by of Statistics (2017) looking at the shifts in labour shares in Australia between 1997 -98 to 2006-07 and 2007-08 and 2016-17, which found that 83 per cent of the change in labour share is driven by within –industry shifts, rather than a between-industry shift in labour share. Import competition would affect between industries, rather than all, making it unclear how the theory of international trade competition and within-industry changes are consistent (Weir, 2018).

2.2.3 Bargaining Power and Unionisation

Another argument is that the decline in union membership has led to a fall in the bargaining power of workers, contributing to low wage growth and subsequent falling labour shares (Isaac, 2018; Leigh and Triggs, 2016). Since 1990s, union membership has fallen from around 40 percent of all employees to around 15 per cent in 2018 (Bishop and Cassidy, 2019). While there are conflicting arguments about the role of declining unionization,[14] labour market power is a worthy cause that requires investigation because Australian labour market is significantly regulated, interventionist wage outcomes and centralisation since 1970s. Little has been done to move away from a centralized labour system and it has been argued that this has restrained wage growth and consequently, led to a fall in labour share (Leigh and Triggs, 2016).

2.2.4 Competition

My research contributes to the recent, yet growing literature surrounding the role of competition and declining on labour shares. Several authors, including Karabarbounis and Neiman (2019a), Schwellnus et al. (2017), De Loecker et al. (2016), Eggertsson, Robbins, and Wold (2018), Autor et al. (2017, 2019), and Barkai (2016) have given evidence on the relationship between concentration and labour share in the United States. The literature, however, has been divided over whether the decline in labour shares from increase in concentration is due to efficient outcomes or due to anti-competitive reasons. This thesis contribute to this literature by documenting this relationship in Australia, which has not been done before.

The mechanism through which growing market power results in falling labour shares can be described in two ways. The first approach reflects pernicious monopoly rent-seeking behaviour. Eggertsson et al. (2018) argue that a 'non-zero rent economy' has emerged, where a decline in competition or increase in barriers to entry has caused the number of firms to fall within an industry and increased concentration. Because of greater market power, firms have raised prices and mark-ups, leading directly to an increase in pure profits. They argue that a standard neoclassical model, augmented with increasing market power and mark-ups, quantitatively and qualitatively explains the increase in profit share, and decrease in both labour and capital share. De Loecker et al. (2016) and Barkai (2016) provide empirical evidence that profit share has increased in the United States, while labour share has fallen, using firm level and industry level data, respectively. Barkai (2016) further

[14] Bishop and Chan (2019)

validates the work of Eggertsson et al. (2018) through their standard general equilibrium model which shows that capital and labour share can only simultaneously fall if there has been a decline in competition. Karabarbounis and Neiman (2019a) however remain sceptical about the pure profit mechanism. They conclude that while the increase in profit share is consistent with empirical data in recent decades, its inconsistent with post world war history.

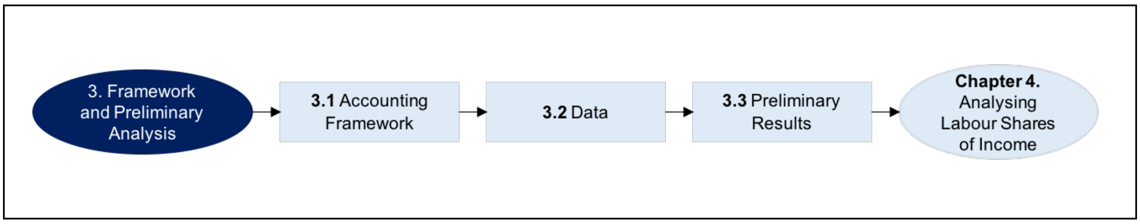
The second approach, in contrast, explains labour share decline in the context of productivity growth and increased allocative efficiency gains. Autor et al. (2017, 2019) and Van Reenen (2018) find evidence that the decline in labour share is driven by a within-industry reallocation to dominant firms. Autor et al. (2017, 2019) use firm level data to show that these are 'superstar' firms - dominant firms which had acquired large market share through increasing returns to scale from technology, network effects or their ability to connect consumers to low cost or high quality firms - had low labour shares. This suggests that an increase in concentration is associated with an increase in allocative efficiency. While the increase in returns to scales reduces labour input to produce the same output, there is also an increase in mark-ups as overhead costs and production costs are split over the large revenue base of superstar firms. Similarly, network effects can also have efficiency gains, but it can also cause a gridlock, giving superstar firms pricing power. Such an approach, hence, predicts a decline in labour share due to the reallocation towards superstar firms who have increased concentration and pricing power because of their productivity. Schwellnus et al. (2017) and Andrews, Criscuolo, and Gal (2015) experience as a winner-takes-all dynamics, where there is a growing divide in productivity trends between frontier and non-frontier firms reducing labour shares. Using cross-country industry- and firm level data, they find no evidence to support that the winner-takes-all dynamics is caused by anti-competitive forces rather than technological dynamism.

The most common measure of competition used in these papers to establish an inverse relationship with labour share decline is sales concentration (Autor et al., 2017; Barkai, 2016). Concentration measures what fraction of sales accrue to top four (C4) or twenty firms in an industry (C20) and can alternatively be measured with a Herfindahl- Hirschman Index. Other measures include profit elasticity and price cost margins as explored in Agarwal, Brown, Bajada, Stevens, and Green (2019). However, as Syverson (2017), Basu (2019) and others point out, concentration is not a perfect metric of competition: both assume that an increase in concentration relates to the decline in labour share, although one carries implications for a decline in competition and productivity efficiency and the other is an increase in competition and allocative efficiency. Syverson (2017) and Covarrubias et al. (2019) argue that ancillary evidence, such as mark-ups, profit shares, leader turnover, business exit and entry rates, should be presented to strengthen the labour share and competition hypothesis.

Chapter 3
Framework and Preliminary Analysis

This chapter constructs labour shares using firm level data to provide insight at the macroeconomic level for the first time.[15] Section 3.1 will describe the accounting framework used to construct firm level labour shares, capital shares and profit shares. Section 3.2 explains how the final dataset was constructed from the Business Longitudinal Analytical Data Environment (BLADE), and Section 3.3 presents preliminary results.

Figure (3.1) Chapter 3 Overview - Framework and Preliminary Analysis



3.1 Accounting Framework

At the firm level, a firm's value added is constructed as the sum of labour costs, capital costs and any retained profits for the sale of goods and services above their average price (Barkai, 2016; Karabarbounis and Neiman, 2019a). While this is generally the framework for the economy, this thesis assume that it is also the true (but basic) model of accounting for an individual firm i at year t:

$$Y_{it} = w_{jt}L_{it} + R_{jt}P^{K}_{j,t-1}K_{it} + \Pi_{it} \tag{3.1}$$

where Y_{it} is gross value added, w_{jt} is average wage at 4-digit industry level j for payroll employees, L_{it} is the number of full time employees at firm i, R_{jt} is the return rate of capital for the 4-digit industry j, $P^{K}_{j,t-1}$ is the price of capital at time $t-1$, K_{it} is the stock of capital for firm i, and Π_{it} is the retained profits for firm i.

Traditionally, value added has been separated into capital share and labour share. However, this is misleading as the residual income not accruing to labour flows to capital, as

[15] Most research on income shares in Australia has been conducted at an aggregate level (La Cava, 2019; Trott and Vance, 2018), so these results are contribution to the understanding of Australian income shares using firm level data.

capital share, and to business owners, as the profit share. Understanding these separate components of income is crucial to understand the evolution of competition across firms, nature of income distribution and implications for regulatory and tax policies (Basu, 2019; Karabarbounis and Neiman, 2019a).

Firm level labour share λ_{it} for firm i, in a given industry j and year t is defined as wage compensation over value added. It is equivalent to labour share over total input costs multiplied by one over mark-ups (Barkai, 2016):

$$\lambda_{it} = \frac{w_{it}L_{it}}{Y_{it}} = \frac{1}{\mu}\left(\frac{w_{it}L_{it}}{w_{jt}L_{it} + R_{jt}P^K_{j,t-1}K_{it}}\right) \tag{3.2}$$

Capital share, φ_t, for firm i in a given industry j and year t is defined as capital costs over value added. This is equivalent to the capital share of total input costs multiplied by one over mark-up (Barkai, 2016):

$$\varphi_{it} = \frac{R_{jt}P^K_{j,t-1}K_{it}}{Y_{it}} = \frac{1}{\mu}\left(\frac{R_{jt}P^K_{j,t-1}K_{it}}{w_{jt}L_{it} + R_{jt}P^K_{j,t-1}K_{it}}\right) \tag{3.3}$$

Profit share, π_t, in year t is retained profit over value added, which is equivalent to the residual of the mark-ups.

$$\pi_{it} = \frac{Y_{it} - w_{jt}L_{it} - R_{jt}P^K_{j,t-1}K_{it}}{Y_{it}} = \frac{\Pi_{it}}{Y_{it}} = 1 - \frac{1}{\mu} \tag{3.4}$$

Accordingly, the sum of all the shares should equal one for a firm:

$$1 = \lambda_{it} + \varphi_{it} + \pi_{it} \tag{3.5}$$

Equation 3.2 suggests that there are three broad potential explanations for changes in the labour share of income. Looking at the required rate of return on capital R_t and relative size of the capital stock, $P^k_t K_t$, an increase could reflect higher interest rates or depreciation rates or alternatively capital augmenting technology. According to Barkai (2016), this would be an efficient outcome, with less welfare distortions occuring. However, another reason for decline could be an increase in the mark up would would reflect rent-seeking and profit motives. This is welfare distorting, and could be associated with consumer welfare losses.

3.1.1 Aggregate Labour Shares

Firm level labour shares are aggregated upwards to calculate macroeconomic level labour shares. This is calculated as a weighted average of individual firm labour shares in the group. For example, the calculation of 4-digit industry-level labour share, λ_{jt}, is the sum of total salary, wages and other payments reported by firms in group j in their Business Activity Statement over the sum of gross value added (see Equation 3.6).

$$\lambda_{jt} = \frac{\sum_j W_{it} L_{it}}{\sum_j Y_{it}} \tag{3.6}$$

3.2 Data

The data for this study comes from a novel firm level panel dataset called Business Longitudinal Analytical Data Environment (BLADE). This is provided by the Australian Bureau of Statistics (ABS), in collaboration with the Australian Taxation Office (ATO) and other governmental agencies. BLADE combines multiple firm level panel datasets including annual government administrative data from ATO, such as Business Activity Statements (BAS), Business Income Tax Filings (BIT) and Pay as You GO Summarises (PAYG), as well as ABS Survey data, like Business Characteristic Surveys (BCS) and Economic Activity Survey (EAS), for an individual firm (see Appendix Figure A.1 for an overview of the datasets). Together, this provides a rich and complete set of characteristics for more than two-million actively trading observations in Australia between 2001-02 to 2016-17.

The data provided by BLADE dataset is also highly confidential, as it contains sensitive information on individual firms. To prevent spontaneous identification of any individual firm, the dataset is representative of only 99.97 per cent of all firms in Australia, and results presented have been aggregated to a four-digit ANZSIC level, even if analysis has been conducted at the firm level. Any industry with less than ten firms have been removed to avoid firm identification. Appendix A provides further detail on the construction of the BLADE dataset, limitations of its use, the confidential nature of its use and restrictions the data can be used and results released after approval from ABS.

Existing research from BLADE is limited, so this thesis contributes to a new, but growing body of work.[16] Existing research on income shares using BLADE is non-existent, so this will set the foundations of further research in income shares.

3.2.1 Primary Data

The dataset is constructed by merging the BAS, BIT and PAYG datasets, which provide the following information:

- BAS contains turnover, employee compensation, capital and non-capital purchases, and export sales on all Australian businesses. Majority of my research relies on the variables provided by BAS.
- BIT contains standard balance sheet data on businesses disaggregated into four broad classes of legal reporting entities, including companies, trusts, partnerships and sole

[16] See for example, Andrews et al. (2019), Campbell et al. (2019), and Bakhtiari (2019).

proprietors. In summary, information collected may include, but is not limited to, assets, liabilities, income and expenses, deductions, opening and closing stocks and wage and salary expenses.

- PAYG contains basic firm level employee data for all businesses. Variables of interest include full time equivalent (derived) and headcount.

Although BLADE provides a very rich dataset, it does not contain several variables that are needed for analysis. This includes firm level gross output, value added, intermediate inputs, capital stock, cost of capital, investment, income shares, total factor productivity, and mark-ups. Several of these are constructed using the variables provided in BAS directly (e.g. value added, gross output, investment), while others are constructed using additional information provided by ABS data at the division level (e.g. capital stock, total factor productivity, mark-ups). Further details on the construction of such variables is provided in Appendix A.

3.2.2 Sample Selection Procedure

After merging the various datasets, there is a lot of data with considerable amount of noise. Table 3.1 summarises the sample selection procedures taken to reach my final dataset, identifying the number of observations for analysis left in the process:

Table (3.1) Creation of Preliminary Data Set

	Original Data Set	Sector Deletion	Inactive Firms Deletion	Outlier Deletion	Non-market Divisions & Finance
Observations	52,733,185	32,716,053	32,816,790	32,080,643	4,637,970
Share of original data (%)	100	62.23	62.04	60.72	51.91

Source: ABS BLADE 2016-17.
This table depicts the sample selection procedure undertaken to reach the final dataset used for this research.

First, general government bodies and not-profit institutions serving households (such as clubs, trade unions, chambers of commerce and churches) are excluded from the dataset. This represents about 37 per cent of observations. These sectors are deleted because it is unclear what value added would mean in the context of government[17] or not-for-profit institutions.[18] Most goods and services provided by either sector are not normally sold at a commercially determined price, so production is valued *at cost* in ABS National Accounts, rather than set by the market.[19]

[17] See Rognlie (2016) p8 for further discussion

[18] There is a similar treatment of government and not-profit institutions serving households in ABS National Accounts

[19] (ABS, 2016)

Second, firms which were identified as *inactive* were deleted, accounting for around 1 per cent of observations. This refers to firms which have missing or zero turnover; missing or zero operating expenditures; missing or zero capital expenditures; and missing or zero full-time equivalent ("FTE") labour data. Cumulatively, all these factors suggest that there are some inactive firms. Alternatively, these observations could be a result of incorrect reporting or some computational method ex-ante. In either case, it is difficult to adjust them in the current environment. Hence, they are dropped, accounting for around 20 per cent of observations dropped from the original data set.

Lastly, BLADE dataset contains considerable noise, which reflects the nature of the data and its collection. The general outlier deletion methodology proposed by the OECD (see Schwellnus et al. (2017), Berlingieri, Blanchenay, Calligaris, and Criscuolo (2017), Andrews et al. (2015)) is used to delete this noise, leading to a deletion of around 2 per cent of observations. The variables of interest which have been subject to outlier treatment include value added (VA), intermediate usage (intuse), gross output (go), employment (fte), labour productivity (go/fte), and capital (cap) (following the approach used by Andrews et al. (2015) and Schwellnus et al. (2017). Outlier detection requires identifying observations that lie above and below three standard deviations (3SD) from the mean of firms in the division group. However, the outlier detection process above is not sufficient to detect shift or level changes in firm's characteristics that may have emerged due to incorrect inputting of administrative data. Hence, to remove such erratic behaviour, this paper follows Andrews et al. (2015) methodology of deleting the whole firm that is identified as part of the earlier outlier detection process. This will avoid any structural or level shifts that may come from firms merging or through acquisitions. By identifying the whole firm, the entire structural shift is removed, removing any abnormal growth or shocks to the firm level data. Once all firms which have abnormal outliers are identified, the outlier deletion occurs all at once. This is to avoid repetitive outlier deletion processes which would reduce the sample size.

For robustness, this was compared with the Percentile and Tukey methods. All three approaches, 3SD, Percentile and Tukey, produced similar industry aggregate labour shares. The 3SD growth approach was chosen as it removed most noise, kept a larger sample size and produced ultimately industry labour shares that were most similar to the ABS ones. One possible limitation of taking the 3SD approach, with erratic firm behaviour deletion, is that it is biased toward small firms who may demonstrate large growth year on year. However, this methodology has been most commonly applied in the literature, particularly by OECD and IMF.

For the purpose of labour share analysis, the dataset is additionally cleaned by removing observations with extreme values for labour share growth. Observations above the 99th percentile of the labour share distribution and below the 1st percentile are dropped (Schwellnus et al., 2017). Additionally, Schwellnus et al. (2017) winsorises observations remaining outside the 0-100% range; however, we do not apply this.

3.2.3 Descriptive Statistics

The resulting dataset is large, containing approximately 32 million observations over 15 years for twenty million actively trading businesses. Table 3.2 outlines the number of observations, total gross output and labour costs for the economy and few selected divisions between 2001-02 and 2016-17.

Table (3.2) Economy and Selected Division Summary Statistics

	No of Observations	**Total Gross Output (2001-02 to 2016-17) ($b)**	**Total Labour Cost (2001-02 to 2016-17) ($b)**	**Average FTE**
Total Economy	32,080,643	$66,094	$9,597	12.6
		Selected Divisions		
Manufacturing	1,364,695	$5,394	$690	17.3
Retail Trade	2,202,355	$5,562	$558	10.6
Wholesale Trade	1,205,382	$5,943	$424	12.1
Professional, Scientific and Technical Services	3,879,694	$3,093	$777	6.9

3.3 Preliminary Results

Figure 3.2a depicts the unadjusted labour share for the entire economy and market sector between 2001-02 and 2016-17.[20] The results suggest that labour shares have fallen by 3 per cent, at a compounded annual growth rate (CAGR) of 0.41 per cent and 0.43 per cent, respectively. These results were constructed by aggregating firm level labour shares according to equation 3.6. Given the complexity and size of the data set, this is a non-trivial task with many measurement and conceptual issues addressed.[21] Figure 3.2a also plots the labour share taken from the Australian System of National Account (ABS 5204.16, 2018) ("ABS National Accounts").[22] While BLADE results are lower than ABS results, they follow a similar downward trend. The large dip starting at 2002-03 is explored in Section 3.3.[23]

[20] The entire economy includes all nineteen divisions according to Australian and New Zealand Standard Industrial Classification ("ANZSIC") Market sector refers to all divisions excluding Healthcare and Social Assistance (Division O), Education and Training (Division P), and Public Administration and Safety (Division Q) according to ANZSIC classification.

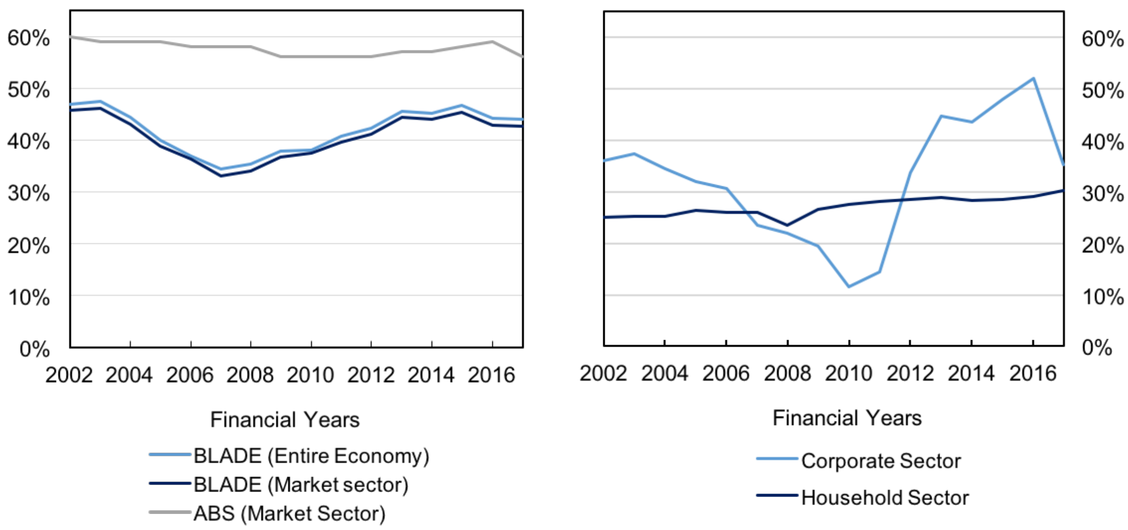
[21] See Appendix for details on the data. For example, value added calculated using BAS statements includes revenue from asset sales so it is likely that it overestimates value added, unlike ABS who can estimate value added by removing asset sales.

[22] Only the market sector results are comparable with ABS, as ABS only produces market sector labour shares in National Accounts.

[23] There is no reason why BLADE and ABS results should be the same. ABS data is collected from survey results, while BLADE is the entire collection of administrative firm level data. While both sources of data have their limitations and biases, arguably BLADE is a broader representation of the Australian economy.

Figure (3.2) Labour Share of Income (unadjusted) using BLADE

(a) Entire Economy & Market Sector **(b) Corporate & Household Sector**



Source: ABS BLADE 16-17, ABS Cat No 5260.14, Author's calculations

These figures graph the labour share of income, taken as the weighted average mean of firm level labour shares (Eqn 3.6). Panel A plots the labour share for the entire economy and market sector, compared with ABS results.Panel B plots the labour share of the corporate sector and the household sector

Figure 3.2b presents the labour share of income for the corporate and household sector. An advantage of constructing labour shares from firm level data is the ability to split the firm level labour shares according to the Standard Institutional Sector Classification of Australia (SISCA), which splits firms into corporate and household sectors.[24] As Trott and Vance (2018) note, this has not been possible before as ABS National Accounts do not split wage and income data between the corporate and household sectors. Most papers focus on the corporate sector (e.g Karabarbounis and Neiman, 2013) because of the difficulty of measuring income accurately in the household sector as well. The figure shows that labour share in the household sector has been flat (even trending upwards), while the corporate sector is the largest driver of labour share decline.

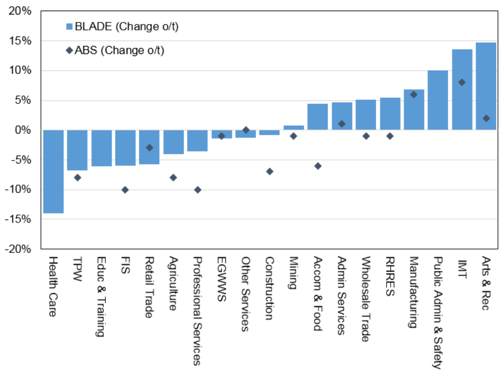
Labour share decline is pervasive in several industries but to varying degrees. Figure 3.3a presents the results of the net change in labour share for divisions (1-digit ANZSIC code) between 2001-02 and 2016-17. The divisions with the largest fall include: Transport and Social Assistance (-14 per cent), Finance and Insurance Services (-6 per cent) and Retail Trade (-5.8 per cent). The industries which recorded the largest increase in labour share include: Arts and Recreations (+ 14.7 per cent), Information Media and

[24] Corporate and non-corporate refer to classification of firms into institutional sectors according to SISCA. These sectors group firms according to similar structural and economic features. Corporate can be split further into non-financial corporations and financial corporations. Non-financial corporations relate to corporations related to the production of goods and services, while financial corporations relate to corporations that engage in financial intermediaries services or similar services. Household sectors refers to unincorporated enterprises which are controlled and owned by households. Generally, self-employed and business owners are classed in this sector (of Statistics, 2017)

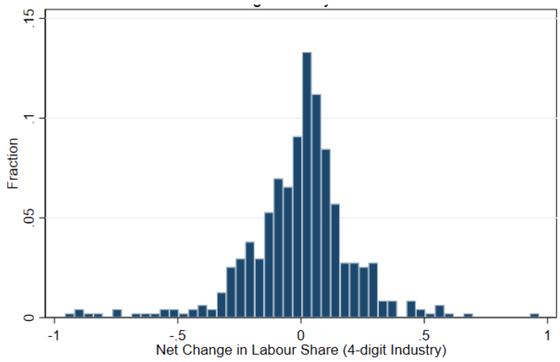
Telecommunications (+13.6 per cent) and Manufacturing (+6.8 per cent).

Figure (3.3) Labour Share trends at the 1-digit ANZSIC level and 4-digit ANZSIC level

(a) Division Level Labour Shares (Change between 2002-17)



(b) 4-Digit ANZSIC level Labour Shares (Change between 2002-17)



Source: ABS BLADE 16-17, ABS Cat No 5260.14, Author's calculations

These figures plots the net change in labour share between 2001-02 and 2016 -17 at the (A) Division level, comparing it with the results of the ABS National account, and (B) 4-digit Industry level. TPW stands for Transport, Postal and Warehousing; FIS, Financial and Insurance Services; EGGWWS, Electricity, Gas Water and Waste Services; RHRES, Rental, Hiring and Real Estate Services; IMT; Information Media and Technology. ABS 5260.0.55.002 – provides only market sector labour shares. Health Care, Education and Training, and Public Administration and Safety labour shares are missing

Diving deeper, around 50 per cent of 4-digit industries have experienced an increase in labour shares and a decline in labour shares. Figure 3.3b shows that the distribution of net labour share changes between 2001-02 to 2016-17 vary from increasing over time to decreasing. However, roughly 90 per cent are within the bounds of a 50 per cent increase or decline. The heterogeneity of declining and increasing labour shares at the industry and firm level cancels out once aggregated. Hence this suggests that stylised macroeconomic facts of constant income shares can be misleading, as there is significant heterogeneity underlying the dynamics.

3.3.1 Exclusion of Financial and Insurance Services

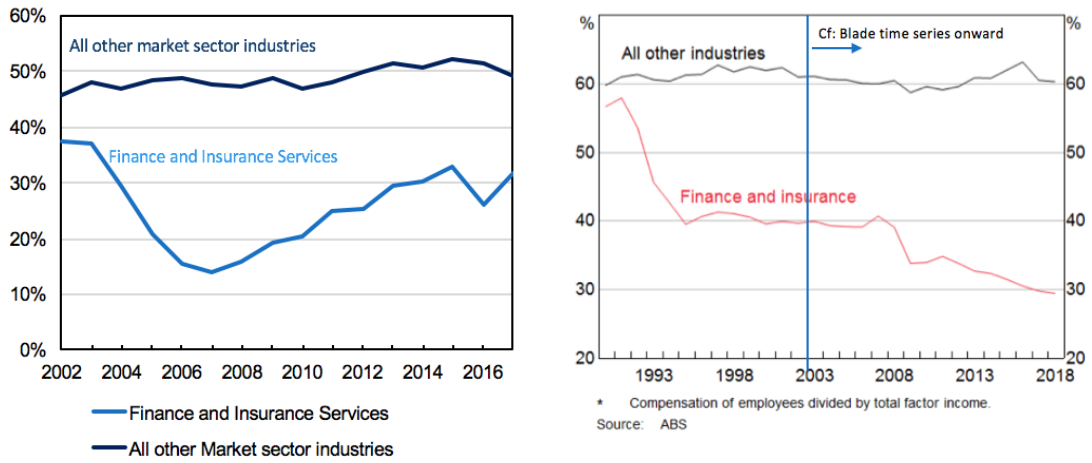
One of the largest drivers for labour share decline in Australia is the Financial and Insurance Service (FIS) Division, specifically the financial corporation sector.[25] Between 2001-02 and 2016-17, the financial and insurance service division experienced a net fall of 6 per cent. Removing finance and insurance services, Figure 3.4a shows that the share of income for workers in all other industries has remained relatively flat. This firm level finding is consistent with ABS National Accounts (See Figure 3.4b, taken from La Cava (2019). Using aggregate data, La Cava (2019) show that the Financial and Insurance Services is the largest driver of labour share decline in Australia, with the share of total

[25] Analysis using BLADE found that

industry income going to finance workers halving since 1990.

Figure (3.4) The labour share for Financial and Insurance Services and other market sectors

(a) **BLADE Results** (b) **ABS Results**

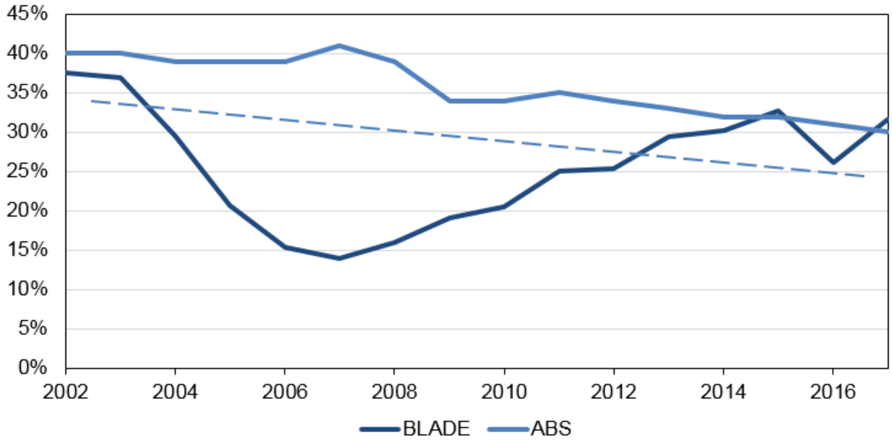


Source: ABS BLADE 16-17, ABS Cat No 5260, La Cava (2019)
Panel A plots BLADE labour share for the Financial and Insurance Services Division between 2001-02 and 2016-17 as well as the aggregate for all other market sector industries. Panel B, taken from La Cava (2019), shows the data points but using ABS data.

Several structural factors explain the large decline in labour shares for the financial sector (La Cava, 2019). Since the 1990s, the industry has gone through wide-spread technological change, including investing significantly in information technology and technological innovation to improve bank efficiency. This has resulted in a massive growth in multifactor productivity, but also a significant decline in the number of employees, such as bank tellers. This has resulted in growth in profit and capital shares but a decline in labour share (La Cava, 2019).

Abstracting from the structural change, output from the financial and insurance division is poorly measured in BLADE. It is widely accepted that value added from bank's business activity statement is poorly measured (Philippon, 2015). An example is the period after 2002-03, where labour share has had a large dip due to a significant increase in the value added for the Financial and Insurance Services Division, which is abnormal. Figure 3.5 depicts that there is a large dip in BLADE measures, but ABS National Accounts is smoothed in comparison. This is because ABS measures financial sector output through imputed service charges known as financial intermediation services indirectly measured (FISIM). FISIM is essentially the spread between the interest rate on loans and deposits multiplied by the size of the banks' balance sheets as measured by the stock of loans and deposits. National accounts take FISIM into account, which smooth the series, while tax data incorporated in BLADE is unlikely to measure it (Philippon, 2015), creating the large increase around the the Global Financial Crisis.[26] Hence, the inconsistencies between how output is measured for this division in the National Accounts and in the ATO tax data, suggests that the results in BLADE could be imprecise.

Figure (3.5) Financial and Insurance Services Labour Share (BLADE v ABS)



Source: ABS BLADE 16-17, ABS 5260.14

These figure compares the labour shares of the Financial and Insurance Services Division calculated using firm level data, and the shares estimated by ABS.

Hence, the Finance and Insurance Services division is excluded from analysis of labour shares hereon. Having to exclude it is not ideal, as it accounts for much of the decline in the labour share over the past few decades (La Cava, 2019). However, it is unavoidable due to inconsistencies between how output is measured for this division in the National Accounts and in the tax data.

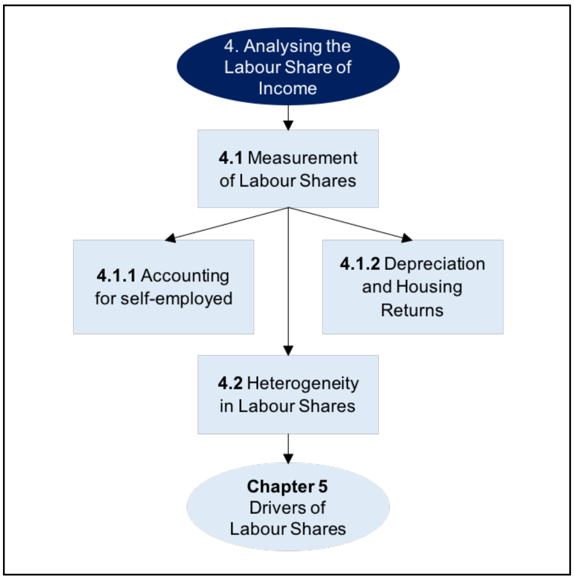
[26]The dotted line in Figure 3.5 represents a hypothetical smoothed version of labour shares in BLADE if FISIM was imputed.

Chapter 4
Analysing the Labour Share of Income

The preliminary results in Chapter 3 suggest that the labour share of income for the market sector (excluding the Financial and Insurance Services Division) has been stable over the past fifteen years.[27] However, this is puzzling given the stagnation in wage growth, slackness in the labour market conditions and decline in labour productivity over this period Treasury (2017). This finding could just be a result of removing the financial and insurance services sector from the results, which is the largest contributor to labour share decline in Australia (La Cava, 2019) or the short sample period of the results (Dao et al., 2017).[28]

Alternatively, Section 4.1 explores whether the measurement of labour shares can influence this long-term trend, including the inclusion of self-employed, depreciation of capital stocks and housing rents. Section 4.2 explores whether firm level heterogeneity prevails, following a series of papers which document firm level trends like Kehrig and Vincent (2017) and Autor et al. (2019). Both sections will be a unique contribution to Australia's understanding of labour shares. Figure 4.1 provides an overview of this chapter.

Figure (4.1) Chapter 4 Overview - Analysing the Labour Share of Income



[27] Financial and Insurance Services as well as non-market sectors were removed due to measurement issues with value added in BLADE. See Figure 3.4a. Further explanation is found in Section 3.3.

[28] Trott and Vance (2018) and La Cava (2019) note that labour share decline occurred in 1990s, while this sample starts in 2001-02.

4.1 Measurement of Labour Shares

Measurement issues with labour share relate broadly to the measurement of the numerator, wages, and to the denominator, value added. Regarding wages, labour share can be underestimated if the wages of self-employed are excluded from payroll estimations of wages (Gollin, 2002; Gutierrez and Piton, 2019) or if it is imputed incorrectly (Elsby et al., 2013; Gutiérrez and Philippon, 2017). Regarding value added, labour shares can be underestimated if value added includes returns to housing (Gutierrez and Piton, 2019) or depreciation of capital stock (Rognlie, 2016) as a form of income. Measurement adjustments are made at the firm level, while most papers conduct this at the economy level.

4.1.1 Accounting for Self Employed

Self-employed individuals and business owners, including individuals who operate as sole proprietors, trusts, family trusts or partnerships, are often excluded from the measurement of total labour compensation in the economy. The preliminary results depicted in Figure 3.2a and 3.4a exclude self-employed as well, as the BAS measure of income ('wages') only reports the wages of employees on a payroll. The 'true' total wage compensation, however, is the sum of the wages of employees on the payroll ($W_t^P L_t^P$) and the income of the business owner or self-employed individual ($W_t^S L_t^S$) for year t:

$$W_t L_t = W_t^P L_t^P + W_t^S L_t^S \tag{4.1}$$

Measuring the income for business owners and self-employed is difficult because first it requires (1) identifying them and (2) assessing how much income self-employed and business owners earn, as they receive a mix of capital and labour income. Hence, self-employed individuals and business owners are often excluded from the measurement of total labour compensation in the economy (e.g. Karabarbounis and Neiman, 2013).

4.1.1.1 Counting business owners and self-employed

Table 4.1 shows the share of firms in the financial corporate, non-financial corporate and non-corporate sector which can be classified as self-employed or business owner. The benefit of firm level data is the ability to directly identify those who operate as sole proprietors, family partnerships, other partnerships and trusts using the Institutional Sector Classification (SISCA) and the type of legal organisation (TOLO) characteristics in BLADE. Table 5.1 shows that nearly 100 per cent of firms in the non-corporate sector can be classified as 'self-employed'. There are also a significant number of sole proprietors, family partnerships, other partnerships and trusts within the corporate sector as well, reflecting Gutierrez and Piton (2019) results. Around 70 per cent of firms that are financial corporations operate as sole proprietors, family partnerships, other partnerships or trust, accounting for around two-third of the turnover in that sector. Around 1 per cent of firms in non-financial corporations can be classed as self-employed too. Hence, it would be incorrect to exclude individuals who are self-employed as they represent a large portion of the Australian economy.

Table (4.1) Businesses Owners and Self-employed in the economy

Sector	Share of total firms (%)	Share of total value added (%)
Non-Financial Corporations	71	21
Financial Corporations	70.88	62
Household Sector	99.92	99.97

Source: ABS BLADE 16-17, Author's calculations

Notes: This table identifies the share of total firms and total value added within the Non-financial Corporate, Financial or Household Sector that can be classified as sole-proprietors, partnerships, trusts or family partnerships.

This thesis introduces a novel method to account for self-employed. Assuming that self-employed individuals and business owners work the equivalent of 1 full time equivalent (FTE) employee, one FTE count and one FTE's equivalent 4-digit ANZSIC industry level wage is imputed to a firm identified as self-employed. It is common practice to impute payroll wages for self-employed following equation 4.2 (Kravis, 1959; Schwellnus et al., 2017). Often this is at the division level. However, BLADE enables a 4-digit level of estimation, which is more reflective of the level of skill, size, structure and labour-intensiveness within that sector. This digit level of estimation is a more refined than assuming the average industry wages is at the 1-digit industry level, which was the criticism of Elsby et al. (2013).

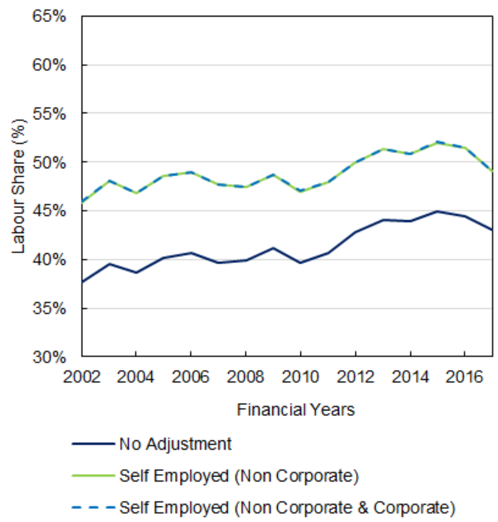
$$W_{jt}^{P} = W_{jt}^{S} \tag{4.2}$$

Figure 4.2a shows the adjustments to the measure of labour share, accounting for the number of business owners and self-employed. The adjustment of self-employed in the corporate and non-corporate sector lifts the labour share by 8 percentage points on average. There is a negligible difference between labour shares which adjust for the income of self-employed in the corporate and non-corporate sector.[29] This is because all the firms which are classified as 'self-employed' exist in FIS financial corporations. Since FIS has been removed, the number of self-employed and businesses owners in both measures are virtually the same.

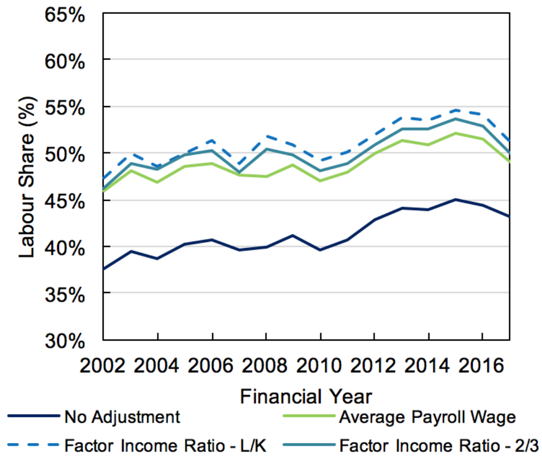
[29] On average, there is a 0.024 percentage point difference between the two measures.

Figure (4.2) Addressing Measurement issues with Wages and Self-employed

(a) Accounting for business owners & self employed individuals



(b) Adjusting the income of self-employed/business owners



Source: ABS BLADE 16-17, Author's Calculations

This figure plots the labour share of income for the market sector of the economy aggregated using firm level data. Panel (A) compares the number of self employed and business owners in the non corporate and corporate sector. Panel (B) adjusts the income they might earn using (1) average payroll wage in the 4-digit ANZSIC level, 2/3 of retained profits, or a factor share derived by the K/L ratio (Groves, 2018)

4.1.1.2 Adjusting the income of self-employed

Figure 4.2b presents three measures of estimating income for self-employed. It takes into account self-employed and business owners that exist in the corporate and household sector. The first method is to impute payroll wages, which was already presented in Figure 4.2(a) and (b). However, imputation can lead to an implausible division of mixed income for self-employed, leading to an overestimation or underestimation of labour shares (Cho et al., 2017; Elsby et al., 2013). The second and third approaches are based on apportioning gross mixed income to the owner (Gollin, 2002; Guerriero and Sen, 2012). In a firm level adapted approach, gross mixed income reflects retained profits, π_t, after capital costs and payroll compensation has been considered. Hence, this approach envisages ways to divide retained profits into capital and labour income, by some factor share ratio, α. The factor share ratio can equal one (Kravis, 1959) or two-thirds (D.G., 1954; Krueger, 1999). Cho et al. (2017) found that the economy-wide allocation of mixed income to labour is quite close to the allocation that is obtained by applying an economy-wide adjustment of two-third. However, Guerriero and Sen (2012) points out that this may reflect a division of income is constant over time, which does not reflect the changing composition of the workforce. Hence a third measure of the factor share ratio is to calculate the 4-digit industry level ratio of payroll compensation and capital costs which changes over time (Groves, 2018).

$$Y_{it} = W_{jt}^{P} L_{it} + W^{S} + R_t P_{t-1} K_{it} + \Pi_{it} \tag{4.3}$$

$$W^{S} = \alpha \Pi_{it} \tag{4.4}$$

where Y_{it} is the value added for firm i at time t, W_{jt}^{P} is the average wage for employees in industry j at year t, L_{it} is the number of employees at firm i, $R_t P_{t-1} K_{it}$ is the capital cost for firm i at time t and Π_{it} are retained. The income for the business owner, W^{S}, is hence a ratio, α of profit Π for firm i.

Figure 4.2b presents the three measures of estimating income for self – employed, who are identified in the corporate and household sector.[30] Overall, imputing average payroll wages, apportioning two-third of gross mixed income, or apportioning a ratio following Groves (2018) increases the level of the labour share and accentuates the trend. During the period of the global financial crisis, during which some sectors of Australia experienced weak growth, the gross income measures experience a sharper dip than payroll measures, reflecting weak profits and sales. Although it lifts the level, it does little to the overall change in labour share trends.

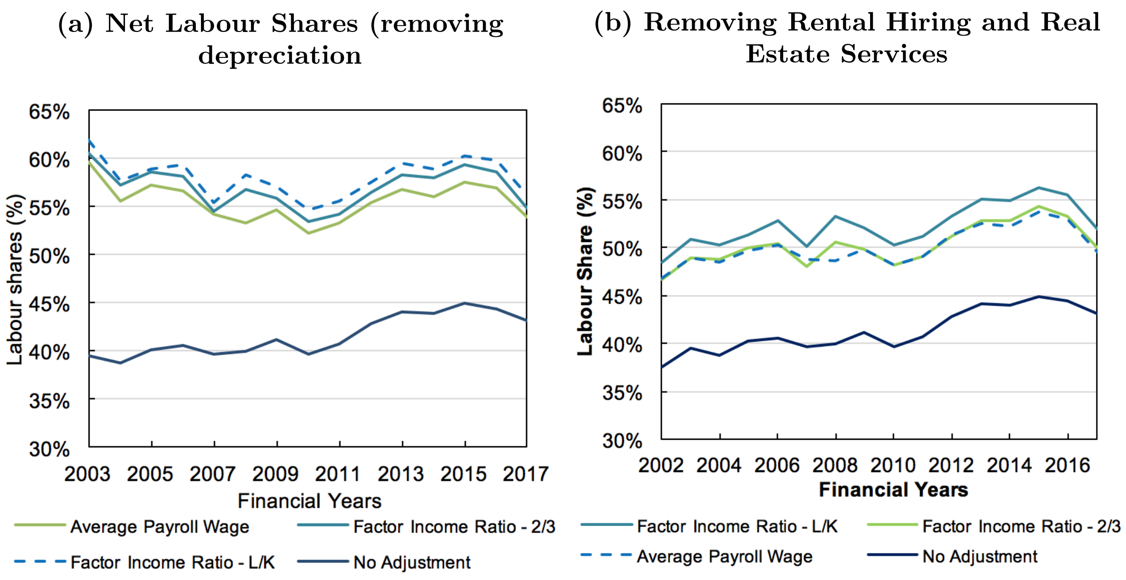
4.1.2 Depreciation of Capital Stock and Housing Returns

Barring measurement issues with value added due to the construction limitations imposed by BLADE,[31] there is a discussion over whether capital depreciation or housing returns should be removed from value added. Bridgman (2018) and Rognlie (2016) argue that the apparent shift away from labour in favour of capital and profits has been exaggerated by the rising importance of depreciation and housing in modern economies.

[30] Arguably the best method for estimating income for self-employed is using a hedonic regression, estimating the hourly compensation for an employee based on their skill, education, age and experience (Office, 2019). This was done by several papers, like Young (1995) and Jorgenson, Ho, and Samuels (2012) who estimated hourly compensation of employees based on census data, cross-tabulated by industry, sex, age and educational attainment level. Even though it may be limited in how it considers entrepreneurial activity (Gollin, 2002), it closely matches the individuals level of the skill, education, age, experience of the owner/entrepreneur. This is not within the remit of this thesis as access to linked employee-employer data is not available; however, this does facilitate a future research opportunity.

[31] For example, value added in BLADE does not split the value of terminated assets from actual value added.

Figure (4.3) Addressing Measurement issues with Value Added



Source: ABS BLADE 16-17, Author's Calculations

This figure plots the labour share of income for the market sector of the economy aggregated using firm level data. Panel (A) presents three versions of labour shares, and excludes depreciation from value added for all measures of labour share. Panel (B) removes the Rental Hiring and Real-estate Services division to remove the impact of rents on income

Figure 4.3a shows the results of gross and net labour shares. Rognlie (2016), Cho et al. (2017), and Bridgman (2018) have argued that income should be measured net of depreciation rather than gross, as depreciation costs do not affect current or future consumption or production.[32] The stock of depreciation has grown considerably over the past ten years, reflecting the increase in intangible assets, like computers and software (Bridgman, 2018; La Cava, 2019). Australia is unique from many of the countries studied by Bridgman (2018) and Rognlie (2016), however, as Australia also experienced a large capital investment in the mining sector during the mining boom (see e.g. Trott and Vance, 2018).[33] Net value added is a better measure of household income distribution, from a welfare perspective, and is a better indicator of whether profits and capital owners are truly gaining over labour. This has policy implications for wealth and income distribution, including capital taxation policy.

Figure 4.3a also shows that removing depreciation, there is a downward trend in labour share, accentuated during the mining boom. Since the mining boom, the labour shares have recovered but have not been able to reach pre-mining boom levels, resulting in a net

[32] Depreciation has been calculated using an estimate of the rate of depreciation constructed from ABS National Accounts. The capital stock which is subject to depreciation is the average investment made by a firm in a year, as provided in BAS statements.

[33] Trott and Vance (2018) also argues that Australia is unique because depreciation as a share of GDP fell slightly between 1960 and 2010 which is unique to the Global 7 Economies. However, the sample measured by BLADE is between 2002-2017, after Trott and Vance (2018)'s sample, and is more representative of the mining boom effects.

decline. Overall, net labour shares have fallen around 6 per cent between 2001-02 and 2016-17. In 2016, there was another large drop in net labour shares due to a jump in depreciation, largely from the mining sector as capital stock investment finally came online. These results are different to many countries studied by Rognlie (2016) and Bridgman (2018), where net labour share was stable or increasing in most countries except Japan. Moreover, Trott and Vance (2018) finds that net labour shares, measured using ABS National Accounts data, reflects historic average. It is difficult to assess whether these measures align with Trott and Vance (2018) perfectly, however, as the time period is different, and the historic average using BLADE cannot be calculated given the short period of the sample.

Lastly, Figure 4.3b depicts the results of labour share, accounting for housing returns. For several non-US countries, Gutierrez and Piton (2019) and Gutierrez (2018) find that the decline in labour share is entirely driven by the real estate sector. The impact is measured by removing the real estate sector, as this contains a lot of the rent.[34] In Australia, this is equivalent to removing the Real Estate and Rental Hiring Services Division. Figure 4.3b shows that removing real estate rents does not change the trend. It only lifts the trend in labour share. It is difficult to assess this as BLADE's measurement of value added does not account for rents.[35]

4.2 Heterogeneity in Labour Shares

Another advantage of firm level data is the ability to examine examines firm level patterns for the labour share of income. In addition to identifying key stylistic facts about the labour share in Australia, it serves a dual process of understanding how firm heterogeneity affects aggregate labour shares and motivating subsequent analysis.

Figure 4.4 plots the average weighted labour share calculated using equation 3.6 from Chapter 3 and the median labour share.[36] It depicts that the average weighted labour share is a level lower than the median labour share. This suggests that most firms in the economy have higher labour shares, but large firms have lower labour shares, pulling down the weighted average. Second, the aggregate trend differs from the median trend. While the aggregate trend has been increasing, the median trend fell around the GFC and has still not recovered to its pre-2008 levels. On net terms, median labour shares have fallen by 1.5 per cent. These trends are overall stable in time. This is a trend unique to Australia. For example, in the manufacturing sector in United States, Kehrig and Vincent (2017) found that aggregate labour shares have been increasing while median labour shares have

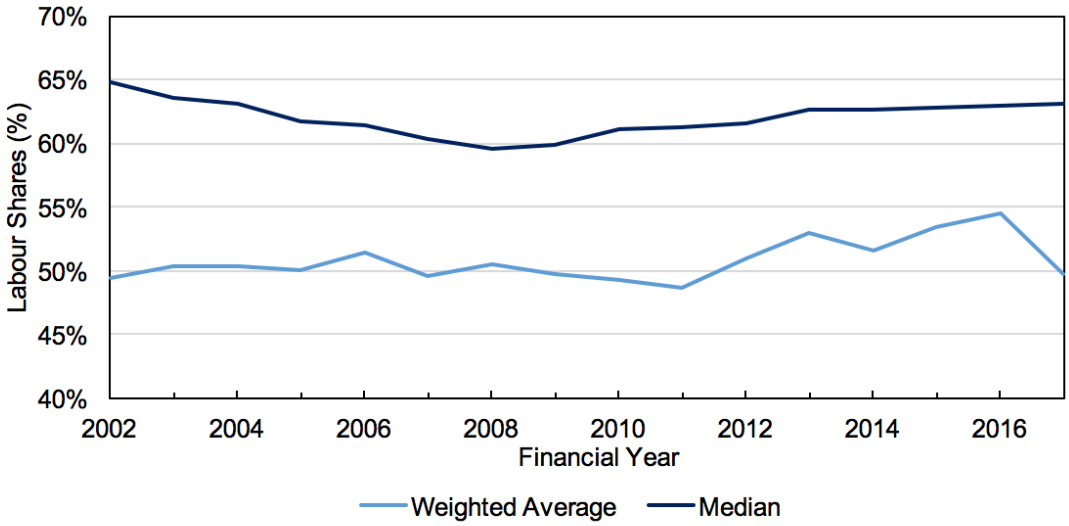
[34] This may over-control for housing returns. Gutierrez and Piton (2019) suggest an alternative method of imputing housing returns from National Accounts. This was outside the scope of this thesis to explore, but presents a future research opportunity.

[35] BIT in BLADE also provides a measure of rent for companies. While this is an alternative way to identify rents, it was limited to a small sample of corporations and there were measurement concerns of how 'rent' was calculated in BIT.

[36] The measure of labour share used is the adjusted labour share - it adjusts for the self-employed and business owners in the corporate and non-corporate sector, imputing payroll income as their wage.

fallen.[37]

Figure (4.4) Median and average labour share of the Economy



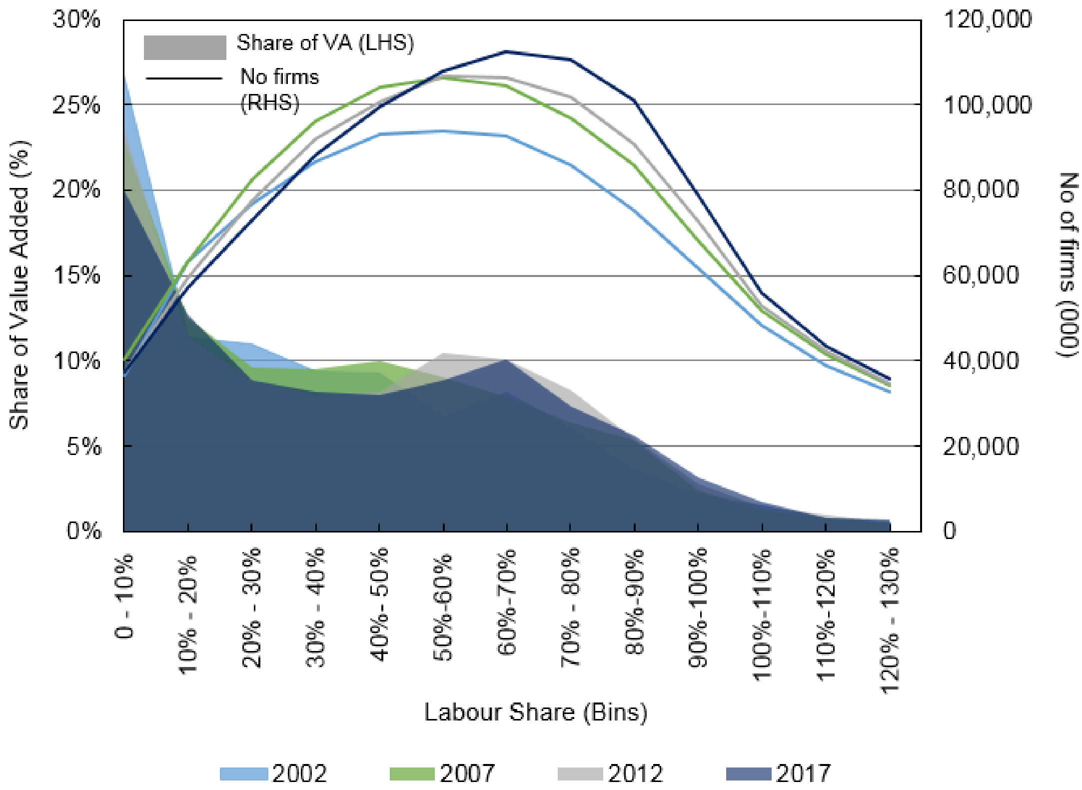
Source: ABS BLADE 16-17, Author's Calculations
This figure plots the weighted average and median labour share for the market sector of the economy aggregated using firm level data.

Another perspective is to plot the distribution of labour shares against the distribution of value added and number of firms in 2017, as shown in Figure 4.5.[38] Firm labour shares are divided into 10 per cent point bins from 0 per cent to 140 per cent each year. Then, the share of aggregate value added and share of firms is calculated for each labour-share bin. These shares are calculated at the 4-digit level, then aggregated up in each bin using the industry's value-added weight in each given year. This is to control for industry specific differences.

[37]It is important to highlight the difference. This is a report of the market sector excluding FIS - corporate sector and non-corporate sector included - while Kehrig and Vincent (2017) uses the manufacturing sector only and reports for the corporate sector.

[38]This reflects some of the analysis conducted by Kehrig and Vincent (2017).

Figure (4.5) Distribution of Value Added and Number of Firms Across Labour Share Bins



Source: ABS BLADE 16-17, Author's Calculations

This figure plots distribution of value added and number of firms across bins of labour share for three periods: 2002-2007, 2007-2012, and 2012-2017.

This chart shows five distinct results:

1. Looking at the bottom axis, there is considerable labour share heterogeneity for individual firms. Majority of firms in the economy have high labour shares, ranging from 50-80 per cent deciles, while only a few firms have labour shares less than 40 per cent.

2. Second, the distribution of value added across labour shares is distinctly left-skewed. Low labour share firms have a high share of value added, and while high labour share firms have a low share of value added.

3. Third, there are very firms which have low labour shares and high share of value added, and many firms which have high labour shares and low share of value added.

4. Figure 4.5 also overlays the distribution of labour share in 2002, 2007, 2012 and 2017. The chart depicts that the distribution of value added has become less left skewed, with value added shifting towards higher labour share firms.

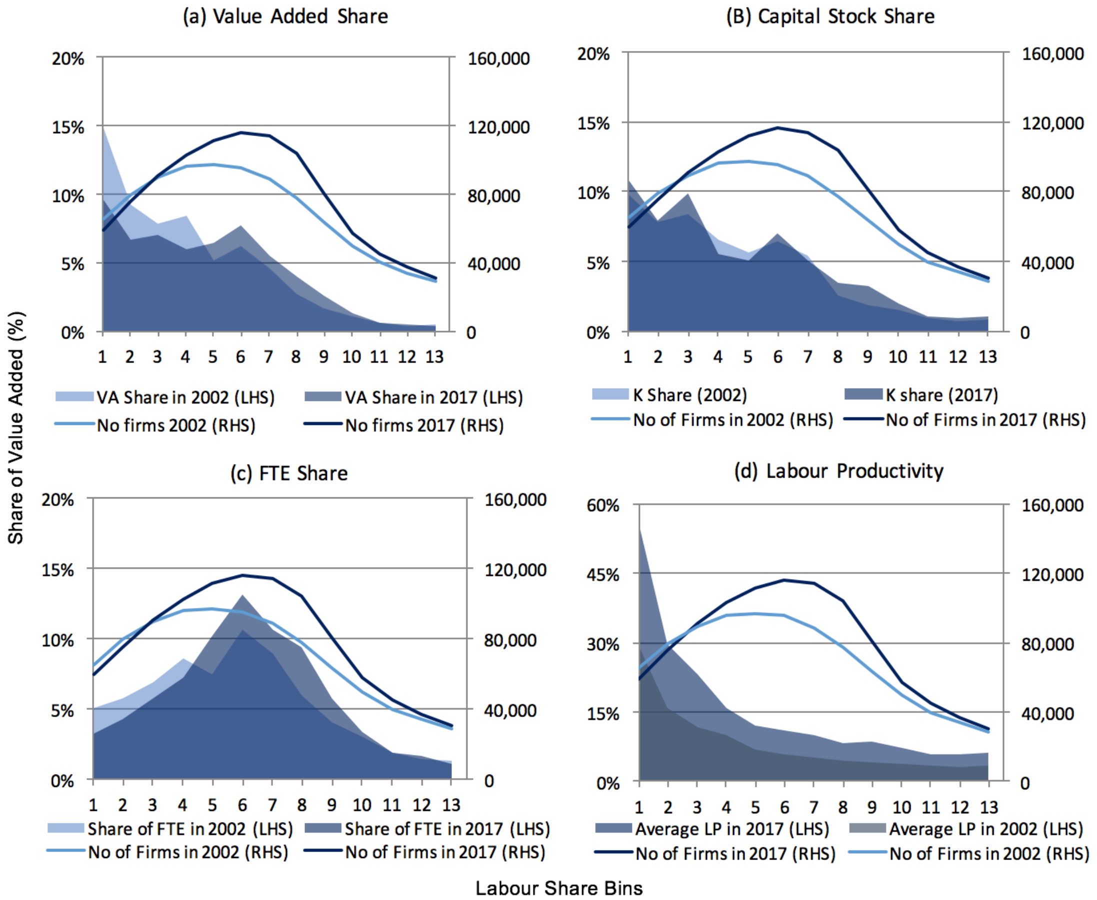
5. The number of firms with high labour shares has also increased with time, while the number of low labour share firms has decreased, but less so.

This findings imply that labour share change at the aggregate level is driven by both (1) a reallocation of value added to high labour share firms, as well as (2) the increase in labour shares within firms. This characteristic is unique to Australia. United States, China and Canada, in comparison, have recorded a reallocation of value added towards low labour share firms, with the number of low labour shares decreasing (Autor et al., 2019; Berkowitz et al., 2017; Gouin-Bonenfant, 2018; Kehrig and Vincent, 2017).

4.2.1 High Labour Share Firms

A natural question that follows this analysis is why has value added shifted towards high labour share firms? What are high labour share firms? Why have the number of high labour share firms increased? Similar questions arise for low labour share firms. In Figure 4.6, Chart A plots the distribution of value added across labour shares; Chart B plots capital stock across labour share bins; Chart C plots employment across labour shares and Chart D presents labour productivity over the labour share bins. These charts depict that on average firms with low labour shares are large businesses, in terms of value added, and are increasingly capital intensive. They are able to enjoy higher productivity, without employing a large share of employees, suggesting that they enjoy large gains in total factor productivity. High labour share firms, on the other hand, are small businesses that employ a large number of employees. They are less capital intensive than low-labour share firms and experience low labour productivity too. This suggests that low-labour share firms are highly productive while high-labour share firms are less. This is consistent with recent empirical research by Kehrig and Vincent (2017) and standard firm dynamic models like Jovanovic (1982) and Hopenhayn (1992), which posit that highly productive firms should also account for a large portion of input use. The analysis suggests that the number of high labour share firms has increased, alongside their share of value added, employment and capital stock. While this could suggest that they are becoming more productive, Chart D shows that their labour productivity has fallen, suggesting that they are not enjoying large gains despite employing a hire share of employment.

Figure (4.6) Distribution of Value Added, Capital Stock, Labour Productivity and Employment Across Labour Share Bins



Source: ABS BLADE 16-17, Author's Calculations

This figure plots distribution of (a) value added, (c) capital stock (c) employment and (d) weighted average labour productivity across bins of labour share for three periods: 2002-2007, 2007-2012, and 2012-2017. The lines represent the number of firms (RHS)

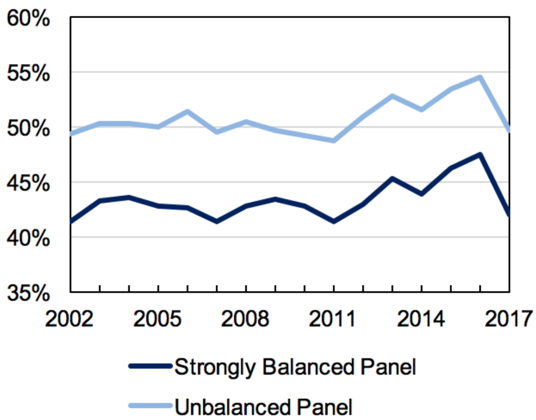
Hence, high – labour share firms have low levels of productivity and low-labour share firms are high in productivity. This aligns with recent analysis of wage growth by the Treasury (2017), which used BLADE to find that high productive firms also pay high wages, though not nearly as high in terms of employment. This explains why these firms have low labour shares. More productive businesses have on average higher capital per worker, and more productive businesses are also larger in size. Though these findings did not relate to labour shares, its consistent with the idea that high productive firms have higher productivity than wages (generating low labour shares), have lower labour shares and are more capital intensive.

The trend of reallocation of value added towards high-labour share low-productivity firms as well as the increase in high-labour share firms is worrying as this suggests declining allocative and productive efficiency at the intensive margin. This could also be driven at the extensive margin if high labour share firms are entering, and low labour share firms are exiting. Panel A in Figure 4.7a plots the aggregate labour share for a strongly balanced sample of firms that remained active through 2002 to 2017 against the unbalanced panel containing the exiting and entering firms. The figure shows that the aggregate labour share trend is largely driven by the incumbent firms. Exiting and entering firms do increase the level of the labour share, as the aggregate labour share of the strongly balanced sample is about 7 per cent points lower than the full sample. The conclusion that can be drawn is that the contribution of the extensive margin to the aggregate labour share trend is prominent, but not influential on the long-term trend. The long-term trend of relatively stable labour shares is driven by surviving firms.

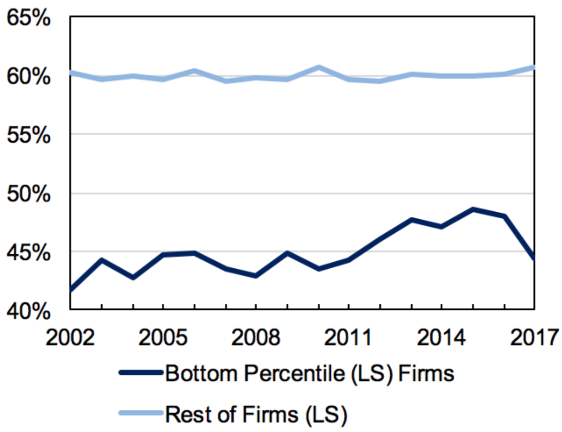
Figure 4.7b plots the aggregate labour share of firms which are in the bottom 20 percentile, in comparison to the rest. This shows that the main trend is driven by low labour share firms, while the rest of the firms have a flat labour share trend that is higher in level. It is therefore apparent that any attempt to explain the pattern in labour share in Australia over the past decade should focus on the distributional changes and reallocation changes in labour share for surviving firms as well as the largest firms.

Figure (4.7) Labour share of income for surviving firms (a) and low labour share firms (b)

(a) Labour share of income for strongly balanced panel



(b) Bottom percentile of the labour share of income



Source: ABS BLADE 16-17, Author's Calculations

This figure plots distribution of (a) value added, (c) capital stock (c) employment and (d) weighted average labour productivity across bins of labour share for three periods: 2002-2007, 2007-2012, and 2012-2017. The lines represent the number of firms (RHS)

Moreover, Kehrig and Vincent (2017) show that low labour share firms are highly transient. Performing a similar exercise, the Markov Transition Matrix in Table 4.2 considers probability of whether a firm is a 'low labour share (LL)' firm and 'high labour share (HL)' firm in 5 years.

Table (4.2) Transition Probabilities of High Labour Share Firm (HL) and Low Labour Share firm (LL)

	HL_t	$LL_t)$
HL_{t+5}	88.21%	43.12%
LL_{t+5}	10.57%	56.62%

Source: ABS BLADE 2016-17.
This table presents the Markov matrix of labour shares, asking the question conditional on an firm's labour share at time t, what is the probability that it will be the same HL/LL firm in $t + 5$. The Markov accounts for the share of aggregate value for each firm.

The probability that a LL remains LL in 5 years time is 56 per cent, which is more than the probability of 46 per cent recorded in USA by Kehrig and Vincent (2017). However, what is surprisingly, is the probability that a firm was a low labour share firm 5 years ago and is now not is 41 per cent. This is very high, in comparison to USA which only measured 13 per cent. As HL firms are less productive, this indicates a decline in efficiency. Similarly, the probability that a firm will likely to move onto being a low labour share firm labour share firms is very low, at 10 per cent. In comparison, this was around 40 per cent in the United States, which indicates that Australia lacks mechanisms to boost efficiency. These statistics suggest that low labour shares are highly transient, with a tendency to become high labour shares over time.

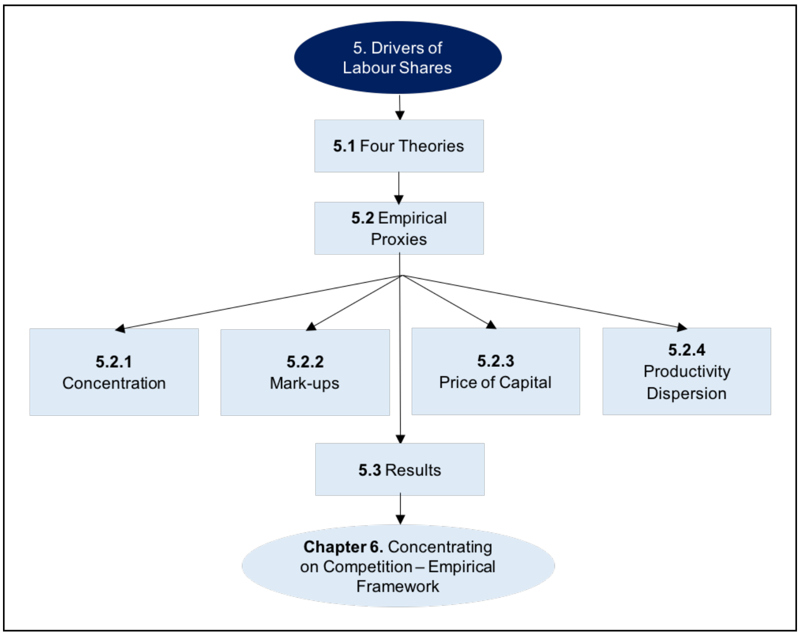
Overall, these findings at the firm level dynamic suggest an increase in the number of high-labour share firms, which are less productive, and a reallocation of value added towards high labour share firms. Increasingly, low labour share firms are unlikely to remain low and productivie, giving rise to concerns about productivity and allocative efficiency in the economy.

Chapter 5
Drivers of Labour Share

The heterogeneity in firm level labour shares and dynamics over time present a strong case to assess the drivers of labour share and understand the forces underlying these dynamics. Several theories have been put forward to explain the trends in labour share of income, none of which have been tested at the firm level in Australia to my knowledge.[39]

Figure 5.1 gives an overview of this chapter. Section 5.1 explains four prominent theories used to explain labour share trends, which were explored earlier in the literature of Chapter 2. Section 5.2 examines the empirical proxies that are constructed to test these theories and Section 5.3 conducts reduced form OLS and non-parametric regressions with fixed effects to identify the drivers, providing some interpretation to the results. To preview findings, concentration and mark-ups are inversely related to labour share, while the price of capital is insignificant in the standard OLS regression. This suggests that there are competition factors driving labour share trends.

Figure (5.1) Chapter 5 Overview - Drivers of Labour Share



[39] Several authors have put forward explanations to describe the changes in labour share e.g. McKenzie (2018), Stanford (2018), Peetz (2018), Weir (2018), La Cava (2019) and have used aggregated income share data to test these results.

5.1 Four Theories

The following section summarises four key theories put forward by the literature to explain changes in labour share.

- **Superstar Firms:** Autor et al. (2017, 2019) and Kehrig and Vincent (2017) believe that the compositional change towards highly productive and low labour share firms and their increase in market share has driven an aggregate decline in labour share. In particular, Autor et al. (2019) links the compositional changes to concentration measures, showing that US labour shares decreased the most in industries that have become more concentrated. Similarly, Schwellnus et al. (2017) argue that the decline has been driven by highly productive firms, while laggard firms experience an increase in labour shares due to diverging trend in labour productivity and real wage growth.

- **Rent-Seeking Behaviour:** Barkai (2016), De Loecker and Eeckhout (2017) and Caballero, Farhi, and Gourinchas (2017) argue that declining competition and increasing market power has led to the decline in labour shares. These papers have established that profit shares, mark-ups and concentration has increased within the US and demonstrated labour share is inversely related to these measures.

- **Role of capital:** Karabarbounis and Neiman (2013) argue that capital and labour are substitutes and that the decline in price of capital has led to greater investment in capital, increased capital accumulation, an increase in capital share and the fall of labour share. In a similar way, Piketty and Zucman (2014) argue that declining productivity growth has led to capital accumulation and the decline in labour share. These findings, however, have been subject to criticism: previous studies of developed countries have found that the elasticity of substitution between capital and labour is less than one suggesting that they are complements, and it has been found that the price of capital has remained relatively stable in the 2000s, with majority of the decline happening prior (Gutiérrez and Philippon, 2017). Other theories like the role of automation come under this section too (Autor and Salomons, 2018).

- **Monopsony power:** Lastly, Gouin-Bonenfant (2018) believes that increasing productivity dispersion explains labour share decline in Canada. In this model, more productive firms offer higher wages to incentivise workers, causing real wage growth to be higher than productivity. Small firms, however, try to cut costs to compete, leading their wages to be less responsive to productivity, while productive firms are shielded from this wage competition. This supports the conjecture surrounding the rising productivity gap between frontier and laggard firms (e.g. Andrews et al., 2015; Weir, 2018).

Besides the four theories explored above, the theories related to international trade and offshoring (Dao et al., 2017; Elsby et al., 2013) and the role of labour market institutionalisation and decline in unionisation will not be explored due to lack of firm level data.[40] This is unfortunate but provides an opportunity for a future research topic;[41] however, as Weir (2018) suggested, trade and unionisation may not play a large role in explaining the within industry changes observed in Section 2, as both of these relate to industry-wide phenomenon. Moreover, many of the labour market changes have occurred since 1970s, and the data only canvases the period after 2002.

Theories related to the measurement of labour share have already been considered in Chapter 4. For example, Rognlie (2016) argues that rise of returns to housing capital is driving the labour share change. The results show that this is not relevant to the story of labour share using BLADE, as removing rent through the Real Estate and Rental services division has no substantial impact on the magnitude or the trend, as rent is not included within the measure of value added in BLADE. Second, Koh, Santaeulalia-Llopis, and Zheng (2018) argue that intangible capital accounts entirely for the decline in the labour share in the US labour share. However, within Australia, intangible capital is estimated within for in the ABS estimates of capital stock, which I use to calculate capital share.

5.2 Empirical Proxies

The proxies constructed to test the above four theories include concentration ratios, mark-ups, productivity, capital density, cost of capital, and productivity dispersion. Below provides an overview of the proxies and their relationship with the theories, with a brief overview of how they were constructed. Appendix B provides further information on how the proxies were calculated and Appendix C presents further results of the proxies not analysed in this chapter.

- **Concentration Ratio of Top 4 firms**, to test the first two theories of 'rent-seeking' and 'superstar firms'. Other measures are also tested like the ratio of top 10 firms, ratio of top 20 firms and the Herfindahl Hirschman Index which are common concentration measures used in the literature (see e.g. Syverson, 2017).
- **Mark-ups**, to test the first two theories of 'rent-seeking' and 'superstar firms'. They have been calculated using the methodology outlined by De Loecker and Warzynski (2012) and subsequent papers, where mark-ups are calculated as the ratio of output elasticity over input share. For this exercise, a gross output production function is estimated to compute output elasticities and intermediate input cost shares are used. This is to avoid endogeneity with labour shares. Further details on how they were constructed is provided in Appendix B and the results are presented in Appendix C.

[40] International trade cannot be tested as my version of BLADE does not contain trade data, and firm level trade data is not available elsewhere.This is unfortunate, as a forthcoming version of BLADE (which I do not have access too) will have trade data. It is still possible to test for industries more exposed to trade through the measure of export sales, but it is difficult to test for import penetration as BLADE does not have this data.

[41] For example, linked employer-employer data with union records or a future version of BLADE where trade data becomes integrated would be beneficial.

- **Capital intensity**, to test the 'the role of capital' theory. This is calculated as the ratio of capital stock over value added. Capital stock is calculated according to the method outlined in Appendix B.3.
- **Relative price of capital, User cost of Capital and Rental rate of return**, to test the 'the role of capital' theory, and whether the decline in the price of capital has caused there to be stronger investment in capital. These prices are calculated from National Accounts data. It is calculated as Gross Fixed Capital Formation (current prices) divided by Gross Fixed Capital Formation (Chain Volume Measures). Further information in Appendix B.3.
- **Productivity Dispersion**, to test the 'monopsony' theory, labour productivity and total factor productivity (TFP) using Olley and Pakes measure is estimated. (Further details are provided in Appendix B). Dispersion measures as estimated as the interquartile range of labour productivity (the top 25% minus the bottom 25%)

Table 5.1 summarises the four theories and the empirical proxies used to test them.

Table (5.1) Empirical Proxies Constructed

Theory	Empirical Proxy	Symbol
Superstar Firms	Concentration ratio of Top 4 firms	CR4
	Mark ups (gross output function)	μ
	Productivity	LP, TFP
Declining Competition	Concentration ratios	CR4
The Role of Capital	Capital Intensity	$\frac{K}{Y}$
	Price of Capital	P^K_{t-1}
	Rental Rate of Return	R_t
Monopsony Power	Labour productivity Dispersion	IQR(lp)
	TFP dispersion	IQR(tfp)

Notes: This table presents a summary of the four theories used to test labour share trends, and the empirical proxies that are constructed to test them.

A brief overview of the trends in the measures constructed are provided. Out of these measures, concentration, mark-ups, labour productivity and the price of capital are factors that have had the largest change at the economy level between 2002-2017.

5.2.1 Concentration

Figure 5.2a shows that concentration of the top 4 firms, top 10 firms, top 20 and HHI has increased significantly over the past sixteen years, in line with a growing body of work in Australia (e.g. Bakhtiari, 2019; Hambur and La Cava, 2018; Leigh and Triggs, 2016; Minifie, 2017). Around 56% of Australian four-digit ANZSIC industries have recorded an increase in concentration between 2001-02 and 2016-17, in terms of the concentration ratio of the top four firms.[42] Mining, utilities, and information media & telecommunication sectors are the most heavily concentrated, while construction, accommodation food services, and professional services are the least concentrated. Figure 5.2b shows that retail, professional scientific and technical services have had the largest increases in concentration of the top four firms, while accommodation and food services as well as electricity, gas services have had the largest falls in concentration. In Appendix C, there are division level disaggregations for concentration.

5.2.2 Mark-ups

Second, Figure 5.2c depicts that intermediate input weighted average mark-ups have grown by 5 percentage points between 2001-02 and 2016-17, which is less than the measured growth by De Loecker and Eeckhout (2017). Mark-ups range from 1.15 to 1.4, depending on the method of measurement and time. These are in line with De Loecker et al's estimations using gross output. Figure 5.2c also shows mark-ups for the economy, aggregated using sales share as a weight, gross output as a weight and intermediate input share as weights. It also reports the unweighted and median estimates (Edmond et al., 2018). All measures have increased, though the value added weighted measure has experienced a larger growth and is a level higher reflecting that a sales weight is biased upwards (Edmond et al., 2018). The level and growth of the median and unweighted mark-ups is lower than the weighted mark-ups, suggesting that small firms have lower mark-ups and that the aggregate trend of increase is driven by large firms. Figure 5.2d plots the changes in mark-up levels for each division. On the most part, divisions which experienced an increase (decrease) in concentration have also experienced an increase (decrease) in mark-ups.

5.2.3 Price of Capital

Trends in the price of capital have been broadly increasing between 1980 to 1990 but have since declined or remained relatively flat. Figure 5.2e confirms this.These trends differ from the United States, where evidence suggests that that the price of capital declined between 1980s and 1990s, not in the 2000s.

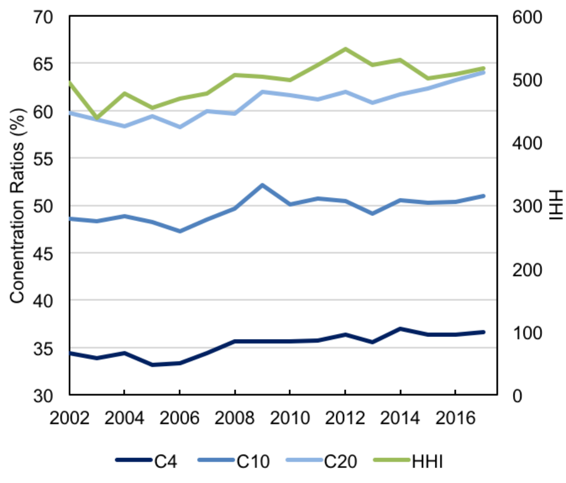
5.2.4 Productivity Dispersion

There is limited evidence for the growth in productivity dispersion. As Figure 5.2f, there has been no net change from 2001-02 and 2016-17. However, in the intervening years there was large growth in dispersion up until 2004-05 after which it fell till 2014-15 and has since been recovering to its 2001-02 levels. This aligns with the findings by Andrews et al.

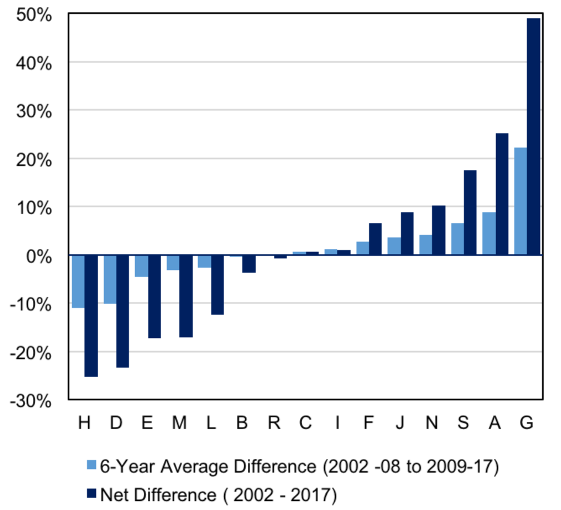
[42] Hambur and La Cava (2018) find that around 78% of 4 digit ANZSIC industries have experienced an increase in concentration. There sample size is larger, including non-market sectors like education and health care which had the 3rd and 8th largest increase in concentration. Hence, their exclusion from our sample would reduce the share of 4-digit industries experiencing an increase in concentration and bias their result upwards.

Figure (5.2) Empirical Proxies Constructed

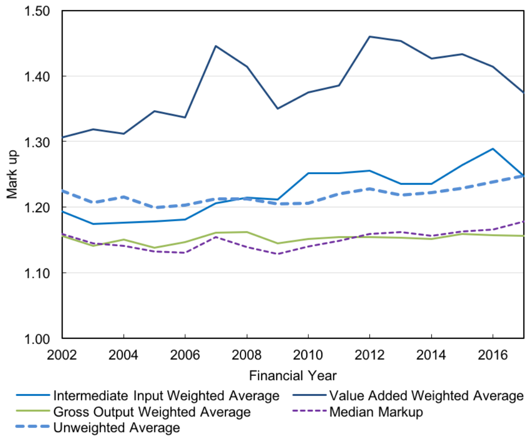
(a) Economy Level Concentration, overtime



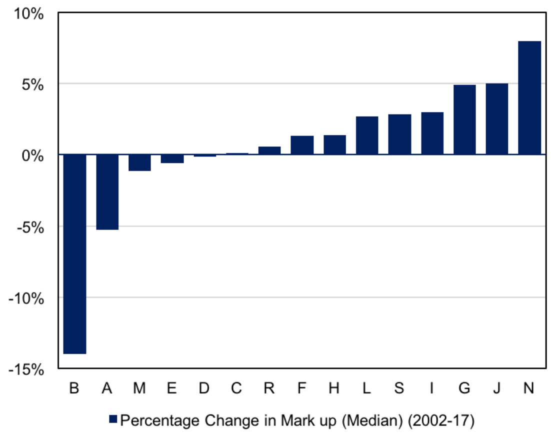
(b) Division Concentration of top 4 firms, changes over time



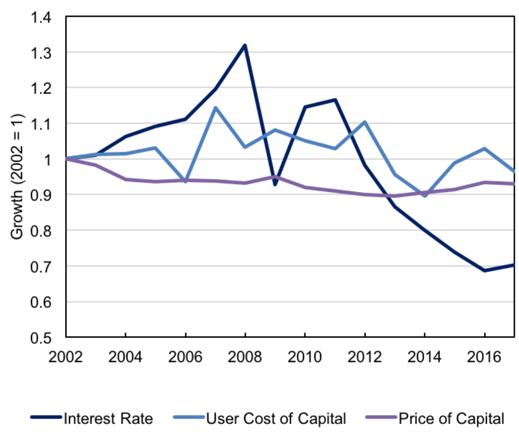
(c) Economy Mark-up, over time



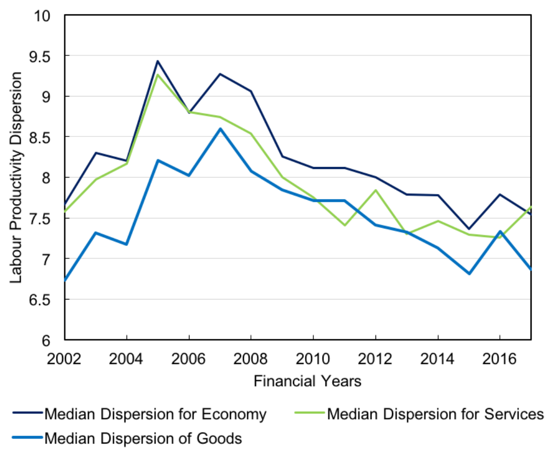
(d) Division Mark-Up (Median), changes over time



(e) Price of Capital, by different measures



(f) Median of Average Labour Productivity Dispersion, by type



Source: ABS BLADE 16-17, Author's Calculations
This chart plots various time series of the empirical proxies

(2019) who argue that there is limited evidence for growing labour productivity dispersion using BLADE. Another paper by Campbell et al. (2019) finds that labour productivity dispersion has increased in select industries, which I find true in the data as well.

5.3 Results

To test the relationships described by the four hypotheses, an OLS reduced form regression is conducted to identify correlative relationships with labour share. The unit of observation is at the 4-digit ANZSIC Industry level,[43] using time-sector fixed effects and standard errors clustered at the 4-digit industry level:

$$\log \lambda_{jt} = \beta_0 + \beta_1 X_{jt} + \beta_2 Z_{jt} + \tau_t + \eta_j + \epsilon_j t \tag{5.1}$$

where $\log \lambda_{jt}$ are log (labour shares) at time t for 4-digit industry j, X_{jt} represents the empirical proxy (no log or log specified in the results table), Z_{jt} represents a vector of industry controls, including size in terms of employment and average capital intensity; τ_t represents a vector of time-sector fixed effects.

Table 5.2 below summarises the regressions for the OLS regression. Overall, the results suggest a significant inverse relationship with labour shares and concentration, mark-ups, and labour productivity dispersion, but not the remaining hypotheses.

Column (1) of Table 5.2 denotes that there is a a striking relationship between labour shares and concentration: a 1 percentage point increase (decrease) in the top-4 firm concentration ratio leads to a fall (increase) in labour share by 1.75 percentage points. This is consistent with Autor et al. (2019) and Barkai (2016), who find that the increase in concentration is a primary driver of labour share decline in USA. In Column (2), the estimated coefficient for the labour productivity dispersion $\beta_{LP} = -0.135$ is negative and statistically significant at the 1% level. This is consistent with Gouin-Bonenfant (2018) hypothesis, where we would expect that the coefficient on labour productivity dispersion to be negative, as firms with the largest productive dispersion are the largest drivers of the decline. The magnitude is overall lower than Gouin-Bonenfant's results, which reflects how labour productivity dispersion has remained on balance, stable between 2001-02 and 2016-17. This suggests that there is both a role for labour productivity dispersion and superstar dynamics in Australia's story of labour share decline. Columns (3) present the results of regressing mark-ups on labour share. It shows that an increase in mark-ups by 10% will drop average labour shares in the industry by 0.4%. This supports the evidence of De Loecker and Eeckhout (2017) who found that mark-ups and labour shares are inversely related.

In Column (5), the estimated coefficient for capital intensity $\beta_{K/Y} = 0.00147$ is positive and statistically significant. In capital intensive industries, there is a higher labour share, suggesting a capital-labour substitution ratio of greater than 1 and a complementary

[43] firm level data has been aggregated up to the 4-Digit Industry Level using weighted means.

Table (5.2) OLS Reduced Form Regression for Entire Economy

	(1) $\log(C4_{jt})$	(2) $\log(IQR_{LP})$	(3) $\log(IQR_{tfp})$	(4) $\log \mu_{jt}$	(5) $\frac{K_{jt}}{Y_{jt}}$	(6) $RelPriceofK$	(7) $\log(R_{jt})$	(8) $\log(uc_{jt})$
$\log(\lambda_{jt})$	-1.753***	-0.134***	-0.126	-0.0419**	0.00147***	0.327	0.906*	0.22
	(0.08)	(0.03)	(0.15)	(0.01)	(0.00)	(0.36)	(0.44)	(0.35)
Constant	4.884***	-1.046***	-1.114***	-0.995***	-1.099***	-1.387***	0.872	-1.060***
	(0.27)	(0.05)	(0.09)	(0.05)	(0.05)	(0.37)	(0.94)	(0.05)
Observations	7193	7188	7182	7190	7193	7193	7193	7193
R^2	0.228	0.042	0.04	0.04	0.073	0.038	0.039	0.038
Adjusted R^2	0.226	0.04	0.038	0.037	0.071	0.036	0.037	0.035
Pseudo R^2								
AIC	17619.7	19026.3	19019.4	19182.8	18935.5	19200.8	19193.5	19202.7
BIC	17729.8	19136.4	19129.5	19292.8	19045.6	19310.9	19303.6	19312.8
F	38.11	8.032	5.723	5.644	6.582	5.194	5.333	5.217
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X

Source: ABS BLADE 16-17, Author's calculations

Standard errors are presented in the parentheses. Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

This table presents the results of an annual fixed effects regression of several empirical proxies on labour share according to the specification in Equation 5.1. Time and industry fixed effects are used, and an industry control of size is used. Standard errors have been clustered according to the 4-digit industry level. The unit of observation is at 4-digit industry level, produced by aggregating firm level data using a weighted mean. The dependent variable is labour share. Each coefficient represents the results of regressing labour share on an empirical proxy. The empirical proxies include the log of the concentration ratio of top four firms (C4), log of the interquartile range of labour productivity, log of the interquartile range of total factor productivity, log of mark-ups, capital intensity, the relative price of capital over labour, the rental rate of return and user cost of capital.

relationship between labour and capital (contrary to evidence by Karabarbounis and Neiman (2013) but consistent with several other papers). After controlling for capital intensity, the coefficients for concentration and labour productivity dispersion remain relatively unchanged as well (Column 5). The magnitude is very low, however, and there is no evidence that capital biased substitution is driving the decline.

This is further supported by Column (6) - (8), which tests the relationship between the price of capital and labour share. According to Karabarbounis and Neiman (2013) hypothesis, a fall in the price of capital would result in capital accumulation, substitution of capital over labour and the decline in labour share. We test three measures for the price including the price of capital, the rental cost of capital and the user cost of capital. All three have insignificant, but negative coefficients. This suggests that the increase in the price of capital leads to an increase in the labour share. An explanation for this could be labour biased substitution or the 'productivity' effect described by Acemoglu and Restrepo (2018), where automation improves the productivity and output of labour. Alternatively, the 'displacement effect' of automation could be counteracted by the creation of new tasks where labour has a comparative advantage. Australia is a service-based economy, and it has shifted towards niche manufacturing and automation jobs.

Out of all these empirical proxies, the coefficient on concentration for the regression on labour share was most significant, in Column (1). This model also had the highest explanatory power in terms of R^2 and adjusted R^2.

5.3.1 Alternate Specifications

The justification for alternative specifications is that the distribution of labour share is slightly right skewed and there is significant heterogeneity in labour shares across firms and industries. It is also a large dataset. First, a quantile regression takes into consideration outliers and heteroskedasticity (see e.g. common for micro panel datasets Gutierrez, 2018). An OLS linear regression may not capture the variation in labour share as it models the conditional mean, whereas a quantile regression models the conditional, is distribution free and semi-parametric method. Second, a non-parametric regression is run to lessen the risk of misspecification as this is a large dataset.

Estimates are found in Appendix D, confirming the findings in Section 5.3 that concentration is most related to labour shares, while mark-ups and productivity dispersion are the next most significant.[44] Results for the quantile regression are presented in Table D.1 and the non-parametric regression, in Table D.2. The interesting finding is that capital cost and relative price of capital are positive and larger in magnitude than OLS regressions, but in the non-parametric regression, the estimates are negative. This suggest that OLS estimates may have been biased by outliers, and there may be a mispecification.

[44]This is also verified through the R^2 and R^2_{adj} which is highest for concentration.

5.3.2 Sub-sample analysis, by Type

Table D.3 and Table D.4 in Appendix D present the results of examining the relationship of labour share and the empirical proxies across different sectors in the economy, and different firm sizes, respectively. The results are consistent with the economy level findings. The effects of concentration and mark-ups are stronger in the corporate sector and in larger firms than the rest. Moreover, the price of capital is significant when you split it between corporate and non-corporate sectors.

Appendix Table D.3 presents the results of regressing labour share on the empirical proxies for the corporate sector versus the non-corporate sector and reveals many interesting results. First, the relationship of concentration and labour productivity dispersion is consistent for the corporate and the non-corporate sector. However, the magnitude of the effect is considerably larger for the corporate sector. An increase in the concentration by 1% leads to a fall in labour shares for both the corporate and non-corporate sector, but the fall is nearly 2% larger for the corporate sector. A second result is that mark-ups impact the corporate and non-corporate sectors differently. At the non-corporate level, there is a direct relationship between mark-ups and labour shares. This could be explained because around 99% of businesses in the household sector are run by those who are self-employed. Hence, any increase in mark-ups leads to a direct increase in profits, which is consumed by the owners of the business in the form of retained profits. At the corporate sector, there is an inverse relationship: an increase in mark-ups by 1% causes the labour share to fall by nearly half a percentage point. This supports the Autor et al. (2019) and De Loecker and Eeckhout (2017) which look at corporate firm level data to find that mark ups and labour shares are inversely related. Third, the relationship between labour shares and cost of capital is now significant and negative. For the non-corporate sector, an increase in the cost of capital by 1% leads labour shares to fall dramatically by around 9%. In comparison, it will fall by only half a percentage more for the corporate sector. This suggests there is capital-biased movement towards capital. A possible explanation for why this relationship was not significant at the economy level is that separating it into the corporate and non-corporate sector teases out the different capital stock arrangements as well as the different costs of capital.

Appendix Table D.4 presents the results of regressing labour share on the empirical proxies, considering different firm sizes. Groups of micro, small, medium, medium large and large businesses are grouped then aggregate them to the economy level.[45] The results are consistent with Table 5.2, but show that as a business gets larger, the impact of an increase in concentration, mark-ups, and labour productivity dispersion is larger on labour shares.

[45] Micro businesses are those with 0-4 employees, Small businesses are those firms with 5-19 employees; Medium businesses are those with 20-99 employees;Medium Large businesses are those with 100- 199 employees; Large businesses are those with 200 or more employees

5.3.3 Robustness Test for Concentration and Mark-ups

Using firm level data, the baseline results highlight a significant and robust relationship of concentration and mark-ups on labour shares, after accounting for industry-heterogeneity and cyclical factors. This is consistent with international literature such as Gutierrez (2018), Autor et al. (2019), and Barkai (2016), who conduct a similar reduced form regression. The cost of capital and labour productivity dispersion were either insignificant or small in magnitude, across various measures and empirical specifications.

Concentration and mark-ups are used as proxies for two of the five theories in Section 5.1, and both of them relate to competition models. While firm level mark-ups are a more direct measure of business competition as it reflects the ability of firms to raise prices above marginal costs (Basu, 2019; Syverson, 2017; Tirole, 1988), concentration ratios have caveats.[46] To confirm the findings found in the previous section, many additional robustness tests for concentration and mark-ups are conducted. For parsimony and space reasons, the regressions tables are listed in Appendix D.

- Appendix Table D.5 presents the results of an annual fixed effects regressing concentration on labour share, with standard errors clustered at the 4-digit level. Three different measures of labour share are used: unadjusted for self-employed, adjusted for household, and adjusted for both household and corporate sector. There are also four measures of concentration used: concentration ratio for top four firms (CR4), top ten firms (CR10), top twenty firms (CR20) and Herfindahl – Hershman Index (HHI).[47] The results confirms that across all measures of labour shares and concentration, concentration is negatively and significantly related to labour share.

- Appendix Table D.6 presents the results of a 6yr and 16 yr long in differences regression, following the specification Barkai (2016) and Autor et al. (2017, 2019). Although annual fixed effects have already been tested which account for more heterogeneity than a regression in difference, these regressions are conducted to check Australia's results against the findings in Barkai (2016) and Autor et al. (2017, 2019). All the coefficients confirm the inverse relationship between concentration and labour share. The magnitudes are overall slightly higher than Autor et al. (2017, 2019) and Barkai (2016).

- These results are also robust to the alternative definition of labour share, where

[46] First, the concentration ratios constructed only consider domestic competition, as BLADE provides data for domestic firms only. Australia is an open economy, however, so competition from imports of goods and services have not been considered. As a result, concentration ratios may overstate concentration in industries with substantial trade, particularly in the manufacturing (e.g. car), mining and retail sector, where there is substantial international market penetration and large import competition. Moreover, while concentration is useful for relatively static markets, it's not very useful for measuring competition in dynamic markets, where there is firm entry and exit. Lastly, the difficulty relying on the HHI estimate is that it has not been calculated on a 'market'. Market can be defined by a physical boundary (e.g. km radius) or even interstate, or cross industry. Here, we have adopted HHI estimate for an industry, assuming the product market is matched to its industry.

[47] These measures have been used frequently to assess the level of competition globally (Dao et al., 2017), within the United States (Autor et al., 2017) as well as Australia (Hambur and La Cava, 2018)

labour share is calculated as wage compensation over gross output. This is shown in Appendix Table D.7. The magnitudes are lower than value-added based measures of labour share, as gross output includes intermediate inputs as well. However, these results support the finding that concentration and labour share have a negative relationship.

- Table D.8, Table D.9, Table D.10 and Table D.11 construct different measures of concentration, using value added, total sales (turnover), full-time equivalent and headcount as alternative measures to gross output. The alternate measures of output, turnover and value added, both produce the same negative and statistically significant relationship between concentration and labour share. In contrast, the concentration measures based on employment and headcounts do not produce statistically significant results with labour share, and the coefficients are positive (with some exceptions). Autor et al. (2017, 2019) argue that this is not a problematic feature of their model, as the appropriate measure of concentration for superstar firms would be sales, not employment, as such firms would hire few people but be human-capital and IT intensive.

- Lastly, Table D.12 presents the results of a firm level OLS regression of firm-mark-ups against industry concentration, with various fixed effects. For all tests, there exists a negative relationship between labour shares and mark-ups, suggesting that when there is an increase in mark-ups, this leads to a fall in labour shares. The results confirms the inverse relationship between labour shares and mark-ups as well. The results are robust to different time fixed effects, division fixed effects, industry fixed effects and firm fixed effects.

Chapter 6

Concentrating on Competition - An Empirical Framework

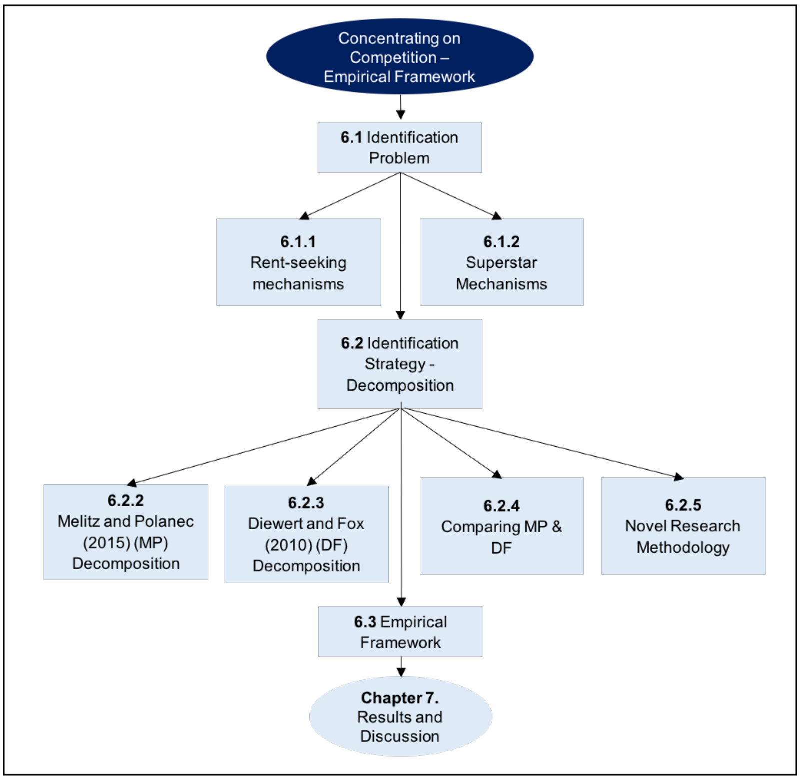
In Australia, concentration and mark-ups are negatively associated with labour shares.[48] This correlation can be explained by two monopolistic competition models briefly explored in Chapter 5: one was called the *rent-seeking* model and the other was referred to as the *superstar* model.

Determining whether the change in labour share is consistent with the rent-seeking or superstar model is important from a policy perspective. The rent-seeking model suggests weakening anti-trust regulations and anti-competitive behaviour (Barkai, 2016; De Loecker et al., 2016; Eggertsson et al., 2018). Conversely, the superstar model indicates that 'winner-takes-all' dynamics through technology and globalisation is improving competition (Andrews et al., 2015; Andrews, Criscuolo, and Gal, 2016; Autor et al., 2019; Van Reenen, 2018). The process of identifying which model is empirically evident in the Australian economy is difficult, however. While concentration ratios and mark-ups are commonly used to measure competition, they are endogenous and they could signal increasing or decreasing competition (Syverson, 2017; Tirole, 1988).

Figure 6.1 gives an overview of how this chapter aims to disentangle the two competition models and evaluate which one is relevant to Australia. First, this chapter will first explain the identification problem in detail in Section 6.1. Second, it will outline a novel identification strategy in Section 6.1.3 and lastly, the empirical framework to evaluate the relationship between labour shares and competition in Section 6.3. This thesis contributes to the literature by proposing a novel method to the identification strategy, building on Autor et al. (2019)'s model and uniquely adapting the Diewert and Fox (2010) productivity dynamic decomposition method. Through this, this thesis argues that it is more effective to decompose labour share changes adapting the Diewert and Fox (2010) productivity dynamic decomposition method than solely relying on the method used by Autor et al. (2019).

[48] Industries with the largest increases in concentration and mark-ups have had the largest fall in labour share (accounting for other factors as well) while industries with the largest falls in concentration have experienced an increase in labour share. It also identified that labour productivity dispersion is affecting the aggregate trend, while the decline in the price of capital has affected the labour shares of only certain industries. In both cases, the coefficient for concentration remained unchanged suggesting that the mechanism for the superstar or rent-seeking model remains intact.

Figure (6.1) Chapter 6 Overview - Concentrating on Competition - An Empirical Framework



6.1 Identification Problem

6.1.1 Rent-seeking mechanisms

The rent-seeking model is a simple monopolistic competition model (Barkai, 2016; De Loecker et al., 2016; Eggertsson et al., 2018; Tirole, 1988). An increase in concentration reflects increased barriers to entry and entrenchment of surviving firms within the sector. This enables firms to charge higher prices and mark-ups, restricting output and increasing profit. In such a model, this leads to a fall in labour share of income, as the share of profit increases and mark-ups increase (refer to equation 3.2 in Chapter 3) for the relationship). In the rent-seeking model, all surviving firms will benefit from the growth in profits and experience a decline in labour share. This suggests a within-industry increase in profit shares and a within-industry decline in labour share. The inverse characteristics would be evident in the decline of concentration.

There has been considerable empirical evidence to support rent-seeking behaviour globally. Barkai (2016) find evidence of increasing profit shares in the United States and connects increasing concentration to declining labour share, using firm level and industry level data. Barkai further validates these empirical results with a standard neoclassical model to show that capital and labour share can only simultaneously fall if there has been a decline in competition. Gutiérrez and Philippon (2017) believes there is also a lower level of investment and productivity growth in this industry, reflecting the inherent nature of entrenchment. Further, De Loecker et al. (2016) argue that mark-ups have increased globally, and that in a standard monopolistic model, keeping other factors constant, this drives a decline in labour share. Eggertsson et al. (2018) argue that a 'non-zero rent economy' has emerged, where a decline in competition or increase in barriers to entry has caused the number of firms to fall and increased concentration. There is also a concern that the increase in market power which has driven labour shares has driven other trends, like declining business dynamism, stagnating wage growth and growing inequality.

6.1.2 Superstar mechanisms

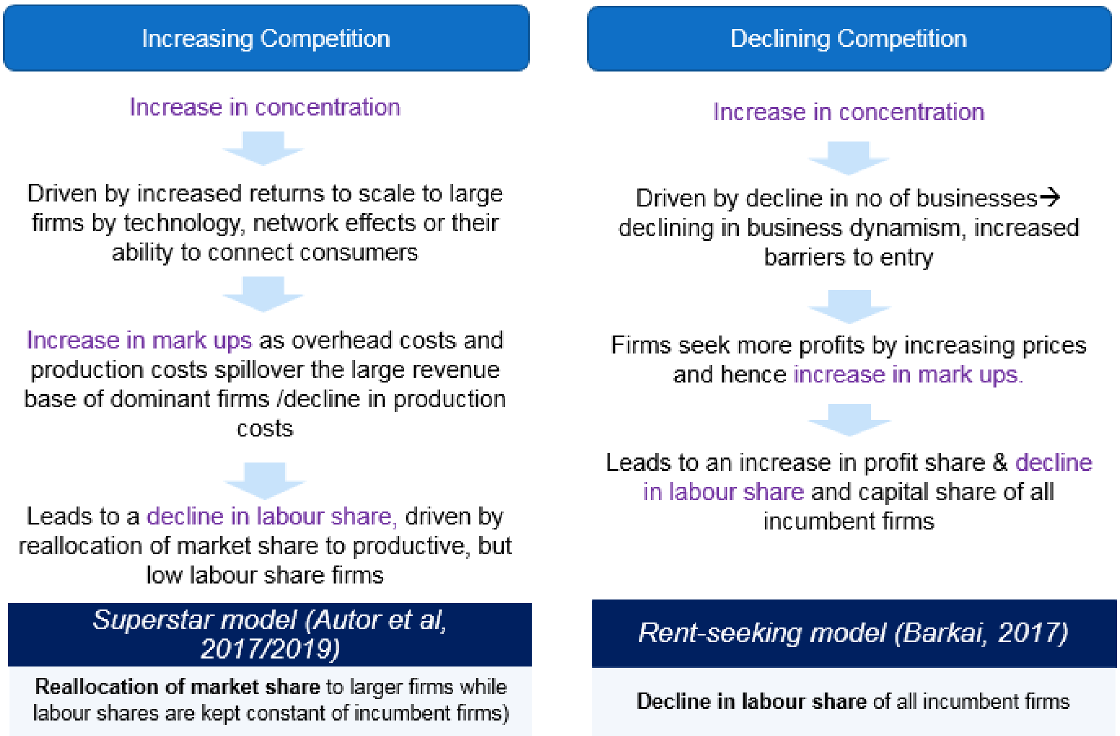
The superstar model is also based on a monopolistic competition model (Tirole, 1988). However, in contrast to the rent-seeking model, the increase in concentration is caused by innovation from superstar firms or scale economies. This can also trigger a fall in the aggregate labour share through a reallocation of value added to the superstar firms who have low-labour shares (Armstrong and Porter, 2007; Autor et al., 2017, 2019; Schwellnus et al., 2017; Tirole, 1988; Van Reenen, 2018). In this model, a decline in labour share is competitive outcome, as is falling prices, improved productivity and greater output. Accordingly, Van Reenen (2018) and Autor et al. (2019) argue that the conclusion that the decline in labour share is driven by relaxed anti-trust competition polices and regulations is *premature*.

Autor et al. (2019) recently gave evidence that the decline in labour share in the USA manufacturing sector has been driven by a reallocation of value added to low-labour share firms. Schwellnus et al. (2017) and Van Reenen (2018) refers to this experience as a 'winner-takes-all' dynamics, where there is a divergence in productivity and labour share of the leading firms and the rest. Using cross-country industry- and firm level data, they find evidence to support that the winner takes all dynamics is caused by technological dynamism. Another ancillary view is that leaders have invested more in intangible assets, such as patents and technology, enabling them to see higher productivity growth.

6.1.3 Microeconomic Mechanisms

Hence, there are two compelling, yet opposing, mechanisms mapping the decline in labour share to increase in concentration and mark-ups as shown in Figure 6.2. The rent-seeking model and the superstar model are both monopolistic competition models, but with differing implications for competition. In the superstar model, increasing concentration and markups is seen as competitive, where the decline in labour share is a competitive outcome from the reallocation of value added to more productivity firms. In the rent-seeking model, increasing concentration and mark-ups are anti-competitive, as the decline in labour share is the inverse consequence of an increase in mark-ups and profit. High barriers to entry and low investment are characteristic of rent-seeking, concentrating industries.

Figure (6.2) Two Competition Models Explained



Based off Barkai (2016) and Autor et al. (2017)'s models, but author created

The key difference is the underlying microeconomic mechanisms which drive the interaction between concentration, markups and competition.

- In the rent-seeking model after (Barkai, 2016)'s paper, there are heterogeneous changes in labour share and profits *of all surviving firms*. Hence, the rent-seeking mechanism reflects a *within-industry* change.

- In the super star model after (Autor et al., 2017)'s paper, there is no change in labour share of surviving firms for simplicity. Hence, the superstar mechanism reflects a *reallocation of value added*to a set of low labour share and productive firms or high labour share and low productive firms.

The microeconomic mechanisms of reallocation to more productive firms or heterogeneous changes within firms is not unique to labour share literature and has been assessed in the context of aggregate productivity growth (see e.g. Andrews et al., 2016; Foster, Haltiwanger, and Krizan, 2001).

The superstar and the rent-seeking models are not mutually exclusive. In the superstar model of (Autor et al., 2017, 2019), once a firm has attained superstar status, the firm could raise mark-ups above production cost. The network that they attain can enable them to establish a gridlock on sales and market power in the industry, enabling them to lift prices. It would then be the case that the increase in mark-ups is skewed towards productive firms. Moreover, investment in intangible investments could create barriers to entry as well, due to the high sunk cost of entering. Hence, it is likely that industries that exhibit superstar-like behaviours may also transcend to rent-seeking behaviour in time, where there are increasing barriers to entry. The benefit of firm level data is that it might be possible to tease these differences out.

Much of the discussion in the literature has been in the context of increasing concentration and mark-ups, and how it has affected the decline in labour share. This has led to a didactic approach, where increasing concentration is classified as 'good' concentration if it contributes to increasing competition and 'bad' concentration if it contributes to declining competition (Covarrubias et al., 2019). In Australia, while concentration has increased at the economy level, I find that there is a 60-40 split between increasing and decreasing competition at the 4-digit industry level. Also, about 50 per cent of industries have also experienced an increase in labour shares. Because of this, it is important to examine the implications of increasing and decreasing concentration on competition and how it affects labour shares. This will make the later analysis about the superstar and rent-seeking mechanisms more complex.

6.2 Identification Strategy - Decomposition

6.2.1 Basic Outline

To evaluate whether the rent-seeking model or the superstar model is prevalent, Autor et al. (2019) rely on the microeconomic mechanisms of a *within-industry* change or *reallocation* change.[49] The Autor et al. (2019) identification strategy is simple:

1. Decompose firm level labour share changes into reallocation and within-industry components;
2. Assess which component is larger;
3. Regress each component on a measure of concentration
4. The within coefficient will be significant if it is a rent-seeking mechanism, and the reallocation coefficient will be significant if it is a superstar mechanism.

This relies on the fact that aggregate labour share, λ_t can be decomposed into the sum of firms' market share and labour share: :

$$\lambda_t = \frac{\sum_i W_{it} L_{it}}{\sum_i Y_{it}} = \sum_i \lambda_{it} w_{it} \tag{6.1}$$

[49]It should be noted that microeconomic mechanisms in respect to labour shares were formalised in this thesis. Autor et al. (2019) does not refer to these two characteristics explicitly or compare the two competition models like this thesis.

where λ_t is the weighted labour share for the economy at time t, λ_{it} denotes the labour share of an individual firm i at year t, and $w = \frac{Y_{it}}{Y_t}$ denotes the value-added share of firm i. The reallocation component of changing labour share is transmitted through changes in w_{it} and the within-industry changes in labour share is transmitted through the changes in λ_{it}.

Further, the identification relies on the fact that with firm level panel data on market share and labour share, it is possible to estimate the contribution of each firm to aggregate labour share changes based on a firm's activity status using decomposition methods. That is, the change in aggregate labour share can be split into the contribution of surviving firms which are active in both periods (denoted as "S"), exiting firms which are active in the first period (denoted as "X") and entering firms which are active in the last period (denoted as "N"). Below is the general form for a labour share decomposition. In period 1, the total labour share in the economy is denoted as the weighted sum of labour shares of all firms that survived beyond period 1 ($i \in S$) and firms that exit after period 1 firms ($k \ \in X$):

$$\lambda_1 = \sum_{i \in S} w_{i,1} \lambda_{1,i} + \sum_{k \in X} w_{k,1} \lambda_{1,k} \tag{6.2}$$

In period 2, the total labour share is the weighted sum of surviving firms from period 1 ($i \in S$) and firms that entered in period 2 ($l \in N$).

$$\lambda_2 = \sum_{i \in S} w_{i,2} \lambda_{2,i} + \sum_{l \ \in N} w_{i,2} \lambda_{2,i} \tag{6.3}$$

Taking the difference of Equation 6.2 and 6.3, the change in labour share ($\Delta\lambda$) is the sum of the change in labour shares for surviving firms, exiting firms and entering firms.

$$\Delta\lambda = \lambda_2 - \lambda_1 = \sum_{i \in S} w_i \lambda_{2,i} - \sum_{i \in S} w_i \lambda_{2,i} + \sum_{l \ \in N} w_i \lambda_{1,l} \ - \sum_{k \ \in X} w_i \lambda_{1,k} \tag{6.4}$$

The above is a general form decomposition of labour share in the three groups. Autor et al. (2019) use the Melitz and Polanec (2015) ("MP") method of decomposition, which is a dynamic Olley and Pakes productivity decomposition with exiting and entering firms included.[50] It further decomposes the surviving component into different parts, which is the key to identifying the 'superstar' mechanisms or the 'rent-seeking' mechanism. Its role as an identification strategy is explored in section 6.2.1. Then, section 6.2.2 proposes another decomposition strategy, by Diewert and Fox (2010) ("DF") and applies it to labour shares. In section 6.2.3. I argue that DF is more effective at identification but can complement MP as well.

[50]While several methods have been developed, MP appears to be the most common in the literature surrounding productivity.

6.2.2 Melitz and Polanec (2015) Decomposition

The MP method decomposes changes in labour share between period 1 and 2, $\Delta\lambda$, into four terms:

$$\begin{aligned}\Delta\lambda = \Delta[\sum(w_i - \bar{w})(\lambda_i - \bar{\lambda})]_s + \Delta\bar{\lambda_s} \\ +W_N^2 \sum_{i \in N} w_{N,2}(\lambda_{N,2} - \lambda_{S,2}) \\ -W_X^1 \sum_{i \in X} w_{X,1}(\lambda_{S,1} - \lambda_{X,1})\end{aligned} \tag{6.5}$$

where $\Delta\bar{\lambda_s}$ is the unweighted mean of the labour share of surviving firms calculated as $\bar{\lambda} = \frac{1}{S}\sum_i^S \lambda_i$; and $\bar{w} = \frac{1}{S}\sum_i^S w_i$ is the unweighted mean of market share. For the entry and entering terms, the aggregate value added shares for group $K \in \{X, N\}$ are defined as:

$$W_K^t = \frac{\sum_{i \in K} w_i^t}{\sum w_i^t}$$

The firm level value added share for group $K \in \{X, N\}$ are defined as:

$$w_{K,i} = \frac{w_i^t}{\sum_{i \in K} w_i^t}$$

The focus will be on the first term, *covariance* and the second term, *unweighted mean*, which Autor et al. (2017, 2019) use to identify the superstar mechanism and rent-seeking mechanism, respectively.

The first term is the covariance component, $[\sum(w_i - \bar{w})(\lambda_i - \bar{\lambda})]_s$, which measures the change in covariance between the firm market share and the labour shares for surviving firms. Autor et al. (2017) refer to the covariance term as the *reallocation* effect, to describe the reallocation of value added between surviving firms (commonly used in the productivity literature such as in Bartelsman, Haltiwanger, and Scarpetta (2013)). It is composed exactly of the two components needed for this interpretation: the first component, $(w_i - \bar{w})$ reflects the difference in market share relative to the unweighted mean of market share, while $(\lambda_i - \bar{\lambda})$ reflects the difference in labour share relative to the unweighted mean of surviving firms' labour share. Hence, if there is a reallocation of value added to high productivity and low labour share firms, the covariance term will be negative. Moreover, when regressing with concentration, "[covariance] shows up as negative and significant in all sectors, indicating that rising concentration predicts a fall in labour share through between-surviving reallocation" (Autor et al., 2017, p23). The inverse is true for declining concentration.

The second term is the mean component $\Delta\bar{\lambda_s}$, which reflects the change in the unweighted mean of labour share of surviving firms. Autor et al. refer to this as the *within* effect to identify the rent-seeking mechanism – that is, the idea that declining competition causes a decline in labour share of all surviving firms, rather than a select few, keeping market share constant. However, as the term is an unweighted mean, it will be biased towards small firms (Riley and Bondibene, 2016). In the rent-seeking mechanism, the mean term will be greater in magnitude than the covariance term and will have a statistically significant and negative relationship with concentration.

The third and fourth terms represent contributions from firms exiting $W_X^1 \sum_{i \in X} w_{X,1}(\lambda_{S,1} - \lambda_{X,1})$, and contributions from firms entering $W_E^2 \sum_{i \in N} w_{E,2}(\lambda_{E,2} - \lambda_{S,2})$, respectively. As per Covarrubias et al. (2019), the feature of exiting and entering firms is essential in understanding the dynamics of competition that prevail in the economy. However, it can be difficult to interpret as the superstar and rent-seeking models are not mutually exclusive (as discussed in Section 6.1.3). In the context of superstar firms, an increase in concentration is not correlated with the entry term but could be associated with an increase in the exit rate. This is because there would be limited costs to entry if the industry remains competitive, while firms may exit, if they are unable to compete with the level of production by the superstar firms. In the context of the rent-seeking model, an increase in the concentration rate is positively associated with the exit rate and negatively with the entering rate. There is an argument that there could be increasing barriers to entry that prevent new firms from entering. The number of firms exiting in the rent-seeking model, however, may fall as entrenched firms stay because they are enjoying the benefits to higher returns. An example where the terms might be difficult to interpret is if the cost of technology or necessity for intangible assets increases in a superstar industry. Then, the cost of entering can become very high (Autor et al., 2019). As a result, the increase in concentration would be associated with a decline in the entry rate as well.

In summary, the identification strategy follows that:

- If there is a reallocation towards certain firms (e.g. superstar firms), according to the superstar model, the covariance term will be large in magnitude and the coefficient on the change in concentration will be statistically significant when regressed with covariance.

- If there is an industry-wide change causing declining labour shares for all surviving firms, the mean term will be larger than the covariance term, and the coefficient of the regression will be statistically significant. This can be used to identify the rent-seeking mechanism.

Accordingly, the role of the decomposition method is thus vital for correctly identifying the reallocation and within component's of labour share, and hence the prevailing causes of labour share change.

However, MP is only weakly effective at differentiating between the superstar and rent-seeking mechanism. This is because the covariance term contains two double negatives, making it difficult for interpretation (Balk, 2016; Riley and Bondibene, 2016).

Mathematically, it is impossible to determine whether the relative market share change $(w_i - \bar{w})$ or relative labour share change $(\lambda_i - \bar{\lambda})$ is the driving component behind the change in the covariance term. In a following paper, Autor et al. (2019) further decompose the MP covariance term into a within-industry change and between-industry change, demonstrating the need to further understand the covariance term and the true drivers of labour share change for surviving firms.

6.2.3 Diewert and Fox (2010) Decomposition

This thesis argues that the Diewert and Fox (2010) ("DF") method is a better for identification and decomposing labour share changes. Like MP, DF is also a dynamic productivity decomposition used to decompose the changes of the aggregate productivity into the contribution of surviving, exiting and entering firms. Its application to labour share dynamics, hence, is novel and a contribution of this thesis.

The DF method, applied to labour shares, can decompose labour share change over period 1 and 2 into four parts:[51]

$$\begin{aligned}\Delta\lambda = &\sum_{i\in S}(\frac{1}{2}(w_{i,s,2} + w_{i,s,1})(\lambda_{i,2} - \lambda_{i,1})) \\ &+ \sum_{i\in S}(\frac{1}{2}(w_{i,s,2} - w_{k,s,1})(\lambda_{k,2} + \lambda_{k,1})) \\ &+ W_E^2 \sum_{i\in N} w_{E,2}(\lambda_{E,2} - \lambda_{S,2}) \\ &- W_X^1 \sum_{i\in X} w_{X,1}(\lambda_{S,1} - \lambda_{X,1}) \end{aligned} \tag{6.6}$$

The first term is the *within* component, measuring the changing in labour share for firm i, weighted by the two-period average market share. The DF within term is a weighted mean in contrast to MP's unweighted mean, so it is more effective at identifying the change in labour share for large firms. As the market share is kept constant, the within term will only identify the change in labour share over the two periods. This makes it ideal for identifying the rent-seeking mechanism. It is proposed that the within term is used to identify rent-seeking mechanism.

The second term is the *between* component, which measures the change in market share over the two periods for all firms, keeping labour share constant over the two periods by using a two period average. As it keeps labour share constant, it is perfect at tracking the change in market share online. This also is a weighted mean, which means it will be weighted towards high labour share firms. The MP covariance term, in comparison, combines the change in labour share and change in market share over the two periods. By clearly isolating the reallocation effect, the DF between term is more reasonably, intuitive

[51] The definition of the terms are the same as the terms in Equation 6.5.

and easier to understand than the MP covariance term. Hence, the between term will be used to identify the superstar mechanism.

The last two terms measure labour share contributions from entering firms and exiting respectively and are the same as MP. In this respect, the MP and DF methodology are robust according to Balk (2016) as both methods decompose the exit and entry terms correctly.

6.2.4 Comparing Melitz and Polanec (2015) and Diewert and Fox (2010)

The main difference between the DF and MP methodologies is how they split the change in labour share of surviving firms. The first two terms in the DF equation 6.6 and the MP equation 6.5 are different, though they both sum to the contribution of surviving firms. For ease of comparison, the two methods are written below:

Melitz and Polanec (2015):

$$\begin{aligned}\Delta\lambda = {} & \Delta[\sum(w_i - \bar{w})(\lambda_i - \bar{\lambda})]_s \\ & + \Delta\bar{\lambda_s} \\ & + W_E^2 \sum_{i\in N} w_{E,2}(\lambda_{E,2} - \lambda_{S,2}) \\ & - W_X^1 \sum_{i\in X} w_{X,1}(\lambda_{S,1} - \lambda_{X,1})\end{aligned} \tag{6.7}$$

Diewert and Fox (2010):

$$\begin{aligned}\Delta\lambda = {} & \Delta\sum_{k\in S}(\frac{1}{2}(w_{k,s,t} + w_{k,s,t-1})(\lambda_{k,t} - \lambda_{k,t-1})) \\ & + \Delta\sum_{k\in S}(\frac{1}{2}(w_{k,s,t} - w_{k,s,t-1})(\lambda_{k,t} + \lambda_{k,t-1})) \\ & + W_E^2 \sum_{i\in N} w_{E,2}(\lambda_{E,2} - \lambda_{S,2}) \\ & - W_X^1 \sum_{i\in X} w_{X,1}(\lambda_{S,1} - \lambda_{X,1})\end{aligned} \tag{6.8}$$

According to Zeng (2019), the DF decomposition is a *true* representation of the within firm and between firm changes in an economy. Following Baldwin and Gu (2006), Zeng (2019) employs a counterfactual specification on within and surviving effects on firm productivity dynamics. For example, comparing a control group where there is no within-industry change with the treatment group where this is a within-industry change, the difference-in-difference estimator reveals a term which is the same as the DF within term. The same counterfactual exercises produces a between difference-in-difference estimator too. Zeng (2019) finds that the difference-in-difference specification clarifies productivity dynamics within the counterfactual context, and confirms that DF is preferable to other dynamic decompositions, such as MP.

Moreover, DF is axiomatically robust, due to its symmetric and time invariant properties (Balk, 2016; Diewert and Fox, 2010; Riley and Bondibene, 2016; Zeng, 2019). The DF decomposition of continuing firms into between and within effects uses a Bennet (1920) type decomposition of labour share change of continuing firms. This treats time in a symmetric fashion so that the industry productivity difference in levels between two periods reverses sign when the periods are interchanged, as do the various contribution terms. This type of symmetric decomposition is used by Griliches and Regev (1995) and has been endorsed by Balk (2003). It can also be given an axiomatic justification, as previously Diewert (2005) showed that the Bennet decomposition of a difference is analogous to axiomatic justification of the Fisher (1992) ideal index in index number theory. In contrast, the MP decompositions rely on a Laspayres (or Paasche) type price index multiplied by a Paasche (or Laspeyeres) type quantity index (as noted by Balk, 2016; Diewert and Fox, 2010). Both of these however, are not invariant with respect to time. Hence, the contribution would change if the time is reversed.

In the literature, Riley and Bondibene (2016) and Balk (2016) among others assert that the DF methodology is more robust and attractive than other dynamic decompositions, including MP. The most important reasons for this thesis is that the double negatives in the covariance term of MP make it difficult to understand whether the reallocation or the within effect is driving the change. The DF method in this respect is better, as it makes the differentiation distinct.

6.2.5 Novel research methodology

Hence, while Autor et al. (2017, 2019) suggest using a Melitz and Polanec (2015) decomposition, I argue that the Diewert and Fox (2010) decomposition provides a theoretically better decomposition for the identification strategy. The new research framework to identify the superstar mechanism builds on Autor et al. (2017, 2019) and adapts Diewert and Fox (2010) in the following way:

1. Decompose firm level labour share changes using the DF method;
2. A large *between* term will indicate the superstar mechanism, while a large *within* component will indicate the rent-seeking mechanism;
3. In the between regression, a statistically significant coefficient on the change in concentration indicates the superstar mechanism, while in the within regression, a statistically significant coefficient on the change in concentration indicates the rent-seeking mechanism.

Abstracting from which method is better, this thesis also shows that DF and MP are complementary decomposition methods for analysis on observation, which builds and improves on the identification strategy used by Autor et al. (2017, 2019). Mathematically, the sum of the MP covariance and mean terms equals the sum of the DF between and mean terms (Equation 6.9), as they both represent the change in terms relating to labour shares for surviving firms. This identity is also true because the exit and entering terms for MP and DF are equivalent. That is, from Equation 6.7 and 6.8, we have the following

$$\begin{aligned}
&[\sum(w_i - \bar{w})(\lambda_i - \bar{\lambda})]_s + \bar{\lambda_s} \\
&= \sum_{k \in S}(\frac{1}{2}(w_{k,s,t} + w_{k,s,t-1})(\lambda_{k,t} - \lambda_{k,t-1})) \\
&+ \sum_{k \in S}(\frac{1}{2}(w_{k,s,t} - w_{k,s,t-1})(\lambda_{k,t} + \lambda_{k,t-1})) \qquad (6.9)
\end{aligned}$$

Equation 6.10 shows that the covariance term can be further decomposed into the DF components as well as the unweighted mean term.

$$\begin{aligned}
[\sum(w_i - \bar{w})(\lambda_i - \bar{\lambda})]_s &= \sum_{k \in S}(\frac{1}{2}(w_{k,s,t} + w_{k,s,t-1})(\lambda_{k,t} - \lambda_{k,t-1})) \\
&+ \sum_{k \in S}(\frac{1}{2}(w_{k,s,t} - w_{k,s,t-1})(\lambda_{k,t} + \lambda_{k,t-1})) \\
&- \bar{\lambda_s} \qquad (6.10)
\end{aligned}$$

This interpretation resolves the difficulty with MP analysis in Section 6.2.2 earlier. As the covariance term in the MP was the key difficulty, by further decomposing it, the endogeneity issue with not knowing if the reallocation or the within term was driving it is eliminated. The further decomposition in Equation 6.10 clearly shows whether the within or the between term is driving the covariance mechanism.

Hence, to interpret the Autor et al. (2017, 2019) method in light of equation 6.10, it should follow that MP and DF are complementary:

- In the superstar mechanism, the MP covariance component is larger in magnitude than the MP mean, and DF between component is larger in magnitude than the DF within term. When regressing each of these components, the coefficient on the change in concentration would be statistically significant.

- In the rent-seeking mechanism, the MP mean component will be larger in magnitude than the MP covariance and the DF within component will be larger DF between term, respectively. When regressing the MP mean and DF within on concentration, the coefficient on the change in concentration would be statistically significant.

It could be the case that the MP covariance term is larger than the MP mean term, but the DF within term is larger than the DF between term. Hence, MP identifies the superstar mechanism, while DF identifies rent-seeking. Reconciling these views using Equation 6.10, the within industry component is dominating the covariance component. Determining whether this is a rent-seeking mechanism or the superstar mechanism, depends on the interpretation of the within component.

6.3 Empirical Framework

This thesis proposes a new labour share decomposition framework in the previous section to test for whether labour shares are driven by the superstar mechanisms or rent-seeking mechanisms, building on the original framework by Autor et al. (2017, 2019) and applying a new decomposition method which adapts the DF decomposition.

First, the DF dynamic decomposition in equation 6.8 is applied to labour shares over a 16-year period to decompose the changes in labour share into the within, between, and net entry contributions of labour share. This is done for the whole economy, using firm level units of observations to calculate 4-digit industry decomposition.

Second, to estimate whether the increase in concentration affects labour share changes through reallocation of value added, within labour share changes or exit and entry rates, each component of labour share change ($C \in$ within, between, exit, entry) is regressed on the change in concentration, $\Delta Conc_j$ using a 16 year long-difference regression at the 4 digit level:

$$\Delta\lambda_C = \beta_0 + \beta_1 \Delta Conc_j + X_t + \epsilon_j \tag{6.11}$$

where $\Delta\lambda_C$ refers to the change in a component of labour share and the term C in the subscript of labour shares represents the different components of the decomposition following DF method. The variable Conc refers to change in concentration, which is measured in four different ways: concentration ratio of top 4 firms, top 10 firms, top 20 firms as well as the Herfindahl-Hirschman Index. The main results presented use the change in concentration for the top four firms (C4). The vector X_t refers to industry controls of size and capital intensity to account for different market structures in the industry. Because a long difference in the labour share component is the dependent variable in 6.11, heterogeneity that emerges from cyclical factors is (largely) purged. Therefore, to take into account industry level heterogeneity, fixed effects at the 1-digit ANZSIC level, 2-digit ANZSIC level and 3-digit ANZSIC level, with standard errors clustered at the 4-digit ANZSIC level are used. The coefficient β_1 identifies the change in the labour share component driven by change in concentration over a 16-year period, considering the structural factors of the industry. This specification is applied to different subsamples such as goods versus services industries, tradeable and non-tradeable industries and primary and non-primary sectors.

Next, this thesis explores how the results from the new labour share decomposition framework align and relate to those of Autor et al. (2017, 2019). The Melitz and Polanec

(2015) decomposition is used as a robustness test to understand the differences in results. This thesis compares the two models theoretically and empirically, and then outlines how they are complementary in analysis using equation 6.10.

Third, this thesis seeks to understand whether the results have changed over time. Between 2002 and 2017, Australia has undergone significant structural changes such as the mining boom in 2007 and the onset of stagnating wage growth from 2012. Hence, an additional model is tested which looks at the year-on-year time specific effects of concentration on labour shares. To document these changes, I split the data into three distinct periods between 2002 - 2007, 2007 - 2012, and 2012 - 2017, and understand the components of labour share. This allows me to conduct a pooled OLS regression where a dummy variable can be used for the time periods to test the change. The following equation is tested:

$$\lambda_{C,t} = \beta_0 + \beta_1 Conc_t + \beta_2 [Conc_t * D_{2007-12}] + \beta_3 [Conc_t * D_{2012-17}] + X_t + \epsilon_{jt} \tag{6.12}$$

where $D_{2007-12}$ is a dummy variable that takes on the value of 1 if it is the period between 2007-2012; $D_{2012-17}$ is a dummy variable that takes on the value of 1 if it is the period between 2012-17. Here, the coefficient β_1 will identify the relationship between the change in concentration and labour share component for industries between 2002 – 2007. Then, β_2 will identify the change in relationship between concentration and labour share for the period 2007-2012 relative to the first five years of the sample. β_3 will similarly identify the change in relationship between concentration and labour share for the period 2012-2017 relative to the first five years of the sample.

There is limited literature estimating the relationship between concentration and labour share. Other than Autor et al. (2019), Barkai (2016) and Gutierrez (2018) have been the only papers to focus on competition and labour shares, where a reduced form regression between concentration and labour share was conducted. Hence, to confirm the role of competition on labour shares, this thesis follows the literature on concentration and competition more broadly, as this is an endogenous relationship extensively tested in the literature. The change in labour share is symptom of the broader competition changes in the economy, so testing overall change in competition will supplement and confirm the analysis of labour shares in Australia.

Hence, to test the general level of competition, Covarrubias et al (2019) methodology is followed, who provides an overview of methods that can be used to test whether the change in concentration is associated with increasing competition or declining competition. A 4-digit industry-level OLS regression of labour productivity, total factor productivity, profit shares and mark-ups on concentration over the period 2002 to 2017 to test for the overall level of competition in the economy is run:

$$Z_{jt} = \beta_0 + \beta_1 \log CR4_{jt} + X_{jt} + \epsilon_{jt} \tag{6.13}$$

where Z_{jt} is the 4-digit level measure of labour productivity, total factor productivity, profit shares and mark-ups; $\log CR4_{jt}$ is the measure of concentration for the top 4 firms in the industry; and X_{jt} denotes industry-year fixed effects. Appendix A.3 provides an overview of how these additional measures were constructed. It should follow that if there is evidence for the superstar hypothesis and relocation between frontier firms and non-frontier firms, then productivity and concentration are positively associated. However, if it is not the case and rent-seeking prevails, then productivity and concentration are negatively associated. Furthermore, if there is evidence for rent-seeking, then mark-ups and profit shares are positively and significant associated with increases in concentration.

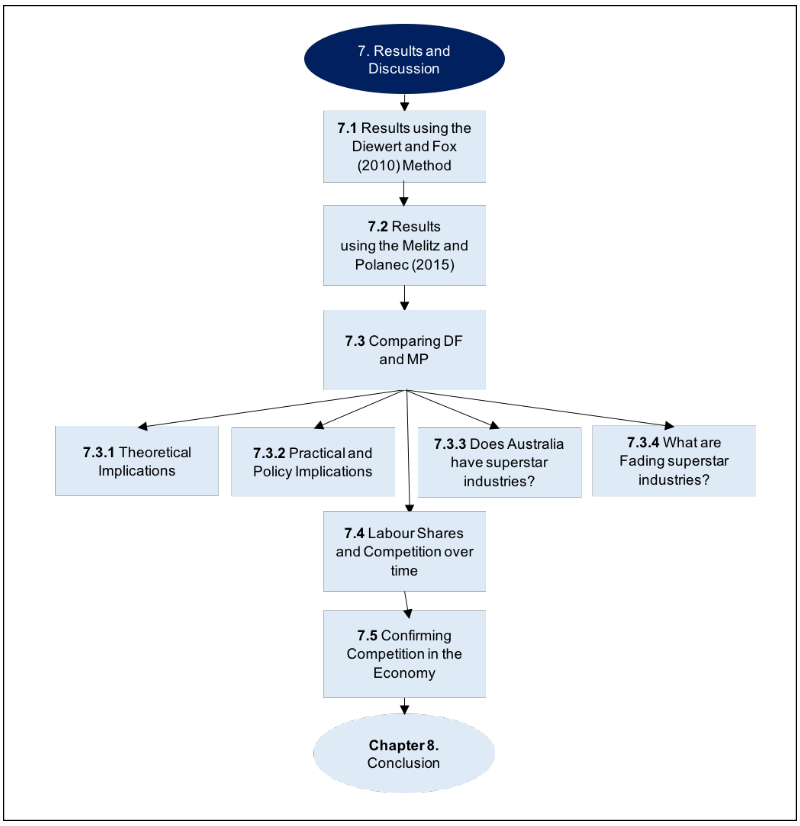
Chapter 7
Results and Discussion

The focus of this chapter is to evaluate how competition has influenced the share of income accruing to labour. Chapter 5 found that competition, measured through concentration and mark-ups, has been a key driver of the labour share in Australia between 2001-02 and 2016-17 and Chapter 6 identified a rent-seeking model and a superstar model which can explain this. This chapter implements the novel identification strategy outlined in Section 6.2.5 and the empirical framework outlined in Section 6.3 at the economy level, division level, across sub-samples and over time to determine whether the rent-seeking or superstar mechanism prevail.

Figure 7.1 provides an overview of how this Chapter proceeds. Section 7.1 presents the results of the main model, which applies the Diewert and Fox (2010) ("DF") productivity dynamic decomposition on labour shares. Then, Section 7.2 presents the results using Autor et al. (2017, 2019)'s method, which applies the Melitz and Polanec (2015) ("MP") decomposition. To see how these results of the new labour share decomposition align with Autor et al. (2017, 2019) model, Section 7.3 compares the two results, understanding the differences theoretically and empirically. Section 7.4 reports the change in relationship between competition and labour share over time. Lastly, the change in labour share is symptom of the broader competition changes in the economy, so this thesis tests the overall change in competition to supplement and confirm the analysis of labour shares in Australia. The results of regressing profit share, productivity and mark-ups on concentration are presented in Section 7.5.

To preview the results, using the DF method introduced in Chapter 6, this thesis finds that changes in concentration affect labour share through within-industry changes to the labour share of all surviving firms. This is particularly evident after 2007, and in services sectors, non-primary sectors and non-trade intensive sectors. Agriculture and Mining Divisions present more evidence for superstar mechanisms, which is confirmed by Autor et al. (2017) method. The thesis compares the DF and MP results, and finds a new empirical feature of the Australian economy: fading superstars dominate in many industries, suggesting declining allocative efficiency and competition within the economy. 'Superstar' firms and 'rent-seeking' firms are evident, though it is limited to a few industries.

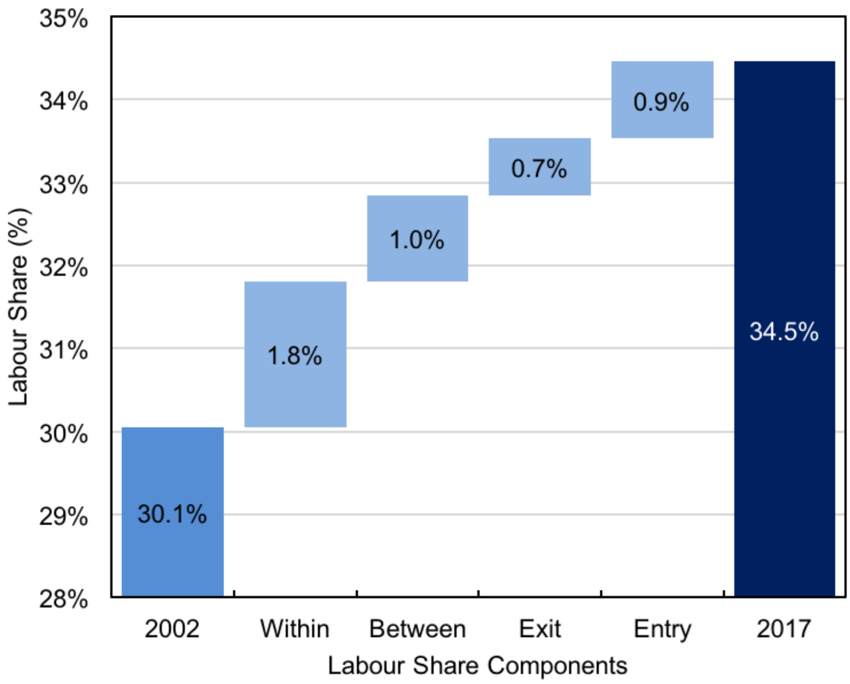
Figure (7.1) Chapter 7 Overview - Results and Discussion



7.1 Results using the Diewert and Fox (2010) Method

Figure 7.2 presents the results of the DF decomposition in equation 6.6 applied to firm level data for an upward estimation of the aggregate economy (market sector excluding finance and insurance services). Between 2002 and 2017, the increase in labour share was driven by a 1.8% increase in the within term, suggesting that, in aggregate, all surviving firms increased labour share; this accounts for 40% of the total change. The reallocation of market share contributed to 24% of the total change (the between term increased labour share by only 1%). In terms of net entry, 16% of the change in labour share is from exiting firms, meaning that exiting firms had lower labour shares; 21% was from entering firms, indicating that firms that entered had a higher labour shares than the surviving firms. On a whole, net entry is positive but has a small contribution. This supports the analysis in Chapter 2 which showed that the trend in labour share was driven by surviving firms, not entering and exiting firms.

Figure (7.2) Decomposition of Labour Share Change Between 2001-02 and 2016-17 using DF method



Source: ABS BLADE 16-17, Author's Calculations

Table 7.1 presents the results of regressing the DF components of a 16-year long change in labour share on the change in concentration in equation 6.11. Panel (A) presents the results of regressing the within component on concentration; (B) for the between term; (C) for the exit term and (C) for the entry term. Because this is a 16-year long difference regression, heterogeneity that may have occurred during this period due to cyclical factors does not need to be modelled. Industry idiosyncrasies and market structures, however, are accounted for by using different levels of industry fixed effects. Column 1 in each Panel presents the results of an ordinary least squares regression; Column 2 with fixed effects at the 1-digit industry level; Column 3 with fixed effects at the 2-digit level; and lastly Column 4 with fixed effects at the 3-digit level. As stricter fixed effects are added, there is an increase in the explanatory power of the model as noted through the R^2 and Adjusted R^2 terms. This could be the case because there is significant heterogeneity between the industries.[52]

[52]While there is a risk that there could be a mechanical increase in the R^2 due to the increase in parameters, adjusted R^2 terms account for this. AIC criterion (omitted from Table 7.1) is less biased towards the number of parameters taken than the BIC criterion (also omitted) and is presented in the Appendix E.

Table (7.1) Industry (4-Digit) Regressions of the components of a DF (2010) Labour Share Decomposition on the Change in Concentration

	(A) Within				(B) Between			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Change in C4	-0.0131***	-0.0131***	-0.0143***	-0.0165***	0.00232	0.00232	0.00475	0.00133
	(0.00315)	(0.00315)	(0.00286)	(0.00285)	(0.00317)	(0.00317)	(0.00461)	(0.00531)
Constant	0.0388***	0.00291	0.0217+	0.0223	0.0113***	-0.00379	-0.0200++	-0.00384
	(0.00618)	(0.0148)	(0.0145)	(0.0361)	(0.00319)	(0.00947)	(0.0107)	(0.0206)
Observations	445	445	445	445	445	445	445	445
R-squared	0.012	0.050	0.283	0.519	0.002	0.053	0.196	0.450
Adjusted R-squared	0.009	0.017	0.141	0.181	-0.001	0.020	0.037	0.064
Industry Controls	X	X	X	X	X	X	X	X
No FE	X				X			
Industry 1-digit FE		X				X		
Industry 2 -digit FE			X				X	
Industry 3-digit FE				X				X

	(C) Exit				(D) Entry			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Change in C4	0.0149	0.0149	0.0127	0.0213++	-0.0299	-0.0299	-0.0360	-0.00526
	(0.0129)	(0.0129)	(0.0125)	(0.0117)	(0.0288)	(0.0288)	(0.0304)	(0.00828)
Constant	0.0121*	0.0219*	0.0181+	0.0268	-0.0252***	0.00160	-0.00346	-0.0116
	(0.00607)	(0.0100)	(0.0117)	(0.0277)	(0.00724)	(0.0114)	(0.0125)	(0.0206)
Observations	448	448	448	448	448	448	448	448
R-squared	0.017	0.045	0.138	0.313	0.055	0.107	0.211	0.752
Adjusted R-squared	0.015	0.012	-0.031	-0.168	0.053	0.076	0.057	0.578
Industry Controls	X	X	X	X	X	X	X	X
No FE	X				X			
Industry 1-digit FE		X				X		
Industry 2 -digit FE			X				X	
Industry 3-digit FE				X				X

Notes: Standard errors are in parentheses. P-values ++ p<0.2 + p<0.1 * p<0.05 ** p<0.01 *** p<0.001"

Notes: This table presents the results of regressing the DF decomposition of labour shares on the change in the concentration ratio of top 4 firms in a 16 -year long difference regression (refer to Model eqn 6.11). Standard errors are clustered at the 4-digit industry level and industry controls (capital intensity, size) are used.

In Panel A, the coefficients on the change in concentration for the within term are all negative and statistically significant. As the model accounts for greater industry heterogeneity, the coefficients increase in magnitude and significance. The coefficients range between $\beta_{DF,within,16yr} = -0.00131$ and $\beta_{DF,within,16yr} = -0.0165$, indicating that an increase (decrease) in concentration for the top four firms by ten percent points has lead to a decline in labour shares for all surviving firms ranging from 1.31% to 1.65%. Panel B presents the results of regressing the change in concentration on the between component of labour share for surviving firms. The coefficients are all statistically insignificant and smaller in magnitude than for the within term regression in Panel A. This is consistent for all tests (Column 1- 4), even with varying industry fixed effects. This implies that, accounting for industry structural and cyclical factors, concentration does not significantly affect labour share through the reallocation of value added to high labour share firms. Neither Exit (Panel C) or Entry (Panel D) regressions have particularly significant coefficients with the change in concentration.

Overall, the results indicate that an increase (decrease) in concentration has caused the labour share of surviving firms to decline (increase), rather than reflecting a shift in reallocation of value added to high (low) labour share firms. The results signify the presence of the rent seeking mechanism in industries with increasing concentration, in which concentration enables firms to raise mark-ups and prices. This reflects the findings of Barkai (2016) and De Loecker et al. (2016), and contradicts Autor et al. (2017, 2019) and Van Reenen (2018), who argue that the decline in labour share reflects a competitive outcome as a result of technological dynamism.

7.1.1 Further Analysis

Additional robustness tests and sub-sample analyses are conducted to confirm this economy-level finding. First, alternative measures of concentration, including concentration ratios of top 10 firms, ratios of top 20 firms, and the Hirfindahl-Hirschman Index (HHI), are used (Section 7.1.1.1). Then, further analysis is also conducted at the division level (Section 7.1.1.2) and sub-sectors Section 7.1.1.3) to understand underlying dynamics. In each regression, the same model specification used earlier in Equation 6.11 is applied at the division level and the sub-sector level. The unit of observation is 4-digit ANZSIC level industry labour share components, three levels of fixed effects, clustering of standard errors and industry controls:

7.1.1.1 Robustness Tests

Table E.1 in Appendix E presents the regression results of regressing other concentration measures on the within, between, exit and entry components of labour share.

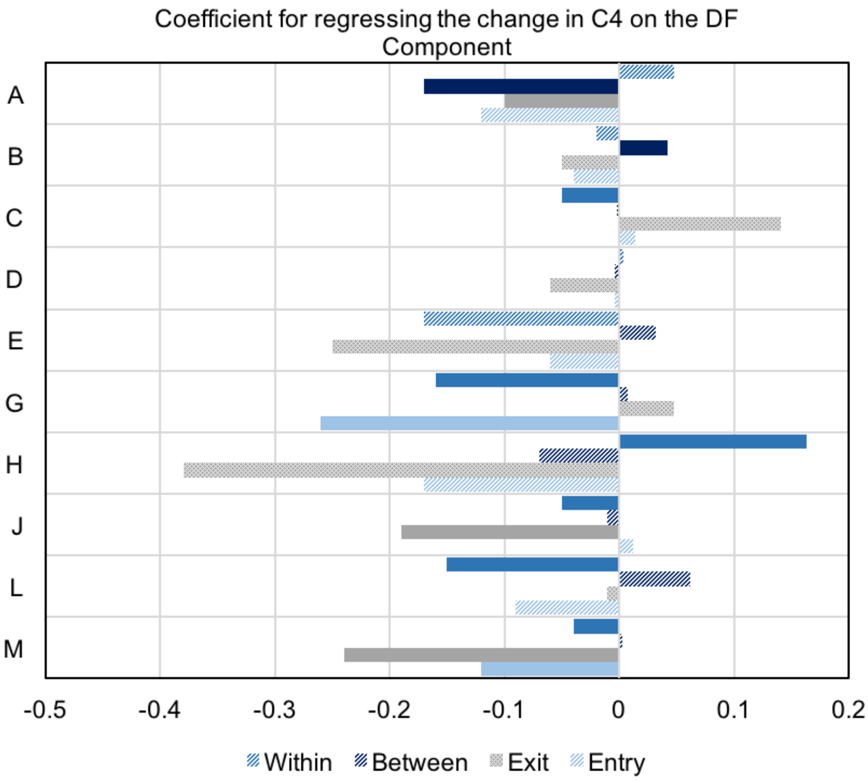
- **Main results are consistent with different concentration ratios (C10, C20, HHI):** The magnitudes of the within coefficients on changes in C10, C20, and HHI are lower in magnitude than the C4 coefficients. They are nonetheless more statistically significant than the coefficients of the between and concentration regressions.

- **Evidence for main results is weaker with mark-ups**. The coefficients for the change in markup on the within component are only statistically significant when there is a 3-digit industry fixed effect. Still, even when it is not significant, the within coefficient is still larger in magnitude than the coefficient from the between term regression, suggesting the presence of an industry-wide change.

7.1.1.2 Division Analysis

Figure 7.3 presents the coefficients of regressing the change in concentration on the DF labour share components for division sub-samples. Figure 7.3 plots the coefficients from the regression. For each industry, the top bar denotes the coefficient for regressing concentration on the within component of labour share; next, on the between component; and the last two on exit and entry component. Coefficients which are significant are shown in block colours, while coefficients which are insignificant are shown as dashed lines. Overall, there is evidence for within- industry changes in labour shares for surviving firms,

Figure (7.3) Division level analysis using DF method



This graph presents the results of regressing the change in concentration of top four firms on each DF component for a division subsample. Each bar in the graph represents the magnitude of the coefficient on concentration, while the shading indicates whether it is statistically significant.The alphabet letters indicate division codes e.g. A = Agriculture, B = Mining, C = Manufacturing, D = Electricity and Gas Services, E = Construction, G = Retail Trade, H = Accommodation and Food Services, J = Information, Media and Technologies, L = Rental Hiring and Real Estate Services, M = Professional, Scientific and Technical Services

rather than a composition shift towards either high or low labour share firms, in most divisions. Among the 10 divisions, 8 out of 10 divisions have a within component from the DF decomposition that is larger in magnitude than their between term. Seven divisions have coefficients on the within component which are statistically more significant than the coefficient on the between component when regressed with the change in concentration. Of these:

- **Rent-Seeking industries** include Retail Trade. Retail trade experienced the largest increase in concentration and a negative significant coefficient on the within term: $\beta_{DF,\ within,16yr} = -0.00169$. Coupled with the increase in concentration and mark-ups, this suggests increasing concentration has driven downt the labour share of all surviving firms, rather than causing a shift to the most productive firms. This suggest an anti-competitive outcome. Administration and support services, Rental Hiring and Real Estate Services, Professional, Scientific and Technical Services, Electricity and Gas are other industries where the presence of within industry changes are present, suggesting rent-seeking behaviour.

- **Non rent-seeking industries** include Accommodation and Food services, which had the largest fall in concentration. Hence, the positive coefficient on the change in concentration when regressed with the within component suggests all surviving firms have increased labour share, as a consequence of price cuts.

- **Agriculture and mining** are exceptions. Their coefficients on concentration for the between regression are more statistically significant and larger than the coefficients for the within regression, suggesting that reallocation of value added is driving labour share changes, rather than a within-industy effect. As both have experienced a decrease in concentration, this suggests that there are not rent-seeking mechanisms at work in this division. Rather this is evidence of superstar mechanisms, and is consistent with Autor et al. (2019) finding, which find superstar effects in the Manufacturing sector.

7.1.1.3 Sub-sample Analysis

Furthermore, Table E.2 in Appendix E presents the results of separating the sample into goods and services divisions,[53] trade intensive and non-trade intensive industries[54] and primary and non-primary sectors.[55] The coefficient on concentration after regressing with the DF within term is still negative and larger in magnitude than the coefficient for the between regression; however, the coefficients are only statistically significant for the services sector, non-trade sector and the non-primary sectors. Concentration has induces Within-industry changes in labour share in those sectors. Superstar mechanisms are evident in

[53] Goods divisions defined as Manufacturing, Construction, Wholesale, Retail Trade, Transport, Agriculture, Mining. Services defined as Accommodation and Food Services, IMT, Rental Hiring and Real estate Services, professional, Scientific and Technical Services, Administration and Support Services, Arts and Recreations and Other Services.

[54] The split between trade intensive and non-trade intensive is based on a 4-digit industry level trade intensity, defined as total export sales over value added. Industries that are in the top 50% of the distribution are 'trade intensive', while bottom 50% are non-trade intensive.

[55] Primary sector is defined as agriculture, mining and manufacturing. These industries are known to have interesting calculations of value added in BLADE. Non primary sectors are all the other divisions.

the primary sector and trade intensive sectors, however, with a larger and statistically significant coefficient for the between regression. Agriculture and Mining Divisions are in this sector, and confirm the division level analysis which found that the between component is larger.

- **Goods and services sector (columns 1 and 2):** the coefficient for the within regression is negative and significant for both groups, although the rent seeking mechanism is much stronger in the services sector. In the goods sector, the coefficient for the within component, $\beta_{DF,within,goods} = -0.0342$ is significant at a 20% level, and 1.5 times larger than the between coefficient. In comparison, the coefficient for the within component, $\beta_{DF,within,services} = -0.205$ in the services sector is significant at a 10% level and 51 times larger than the between coefficient. The large difference indicates that changes in concentration in the services sector have a much stronger within-industry impact on labour shares than the goods sector.

- **Trade intensive and non-trade intensive industries (Columns 3 and 4):** Within-industry changes in labour share are not significant in the trade intensive sector. The between component is not significant either, however, it is larger than the within component, suggesting evidence of reallocation effects. In the non-tradeable sector, the coefficients for the within and between term are both statistically significant. Within, $\beta_{DF,within,non-trade} = -0.09$ is 3 times larger and more significant than the between coefficient, $\beta_{DF,between,non-trade}$ suggesting that rent seeking mechanisms dominate in the non-tradeable sector.

- **Non-primary industries and primary industries (Column 5 and 6):** An exception is the primary sector, where the coefficient on concentration for the between term, $\beta_{DF,between,primary} = -0.0264$ is more significant and 2.85 times larger than the coefficient on concentration for the within regression. This suggests that the concentration has driven a reallocation of value added, which is the main driver of labour share changes in the primary sector. The non-primary sector, in comparison, has a coefficient on the within regression that is significant and at least ten time larger in magnitude than the between coefficient. Hence, primary sector is the only sector which has evidence that aligns with the superstar mechanisms.

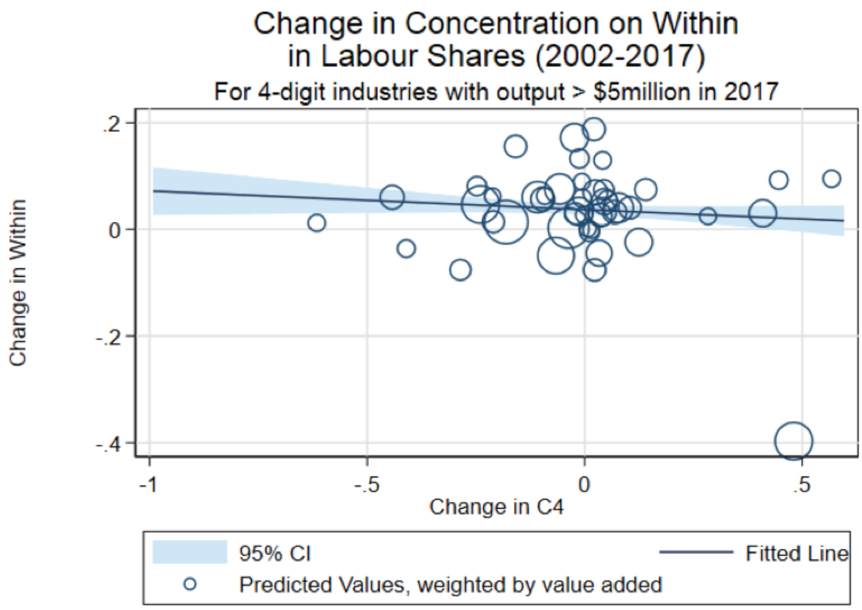
7.1.2 Understanding the results

To understand the results in the context of the Australian economy, Figure 7.4 plots the change in concentration of top four firms and the predicted change in the labour share of all surviving firms between 2001-02 and 2016-17 (i.e. the within component) for the regression with 3-digit industry fixed effects.[56] To avoid cluttering the graph, the graph also only plots the predicted values of industries with total value added greater than $5 million in 2017. The main takeaway is that there is significant heterogeneity in the results, reflecting how there is an split of industries experiencing an increase or fall in concentration as well

[56] The between component is not assessed at the aggregate level because its not significant at the aggregate level. It will be examined at the industry level in section 7.5.

as labour share. The chart can be split into four quadrants along the X and Y axis, of which this thesis will focus on two. First, there are many industries clustered at the bottom right quadrant, where firms have experienced an increase in concentration and decline in the within component. According to a monopolistic model described by Barkai (2016) and Tirole (1988), the industries in this quadrant are experiencing a large within-industry decline in labour share as concentration increases. This suggests rent-seeking behaviour. The second quadrant is the top left quadrant, where surviving firms are experiencing an increase in labour share as a result of a decline in concentration. Accordingly, this is evidence of competitive behaviour.

Figure (7.4) Predicted Values of regressing the change in C4 on the within component of labour share change 2002 -2017



Source: ABS BLADE 16-17, Author's Calculations

Industries are also within the bottom left and top right quadrants, in which there is direct relationship with labour share and concentration. It could be the case that the within change is still significant in these industries, but other factors (such as the price of capital) outweigh the change in labour share at the aggregate level. This makes sense as the quantile and OLS regressions in Chapter 5.3 showed that other factors explained variation in 4-digit industry data. As this thesis will only focus on the top left and bottom right quadrant, this is only a subsample of the entire economy as Figure 7.4 shows. Hence, it is important to not overstate the role of rent-seeking industries and non rent-seeking industries, as there are other industries that will not be explored in this thesis.

This distinction of a rent-seeking quadrant and non rent-seeking quadrant is apparent in the goods and services sector,[57] tradeable sector and non tradeable sector,[58] as well as primary and non-primary sector[59] as shown in Figure 7.5.

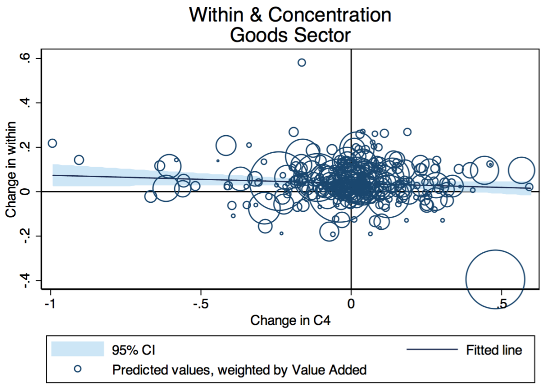
[57]Goods divisions defined as Manufacturing, Construction, Wholesale, Retail Trade, Transport, Agriculture, Mining. Services defined as Accommodation and Food Services, IMT, Rental Hiring and Real estate Services, professional, Scientific and Technical Services, Administration and Support Services, Arts and Recreations and Other Services.

[58]The split between trade intensive and non-trade intensive is based on a 4-digit industry level trade intensity, defined as total export sales over value added. Industries that are in the top 50% of the distribution are 'trade intensive', while bottom 50% are non-trade intensive.

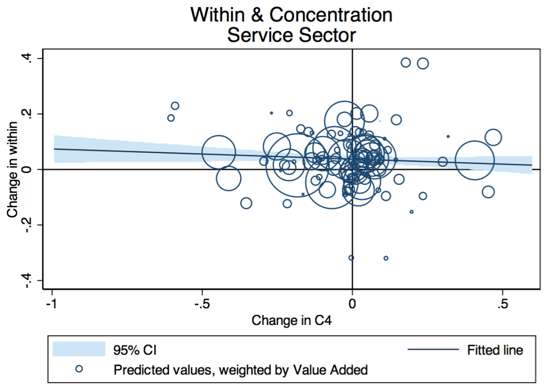
[59]Primary sector is defined as agriculture, mining and manufacturing. These industries are known to have interesting calculations of value added in BLADE. Non primary sectors are all the other divisions.

Figure (7.5) Predicted Values of Sub-sample regressions, using DF decomposition

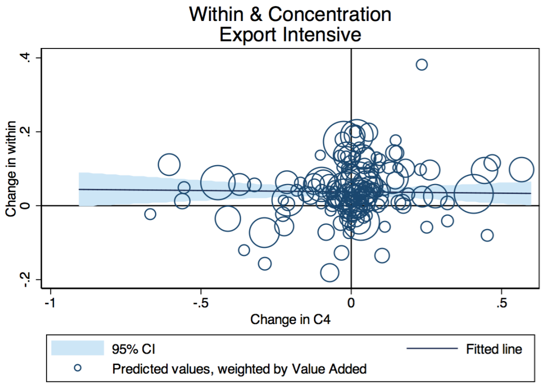
(a) Goods Sector



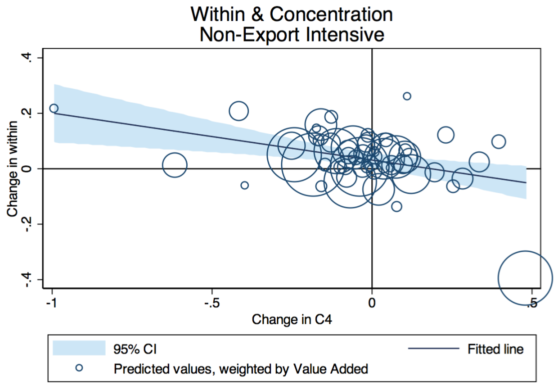
(b) Services Sector



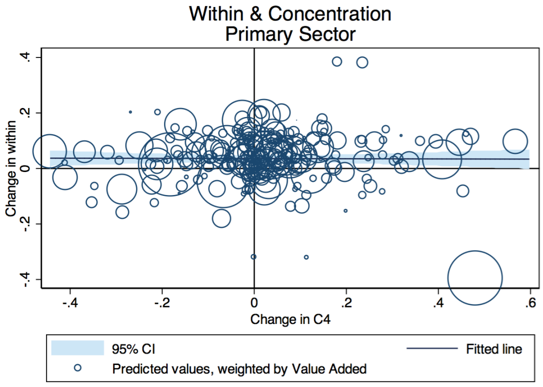
(c) Export Intensive Sector



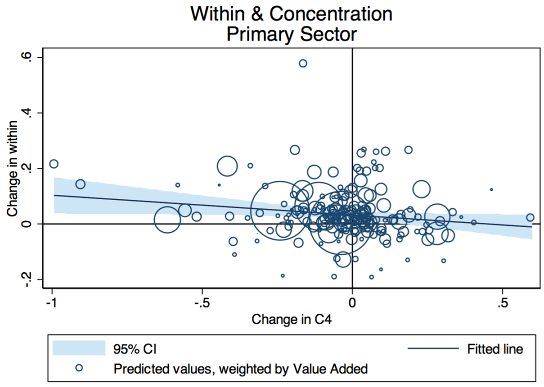
(d) Non-Export Intensive Sector



(e) Primary Sector



(f) Non-Primary Sector



Source: ABS BLADE 16-17, Author's Calculations

Charts plot change in concentration of top four firms over the predicted values in the within component of labour share for 6 sub samples

7.1.2.1 Rent Seeking Industries

This section explores some of the industries that can be classified as rent-seeking to gain a better understanding of the results. These are industries in the bottom right quadrant in the Figure 7.4 above. This suggest the increase in concentration has caused labour share of all surviving firms to fall (hence, a significant and negative coefficient after regressing the change in concentration on the within component). Since this is a weighted mean, it also indicates that the labour share of larger firms has fallen proportionally more than the labour shares of the small firms. Key characteristics include:

- Rent-seeking industries account for 18% of total value added (19% of gross output) in 2017.
- The main 4-digit ANZSIC industries which are in the goods sector come from Manufacturing, Agriculture, Transport, Postal and Warehousing and Retail Trade.
- Service industries account for a quarter of these industries as well, with about 5% coming from Information, Media and Technology Services, Professional, Scientific and Technical Services and Admin and Support Services Division each.

Table E.1 in Appendix E provides a list of the top industries in this industry, characterized by value added more than $5 million in 2017. It shows that the labour share and average labour productivity of these industries is 15.9%, which is 1.1% less than the total economy average. One interpretation is that this reflects the rent-seeking hypothesis: that large firms as they gain market control can raise prices and margins to increase profits, without contributing to productivity improvements, which leads to a fall in labour share.

7.1.2.2 Non Rent-Seeking Industries

There are several more industries which have experienced an increase in the within term and the decline in concentration. Following the model outlined by Barkai (2016) and the identification strategy suggested by Autor et al. (2017, 2019) a decline in concentration has caused the labour share of all surviving firms to fall. The inverse to an increase in labour shares is a fall in mark-ups, which suggests that firms are cutting prices and margins to remain competitive. Key features include:

- Represent around half of total industries within the economy, and slightly more than 50% in terms of value added in 2017.
- There is no singular division which is represented in the non rent-seeking quadrant. Hence, this phenomenon is division-wide.
- Service sector account of 40% of industries and 52% of value added. The largest divisions in this sector, in terms of value added, are Professional, Scientific and Technical Services and Real Estate and Rental Hiring Services, which account for 11% and 12% of the total value added.

- Goods sector is represented largely by the Manufacturing and Wholesale Trade, which account 16% and 8% of total industries, respectively, and 10% and 7% of total value added.

This supports the idea of increasing competition, rather than declining competition. Table E.2 in Appendix E outlines the largest industries in this sector. Interestingly, legal services have had the largest increases in labour share, and the second largest increase in the within component. It also shows that labour share and its growth are higher than the economy level. Labour productivity is less, indicating while there may be improving competition, it hasn't translated to productivity gains.

7.1.3 Summary and Implications

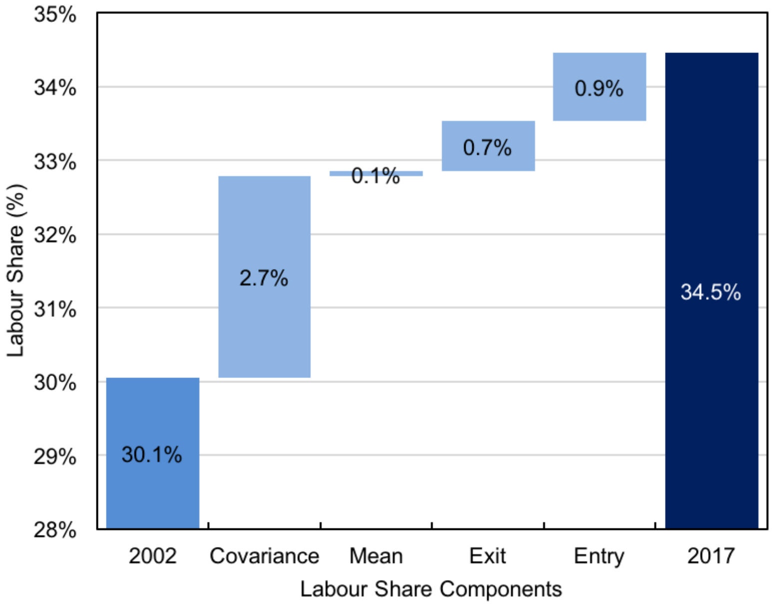
This new empirical framework, which combines Autor et al. (2019)'s identification strategy with a unique method of adapting the Diewert and Fox (2010) dynamic decomposition method to labour shares, gives evidence that within-industry changes are largely driving labour share trends. The within-industry effect is stronger in services industries, whereas primary industries like Agriculture and Mining have had a reallocation of value added driving changes. In industries that have faced an increase in concentration like Retail Trade, the finding that all firms have had a fall in labour shares implies declining competition. From a policy perspective, this signals weakening anti-trust policy and suggests further investigation. On the other hand, the increase in the within component for Accommodation and Food Services suggests that competition policy is effective and could form a case study for other matters.

7.2 Results using the Melitz and Polanec (2015) Decomposition Method

As a sensitivity analysis, this section follows Autor et al. (2019)'s empirical framework, which relies on the Melitz and Polanec (2015) dynamic decomposition to identify the components in labour shares. This section will explore the results from the main model and division level analysis, with robustness tests available in Appendix A.

Figure 7.6 presents the results of applying the MP decomposition on Australian labour shares between 2002 and 2017. The increase in labour share is driven by a 2.73% increase in covariance between firm market share and labour share. This suggests that 62% of the overall change in labour shares between 2002-2017 has been driven by a reallocation of market share to firms with high labour shares. Moreover, around 2% of the total change (equivalent to 0.07% increase) is driven by the change in the unweighted mean of labour share. The exit and entry terms are the same as the DF terms.Interestingly, reallocation is the largest driver of labour change in Australia, consistent with Autor et al's finding (see Figure 7.6). This is inconsistent with the analysis in section 7.2.1, where DF found that within-industry changes are the main driver.

Figure (7.6) Decomposition of Labour Share Between 2001-02 and 2016-17 using Melitz and Polanec (2010)



Source: ABS BLADE 16-17, Author's Calculations

Table 7.2 presents the results of a 16-year long difference regression of each of the components of labour share (covariance, mean, exit and entry) on the change in concentration of top four firms (CR4). The industry fixed effects are the same as the specifications used for Diewert and Fox. The OLS regressions 1 – 4 in the table above find a significant and negative relationship between the change in concentration and the covariance term, with growing significance as the severity of fixed effects increase. The results indicate that a ten-percentage point decline (increase) in concentration within the economy, is associated with a 1 percentage increase (decline) in the labour share driven by the reallocation of value added of market share to surviving high (low) labour shares. The unweighted mean is not significant and smaller in magnitude than the covariance term for all specifications. The relationships with concentration and the covariance term match the results in Autor et al (2017, 2019) superstar model, suggesting that superstar mechanisms significant in the United States are also significant in Australia. The magnitude of the coefficients is also similar.

Table (7.2) Industry (4-Digit) Regressions of the components of a MP Labour Share Decomposition on the Change in Concentration

	Mean				Covariance			
Change in C4	-0.0016	-0.00219	-0.00357	-0.00198	-0.0102**	-0.0108*	-0.00801	-0.0135+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.0000402	-0.000907	0.00896	-0.0124	0.0475***	-0.0031	-0.00718	0.0335+
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	435	435	435	435	435	435	435	435
R-squared	0.001	0.066	0.246	0.489	0.008	0.083	0.247	0.466
Adjusted R-squared	-0.002	0.033	0.094	0.13	0.006	0.051	0.095	0.092
Industry Controls	X	X	X	X	X	X	X	X
OLS	X				X			
Industry 1-digit FE		X				X		
Industry 2 -digit FE			X				X	
Industry 3-digit FE				X				X

	Exit				Entry			
Change in C4	0.0219*	0.0217*	0.0202++	0.0221++	-0.00594	-0.0053	-0.00653	-0.00493
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.00868+	0.0242*	0.0205+	0.0279	-0.00879*	0.00519	0.00000695	-0.00956
	(0.01)	(0.01)	(0.01)	(0.03)	(0.00)	(0.01)	(0.01)	(0.02)
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	437	437	437	437	437	437	437	437
R-squared	0.036	0.06	0.152	0.3	0.006	0.043	0.202	0.425
Adjusted R-squared	0.034	0.026	-0.019	-0.193	0.004	0.008	0.041	0.021
Industry Controls	X	X	X	X	X	X	X	X
OLS	X				X			
Industry 1-digit FE		X				X		
Industry 2 -digit FE			X				X	
Industry 3-digit FE								X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This table presents the results of regressing the MP decomposition of labour shares on the change in the concentration ratio of top 4 firms in a 16 -year long difference regression (refer to Model eqn 6.11. Standard errors are clustered at the 4-digit industry level and industry controls (capital intensity, size) are used.

Source: ABS BLADE 16-17, Author's calculations

7.2.1 Further Analysis

This section examines the robustness of the MP results to further analysis. The tests are the same as DF results, with additional concentration ratios division analysis and (3) sub-sample analysis. Results are presented in Appendix E for conciseness.

7.2.1.1 Robustness Tests

A series of robustness tests were conducted similar to the analysis for DF. Table **??** in Appendix E presents the regression results of using other concentration measures, like C10, C20 and HHI and mark-ups. The coefficient on the change in concentration regressed with covariance is statistically significant and negative across all measures of concentration. For mark-ups, there is only a statistically significant relationship between concentration and covariance when 2-digit and 3-digit industry fixed effects are applied

7.2.1.2 Division Analysis

Appendix Figure E.4 presents the results of regressing the MP components of labour share with the change in concentration for ten divisions. The results suggest that the superstar mechanism are apparent in the Retail Trade, Manufacturing, Electricity and Gas Services, Construction, Mining and Agriculture Divisions, determined on the basis that the coefficient for the covariance regression is more statistically significant and larger in absolute magnitude than the coefficient for the mean regression, as shown in Figure E.4. For example, in Retail Trade, the increase in concentration predicts a reallocation of value added towards low labour share firms, suggesting increasing competition and an increase in allocative efficiency for the labour share decline. In contrast, Mining has experienced an increase in labour share and decline in concentration. The positive coefficient on concentration for the covariance regression predicts that the decline in concentration has driven a reallocation of value added away from low labour share firms to high labour share firms. Manufacturing is another industry like this, leading to declining competition and less allocative efficiency. Mining and Manufacturing are both examples of fading superstars where the decline in concentration has meant that value added has been reallocated towards less productive, high labour share firms, leading to a fall in allocative efficiency and increase in labour shares.

The rest of the industries show evidence of division-wide changes, as their mean component is larger than the covariance term. The two largest industries where this has occurred are the Professional, Scientific and Technical Services Division and Rental Hiring and Real Estate Services Division. In both industries, the coefficient of concentration after regressing on the unweighted mean is negative and statistically significant, suggesting that the increase in concentration has caused the decline in labour share of all surviving firms. Following Autor et al. (2017, 2019) non rent-seekings identification strategy, this suggests that the decline in labour share has occurred because of rent-seeking behaviour, driven by an increase in mark-ups. Hence, Professional, Scientific and Technical Services Division and Rental Hiring and Real Estate Services Division are examples of divisions where the change in labour share is driven, at least partly, by anti-competitive reasons. By contrast, Accommodation and Food services and Information, Media and Technology have a positive coefficient for the mean regression. The coefficient predicts that a fall in concentration has caused the labour share of all firms to increase, as increased price competition causes all firms to cut mark-ups which leads to an inverse increase in labour shares.

7.2.1.3 Subsector Analysis

Furthermore, Appendix Table E.4 presents the results of separating the sample into goods and service divisions,[60] trade intensive and non-trade intensive industries[61] and primary and non-primary sectors[62]. The coefficient of the change in concentration after regressing on the MP covariance term is still negative and statistically significant, implying superstar mechanisms. However, they also indicate that superstar mechanisms are most prominent in services divisions and nontrade-intensive industries, as discussed below:

- **Goods and services sector (columns 1 and 2):** the coefficient for the covariance regression is negative and statistically significant for both Goods and Services Sector. The coefficient is much larger in the services sector, however: a 1% increase in concentration, will lead to a fall in the covariance term of labour shares by less than 14% in services sector, but a fall in the covariance term by 7% in the goods sector. This indicates that superstar mechanisms are stronger in the Services Sector.
- **Trade intensive and non-trade intensive industries (Columns 3 and 4):** Similarly, the coefficient for concentration regressed with the covariance component of labour share is larger than the coefficient for the mean regression in both sectors. The coefficient is significant only in the non-trade industries, though. This is an important result, as non-trade intensive industries might not be exposed to international competition as much. Hence, the concentration measure could accurately reflect domestic competition. Alternatively, the trade coefficient for covariance may not be significant because concentration does not measure correctly the level of international and domestic competition.
- **Non-primary industries and primary industries (Column 5 and 6):** Both samples have a statistically significant coefficent for covariance regression, suggesting a role for superstar mechanisms. The coefficient is larger in magnitude than the coefficient when regressed for the non-primary industry by more than 10%.

7.2.2 Understanding the results

Figure 7.7 plots the changes in concentration between 2002-2017 and the predicted changes in the 'covariance' component of labour share.[63] Like in the DF analysis, the chart can be split into four quadrants along the X and Y axes, of which this thesis will focus on two.[64]

[60] Goods divisions defined as Manufacturing, Construction, Wholesale, Retail Trade, Transport, Agriculture, Mining. Services defined as Accommodation and Food Services, IMT, Rental Hiring and Real estate Services, professional, Scientific and Technical Services, Administration and Support Services, Arts and Recreations and Other Services.

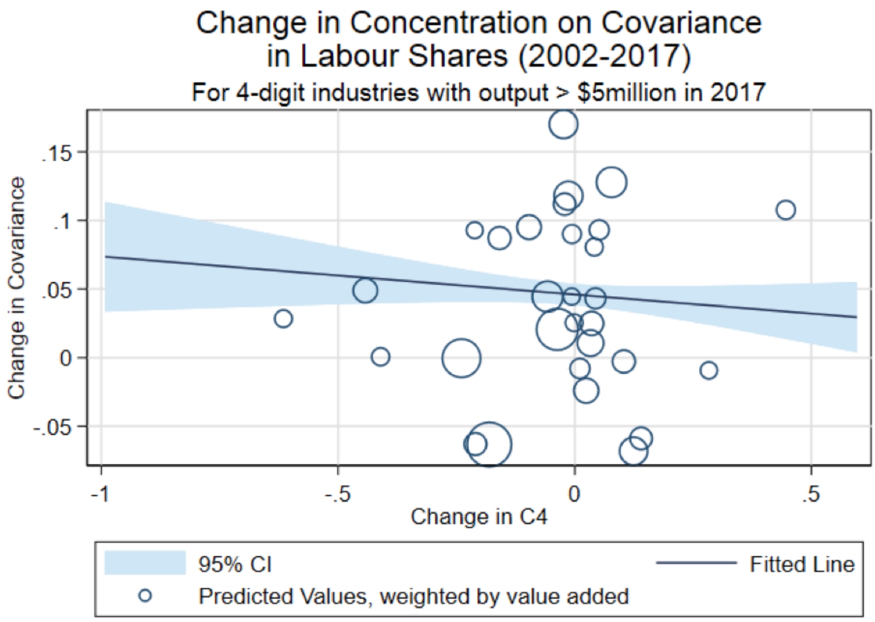
[61] The split between trade intensive and non-trade intensive is based on a 4-digit industry level trade intensity, defined as total export sales over value added. Industries that are in the top 50% of the distribution are 'trade intensive', while bottom 50% are non-trade intensive.

[62] Primary sector is defined as agriculture, mining and manufacturing. These industries are known to have interesting calculations of value added in BLADE. Non primary sectors are all the other divisions.

[63] The graph also only plots the predicted values for 4-digit industries with output greater than $5 million in 2017.

[64] Again, there is significant heterogeneity with firms, as some industries with the largest increase (decrease) in concentration have also had the largest increase (decrease) in labour shares over the past fifteen years. Its outside the scope of this thesis to explore these industries, however.

Figure (7.7) Labour Share decomposition



Source: ABS BLADE 16-17, Author's Calculations

Clusters of industries exist in the bottom right quadrant, where superstar firms exist, and the left quadrant, which this thesis characterises and defines as **fading superstar**.[65] This distinction of the superstar quadrant and the fading superstar quadrant is apparent in the good sector, services sector, tradeable sector or non-tradeable sector as well (See Appendix Figure E.3 in Appendix). Like the DF analysis, it is also clear that the importance of superstar phenomenon should not be overstated. As the Division analysis also suggested, superstar industries only exist in a few industries. They account for 12% of four-digit industries, and only 15% of total value added. Hence, they make a small contribution in our economy majority are fading superstars. **Fading stars**, in comparison, make up a third of total industries and 40% in terms of value added exist in this quadrant, indicating that fading superstars outweigh superstars. Around 50% of industries are not accounted for in this analysis.

7.3 Exploring the MP results through the lens of DF analysis

This section compares the DF results from Section 7.1, which presents new insights using the proposed methodology, and MP from Section 7.2, which presents the results from Autor et al. (2019)'s original empirical framework applying the Melitz and Polanec (2015) decomposition. In summary, DF and MP provide very different insights into the role of competition on labour shares in Australia at the economy level. Each have starkly different policy implications:

[65] Fading superstar refers to industries where there has been a decline in the productivity of the largest firms, as obsolesce hits and the market matures (See e.g. Porter), causing value added to shift away from productive firms.

- DF analysis shows that the inverse relationship between the change in concentration and the within component of labour shares is statistically significant. This predicts that concentration is driving labour share trends through within-industry changes. This is evidence for Barkai (2016)'s rent seeking model, and indicates that for industries with increasing concentration, the decline in labour share is a result of anti-competitive behaviour. From a policy perspective, this indicates that the weakening of anti-trust policies and competition policies has lead to a decline in competition and increase in concentration, fueling the decline in labour share.

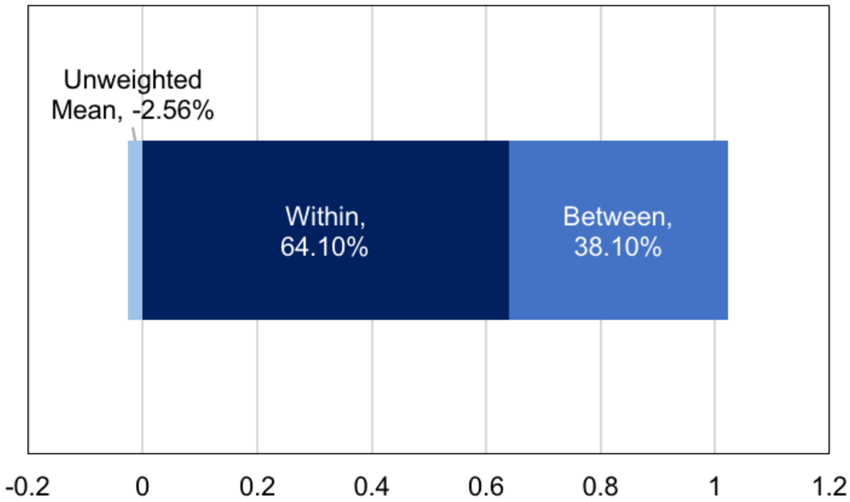
- Conversely, MP results show that concentration is significantly and negatively related with the covariance term, giving evidence that reallocation of value added is driving trends in labour share. From a policy perspective, an increase in allocative efficiency due to innovation and scale economies suggests that the decline in labour share is a competitive outcome (Andrews et al., 2015; Autor et al., 2019; Van Reenen, 2018).

7.3.1 Theoretical Implications

Understanding the differences between DF and MP results is vital to understanding the true driver of labour shares. It is will also signal how policy makers can address concerns with labour shares, but other ancillary issues as well like stagnating wage growth, declining business dynamism and increasing inequality.

Section 6.2.3 identified a novel strategy to understand the differences between DF and MP (see Equation 6.9). Chart 7.8 presents the components of the covariance term, as the sum of the DF between term, DF within term and the MP unweighted mean term for the period 2002-2017. The within term overwhelmingly accounts for the 64% of the increase in the covariance term, while 38% of it is driven by the within term. Small firms have experienced a decline in labour share which offsets the increase in the covariance term by 2.56%.

Figure (7.8) Further Decomposition of the MP Covariance term

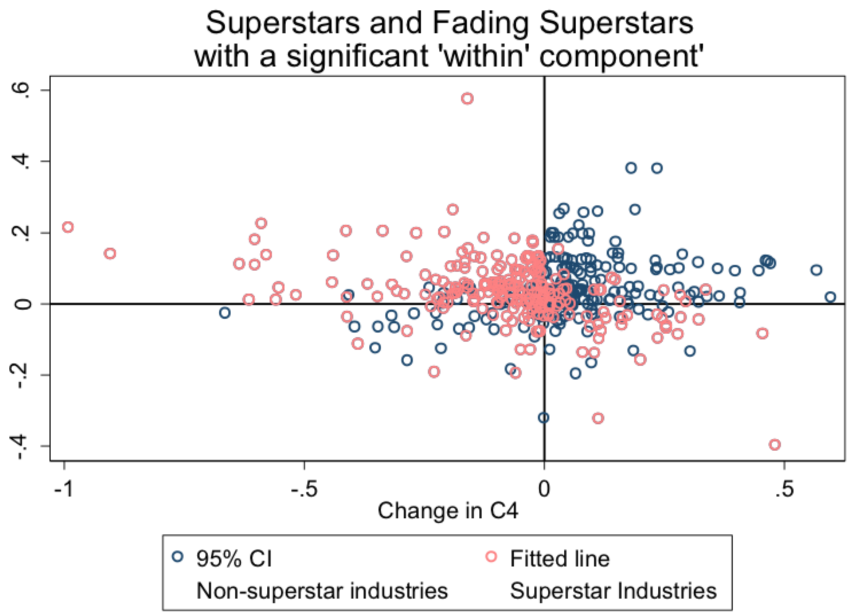


Source: ABS BLADE 16-17, Author's Calculations

The fact that the within component is a driver of the covariance term is consistent with the literature. of Statistics (2017) and Weir (2018) both find that labour shares in Australia are driven by within components. Autor et al. (2019)'s revised paper uses a five-part decomposition to show that the within component is driving their 'between' reallocation term as well. Research from the USA also show that labour share is primarily driven by the 'within' change as well (Kehrig and Vincent, 2017). This suggests that although there is a reallocation of value added, it is largely been driven by a within-industry change in value added. This reflects descriptive statistics in Chapter 4.

Moreover, regression results also present a similar story. Chart 7.9 plots the change in concentration and the DF predicted within component, highlighting industries which were identified as superstar or fading superstar industries in the MP analysis. The Chart shows that many superstar or fading superstar firms have a significant within component when regresed with concentration. Moreover, most fading superstars have a large within component (suggesting the decline in rent seeking) while a few superstar firms have a large within component (suggesting the presence of rent seeking). Hence, comparing the MP and DF analysis can be useful exercise to understand the competition drivers of labour share.

Figure (7.9) Plotting Predicted values of the DF Analysis, identifying Superstar Industries



Source: ABS BLADE 16-17, Author's Calculations

While other studies agree with Autor et al. (2019)'s analysis such as Van Reenen (2018), the analysis in this thesis suggests that it is premature to rely soley on Autor et al. (2019) empirical framework or the implications of their findings. The DF decomposition shows, at least on Australian data, that the MP covariance term is mostly driven by the within component, giving evidence that the Autor et al. (2017) methodology could be misleading if it is believed that only superstar mechanisms are prominent. Hence, this thesis challenges and overturns the methodology and findings of Autor et al. (2019) by using a new framework which adapts the Diewert and Fox (2010) dynamic decomposition method to labour share data. In particular, it suggests three points:

1. First, Autor et al. (2019) results are sensitive to the decomposition method used. The DF method, prima facie, gives evidence for rent-seeking mechanisms within the economy (see Section 7.1). The original DF method for studying productivity decompositions has been used and identified in the literature as an axiomatic robust method (see e.g. Balk, 2016) in comparison to MP and other methods.
2. Second, relying entirely on the MP method does not give a clear picture of competition in the economy, as the joint market share and labour share difference terms form the covariance term. Using the DF method gave us some insight into this, and was a useful tool to tease out the real drivers of labour share in an industry (see Figure 7.9)
3. Third, this thesis suggests that the original results in the Autor et al. (2017, 2019) could be overturned, with further analysis. Perhaps by using new methodology

proposed in this thesis in Section 6.3 on the data of Autor et al., their results may align with with the broader literature which identified within-industry changes in labour share for manufacturing and other US sectors.

7.3.2 Practical and Policy Implications

This section aims to understand the practical implications of finding a superstar industry under Autor et al. (2019)'s original framework, and how this relates to the findings in the new empirical framework.

7.3.2.1 Does Australia have superstar industries?

Superstar industries reflect the idea that there are superstar firms within an industry, akin to Google or Amazon (Autor et al., 2019; Van Reenen, 2018), which are acquiring market share through innovation and economies of scales. Typical outcomes include aggregate productivity growth (Autor et al., 2019), increased productivity dispersion (Schwellnus et al., 2017), higher levels of capital investment and growth in the industry.

Hence, this section aims to understand the practical implications of finding a superstar industry under Autor et al. (2019)'s original framework. In particular, do they truly exist, even under the new empirical framework? Are they as important as many authors suggest?

While superstar firms exist in Australia, according to the MP analysis this is limited to only a few industries, namely in the Retail Trade Sector. They account for 15% of value added and 12% of total industries. Hence they only have a small contribution to total economy.

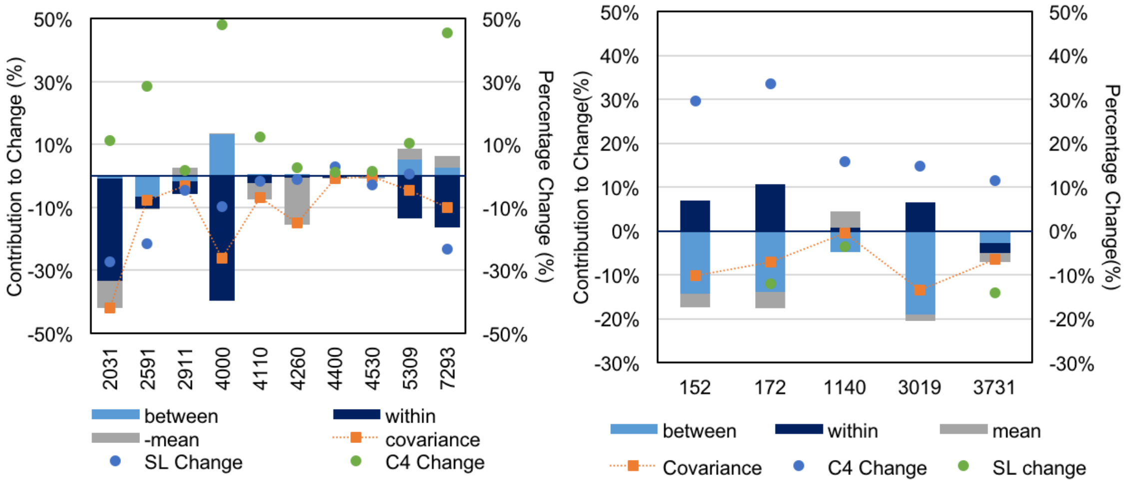
Using the new empirical framework, decomposing labour share changes further into DF components suggest that:

- In many superstar industries, the within term is driving the covariance term, not the between term (see Figure 7.10a). An example is the supermarket and grocery stores industries (4-digit ID 4110), which is identified as a key superstar industry under MP analysis. Using DF analysis, however, the between term explains only 8% of the fall, while the within and mean term combined contribute on average to 54.5% of the fall in the labour shares for. This suggests that in industries where there has been an increase in allocative efficiency, labour shares of the largest firms, that is the superstar firms, have fallen more than the small firms. This phenomenon of superstar industries which have a large within component is not trivial, as they represent 60% of the total industries in the rent seeking quadrant, and 65% of the total value added.
- Only small industries are pure superstars, where covariance term is composed of a between term which is larger than the within term. Figure 7.10b shows the remaining superstar industries identified in the MP analysis, which do not have a

significant within component, but a significant between terms positively correlated to concentration. For example, Cotton Growing (ID 152) experienced a fall in covariance 7 percentage points, of which nearly half was experienced by a decline in the between term too. Interestingly, these industries have a low contribution in terms of value added. Combined, they only contribute to less than 1% of value added in 2017. This is contrary to the intuition behind superstar firms, which tend to be large and high productive.

Figure (7.10) Further Decomposition of MP using DF method for Superstar Industries

(a) 'Rent Seeking' Superstar Firms **(b) 'Pure' Superstar Firms**



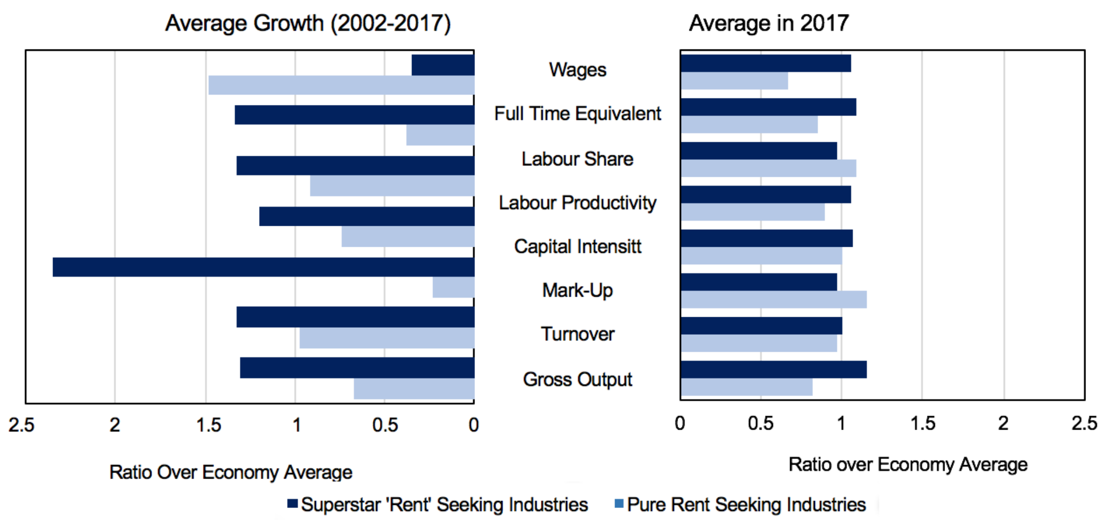
Source: ABS BLADE 16-17, Author's Calculations

One interpretation of these results is that superstar firms are engaging in rent seeking behaviour, where the reallocation of value added to large firms enables them to raise the prices and hence lower mark-ups due to their gridlock on demand. This is anti-competitive behaviour and would reflect Barkai (2016)'s model, where firms raise prices above marginal costs to increase profits. However, Autor et al. (2019) argue that higher mark-ups are consistent with large and more productive firms, as large firms increase mark-ups to compensate for the increased costs of production and overhead due to a larger production and revenue base. Alternatively, an increase in the within component could support Edmond et al. (2018)'s argument that industries are facing inelastic demand functions and that an increase in concentration increases market shares and reduces demand elasticities. Consequently, firms charge higher mark-ups in response to the increased demand for their product. As labour shares are an inverse of mark-ups, this leads to a natural decline in labour shares (Edmond et al., 2018). Edmond et al. would argue that the increase in the within component is pro-competitive, supports the general idea that allocative efficiency has increased.

In summary, Australia has only a limited number of industries where superstar phenomenon is evident. DF demonstrates in most cases, the within-industry component outweighs any reallocation, indicative of potentially anti-competitive behaviour. Nonetheless, they are significant from a policy point of view due to the benefit that they bring the economy. Panel A in Figure 7.11 shows that superstar industries are on average larger, more productive, employee more staff and are more capital intensive than non-superstar firms. Similarly, Panel B also shows that the superstar industries have had stronger growth in labour productivity and capital intensity, and hire considerably less employees than the non-superstar firms, supporting the idea that superstar firms have gain market share through technology or globalization that improves labour productivity and increased returns to scale. While mark-ups are relatively the same in Panel A, Panel B shows that the mark-up-growth experienced by superstar firms is extraordinary. This reflect the idea that these superstar industries have engaged in rent-seeking behaviour or face an inelastic demand curve.

Hence, this analysis brings to light a dichotomous tension about superstar industries and their rent-seeking behaviour. While they may be boosting aggregate productivity, it is at risk of leaving other firms behind and raising prices.

Figure (7.11) Comparing the average level and average growth rate of Superstar Industries with the rest of the Economy



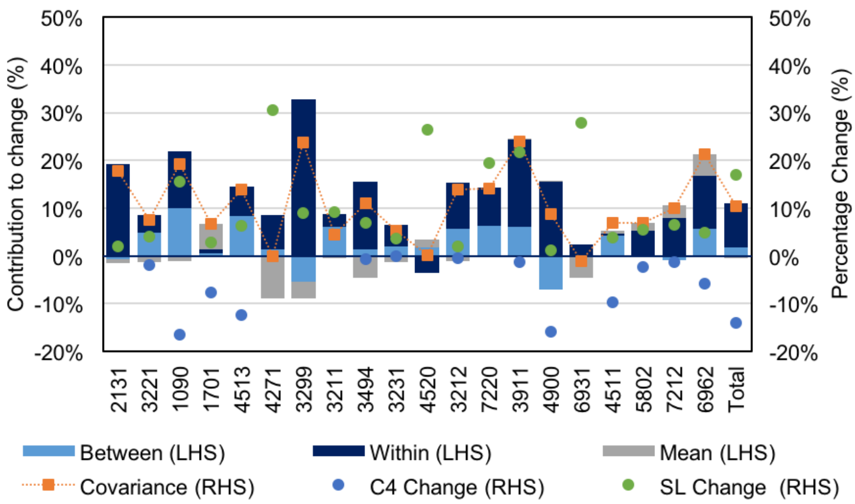
Source: ABS BLADE 16-17, Author's Calculations

7.3.2.2 What are fading superstar industries?

MP analysis identified that there are many fading superstars in Australia. This is a policy significant finding, as fading superstars indicate declining allocative efficiency. Fading superstars account for more than a third of industries and represents 40% of total value added in 2017. Superstar firms are limited to only a few industries and 15% of total value added in 2017. Together, more than half of the change in Australia's labour shares can be explained by fading superstar mechanisms. Given fading superstars are more representative in the economy, the results indicate that fading stars are more significant in Australia in terms of aggregate trend and policy. Fading stars industries should be prioritised.

Further, applying the new empirical framework, the DF decomposition confirms the finding of fading superstars. Taking the industry average of fading superstars, 88% of the within term explains the covariance term, offset by a fall in 4% by the unweighted mean term, while the between term only accounts for 18% of the total variation. The within term is weighted, suggesting that although there has been a decline in allocative efficiency, taking value added away from low labour share firms, it has disproportionately affected low labour share and large firms. Hence, low labour share firms have experienced the largest cuts in mark-ups and largest increases in labour shares in the industry. This supports the analysis in Chapter 2 which showed that it is the low labour share firms which are driving the aggregate trend of increasing labour shares. Fading superstar industries roughly represents 60% of the total industries in the non rent-seeking quadrant, and 59% of the total value added for non rent-seeking stars. Figure 7.12 presents the results for the top 20 industries in this segment as well as the industry average, comparing the DF analysis and MP analysis.

Figure (7.12) Decomposition of Fading Superstars, using Diewert and Fox (2010)



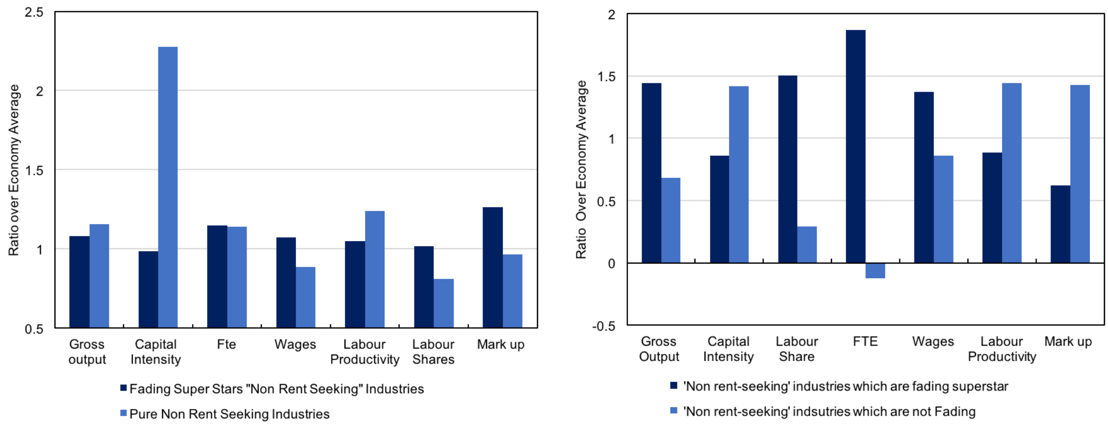
Source: ABS BLADE 16-17, Author's Calculations

The question on whether the increase in the within component is a competitive or anti-competitive outcome depends on the interpretation, again. Barkai (2016) would argue that this is an overall pro-competitive outcome, as cuts to mark-ups suggest price competition and firms pricing products according to marginal costs. Edmond et al. (2018) would argue that the large decline in mark-ups and hence increase in labour shares reflects increasing inelasticity in the industry. Reduced demand for low labour share firms causes them to reduce production and cut mark-ups to compensate for costs. According to Edmond et al. (2018), the decline in mark-ups is an efficient outcome of the market with inelastic demand function and should not require government intervention. While this reflects declining allocative efficiency, Edmond et al. (2018) argues that this is a competitive outcome in the economy, and one that is natural and should not require an intervention. Hence, the analysis suggests, that despite overall declining allocative efficiency, the cut in mark-ups and increase in labour shares by large firms is not an anti-competitive outcome – at least for the large firms.

Overall, DF analysis confirms that there are several fading superstar industries in the economy. Panel A of Figure 7.13 confirms this - these fading superstar industries are on average smaller, less productive, less capital intensive and employ more staff than non-superstar firms in this non rent-seeking quadrant. Panel B also shows that the fading superstar industries have had weak growth in labour productivity and capital intensity but hired considerably more employees than the non-fading superstar firms, supporting the idea that fading superstar firms compensate for reducing scales of return by hiring more input. The DF analysis suggests that large firms have disproportionately dropped mark-ups and dropped labour share – this is not an anti-competitive outcome according to Barkai (2016) and Edmond et al. (2018). While mark-ups are relatively the same in Panel A, Panel B shows that mark-ups have fallen considerably for fading firms, reflecting the idea that these fading superstar industries are engaging in non rent-seeking behaviour.

Figure (7.13) Comparing the average level and average growth rate of Fading Superstar Industries with the Rest of the Economy

(a) Average Growth in 2017 **(b) Average Growth (2002 - 2017)**



Source: ABS BLADE 16-17, Author's Calculations

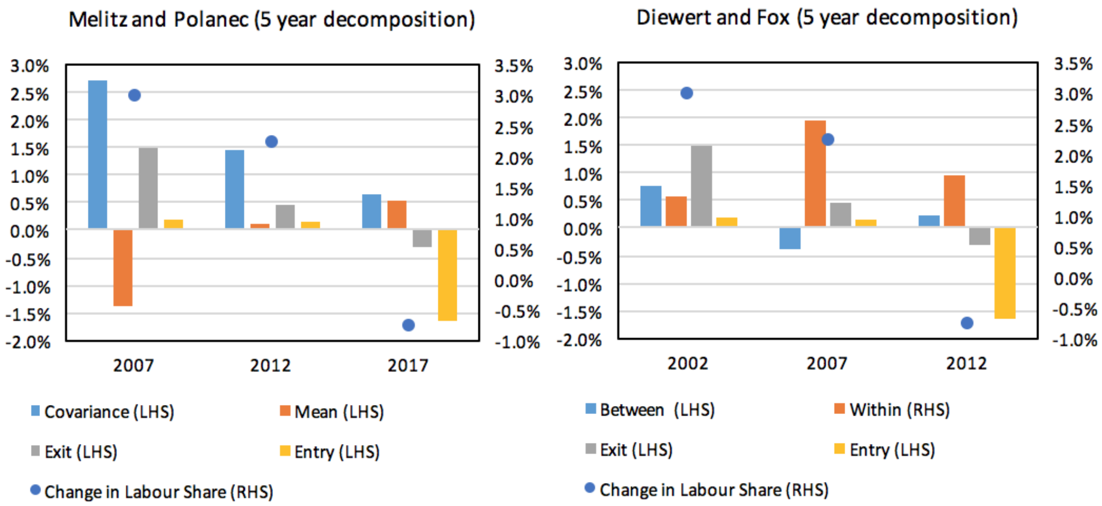
The results indicate that the increasing labour share driven by fading superstar is not a competitive outcome in the economy. It is reflective of broader policy outcomes in the economy, like declining business dynamism and stagnating wage growth. Section E.3 in

Appendix E conducts a further examination of the differences between superstar and fading superstar firms.

7.4 Labour Shares and Competition over time

This section will explore the trends in concentration and labour share over time. Figure 7.14 demarcates three distinct periods spanning five years: 2001-02 to 2006-07, which coincides with the pre-mining boom period; 2006-07 to 2011-2012 which coincides with the mining boom, but also a period of weak growth in other sectors; and 2011-12 to 2016-17, which was post mining boom. In the figure, the left-hand side presents the MP Decomposition and the right-hand side presents the DF decomposition.

Figure (7.14) Dynamic Decomposition of Labour shares across 2002-07, 2007-12 and 2012-17



Source: ABS BLADE 16-17, Author's Calculations

Across all three periods, the covariance term is larger than the mean term, suggesting that superstar mechanisms exist within the economy (following Autor et al. (2017) identification). Comparing this to DF, the relative importance of the within and between component changes over time. In 2002-2007, the between component is larger than the within term, confirming that reallocation of value added to high labour share firms is driving labour share changes during this period. After 2007, however, the within component is larger than the between term. This indicates that the increase in the covariance term in the MP analysis experienced during this time is largely driven by a within change in industry labour shares. This is an interesting trend, as it suggests a shift from mechanisms which promote allocative efficiency to productive efficiency.

Table 7.3 presents the results of regressing the change in concentration of the top four firms (C4) over the components of labour share over the entire period, as well as the periods of 2002-2007, 2007-2012, and 2012-2017. In contrast to Section 7.1 and 7.2 where the period of change was between 2002-2017, the period of change is year-on-year. Hence, the unit of observations are firm level decomposition year-on-year aggregated to the 4-digit industry level. The first row presents the results of regressing surviving components for MP over concentration and the next two for DF components. MP and DF share the same exit and entry results, and they are presented last. This analysis is conducted for the entire economy (market sector excluding financial and insurance services), but also a sub-sample, removing primary sectors mining, manufacturing agriculture. This is done because Section 7.1.1.3 showed that the primary and the non-primary sector had distinct trends.

7.4.1 Full Economy Sample between 2002 - 2017

The results for the Diewert and Fox (2010) decomposition give evidence that concentration is drivers the reallocation of value added is driving labour share changes year-on-year (Column 1). This is because, the coefficient on the the change in concentration for the between regression is larger in magnitude and more statistically significant than the coefficient for the within regression for the period 2002-2017 and sub-period 2002-2007. However, after 2007, the results change. The coefficient for the change in concentration switches to being more statistically significant and larger in magnitude than the coefficient for the between regression in 2007-2012 and 2012-2017. This suggests that over time, the influence of concentration has changed from driving a reallocation of value added to influencing within-industry changes for all firms. Regarding the MP analysis, this indicates on observation that the covariance term was driven by the between component initially, but has changed to the within component since 2007.

7.4.2 Non-Primary Sector between 2002 - 2017

The following section focuses on the results of the non-primary sector. This is useful in two ways: first, the primary sector seemed to be the main divisions experiencing the superstar mechanisms, confirmed with DF analysis as well. Compositionally, they make up one-fifth of total value added in the economy, less than one-fifth of total employment but they account for 46% of total industries. Hence, they represent a large portion of the sample, despite only contributing one-fifth to the aggregate economy trend, and could be driving the trend through sample size along. If the primary and non-primary sectors are pooled, there is heterogeneity that could be concealed. Separated, the drivers of the non-primary sector become evident. It is also important to divide the non-primary sector as they employ about 83% of the total economy and represent 80% of the total value added in the economy in 2017 (according to BLADE statistics).

The MP analysis for the non-primary sector is consistent with the MP analysis for the whole economy. That is, there is a negative relationship with covariance and concentration which is significant at the 1% level. In the subsamples of 2002-2007, 2007-12 and 2012-17, this is also the case. Similar to the whole economy sample, the coefficients increase in magnitude over time, suggesting greater evidence of reallocation over time. The mean

Table (7.3) DF and MP Analysis Regression, Through Time

Period	2002-2017		2002-2007		2007-2012		2012-2017	
Independent Variable	**Change CR4**		**Change CR4**		**Change CR4**		**Change CR4**	
Sample	*All Economy*	*Subsample*	*All Economy*	*Subsample*	*All Economy*	*Sub Sample*	*All Economy*	*Sub Sample*
Covariance	-0.123***	-0.136***	-0.0994***	-0.111***	-0.117***	-0.136***	-0.161***	-0.175**
	-0.0201	-0.0251	-0.0205	-0.0239	-0.0312	-0.0395	-0.0457	-0.0599
Mean	0.00431+	0.00156	-0.00302+	-0.00479	0.00886+	0.0068	0.00554	-0.0402*
	-0.00313	-0.00367	-0.00618	-0.00673	-0.00539	-0.00616	-0.00551	-0.016
Between	-0.0560***	-0.0593***	-0.0394**	-0.0488**	-0.0291**	-0.0605**	-0.0376**	-0.0506**
	-0.01	-0.013	-0.015	-0.0173	-0.021	-0.0274	-0.018	-0.0181
Within	-0.0323***	-0.0396***	-0.0309**	-0.0303**	-0.0779***	-0.0802**	-0.0541**	-0.0390*
	-0.00711	-0.0087	-0.01	-0.0114	-0.011	-0.0135	-0.014	-0.0188
Exit	-0.0428***	-0.0395***	-0.0582***	-0.0572**	-0.0328**	-0.0217++	-0.0362**	-0.0402*
	-0.00845	-0.00968	-0.0172	-0.0203	-0.0119	-0.0122	-0.0126	-0.016
Entry	-0.0351***	-0.0291***	-0.0311**	-0.0314**	-0.0434***	-0.0325***	-0.0285**	-0.0209**
	-0.00566	-0.00601	-0.0102	-0.0117	-0.00942	-0.00954	-0.00861	-0.00769
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X
Observations	5337	4427	1790	1486	1770	1471	177	1470

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This table presents the results of a OLS regression of the change in concentration year -on -year with the change in labour share decomposed by DF methods and MP methods. The standard errors are clustered at four digiit levels, with industry and year effects as well as industry controls.

Source: ABS BLADE 16-17, Author's calculations

term is not significant anymore, despite being positive and small in magnitude. As the mean term is an unweighted mean and is biased towards small firms, it suggests that concentration has not affect the labour shares of small firms significantly.

The DF analysis for the non-primary sector is very different to the DF analysis of the whole economy, signalling different time trends over the samples. Over the whole time period, the between term is larger in magnitude than the within term: an increase (decrease) in concentration of top ten firms by 10% causes a reallocation of labour share to low (high) labour share firms by 0.5% , but also all firms to lower (increase) labour share by 0.3%. This is consistent with the idea that reallocation is the prominent driver of labour share trends in Australia and reflects Chapter 2 analysis.

If we look at different time periods though, we see a change in the relative weights of the between and within shares. Prior to 2007, the between term was also larger in magnitude than the within term, confirming the reallocation of value added during this period. However, after 2007, there is a shift, where the coefficient for the 'within' regression becomes larger and more statistically significant than the coefficient for the 'between' regression. These results indicate that rather than compositional change, concentration has led to an increase (decrease) in mark-ups and inverse change in labour share in all surviving firms. This supports the analysis in the previous sections, which found a greater role for the within component.

7.5 Confirming Competition in the Economy

Competition driven changes in labour share must reflect a broader issue of competition in the economy. Hence to supplement and confirm the analysis that within-industry changes are driving labour share changes found in Section 7.1, this thesis tests for the relationship of concentration with (1) profit share, (2) mark ups, (3) productivity and (4) productivity dispersion. The model specification follows Equation 6.13, which is an OLS 4-digit industry level regression with time and sector fixed effects. For space and parsimony reasons, the results are omitted here and kept instead in Appendix E.4. The results are of interest for two reasons: First it will confirm whether within-industry or reallocation is driving labour share changes; Second, it will also verify whether the MP or the DF method is more effective at identifying competition changes.

7.5.1 Profit Shares

Basu (2019) argues that profit shares are most appropriate measure of competition.[66] Appendix Table E.6 presents the results of regressing multiple concentration measures with 4-digit industry profit share in an annual fixed effects regression. Column 1 shows that industries with an increase in concentration of the top 4 firms (in terms of value added)

[66] In a survey of different competition factors, Basu (2019) finds that profit shares and mark-ups are most effective at measuring competition

experienced an increase in industry profits by 0.82 percentage points. This is controlling for cyclical factors. When industry fixed effects are introduced and progressively become stricter, the coefficient reduces but it remains significant. These results are consistent for other measures of concentration, as shown in column 4 to 12, with various fixed effects as well. This is consistent with Barkai (2016) who finds evidence that profit shares have increased and Gutierrez (2018) who finds that changes in concentration are correlated with profit shares.

7.5.2 Mark-Ups

The results of regressing 4-digit industry mark-ups with concentration are shown in Appendix Table E.7. Consistently across all three measures of concentration, the coefficients on concentration are positive and statistically significant. This predicts that an increase (decrease) in concentration leads to an increase (decrease) in mark-ups. This relationship is evidence of Barkai (2016); De Loecker et al. (2016) rent-seeking models. However, the magnitude is very small with a small R^2, suggesting little explanatory power.

7.5.3 Productivity

Appendix Table E.8 regresses concentration measures on the labour productivity of 4-digit industry level using annual fixed effects. The results suggest that an increase in concentration by 1 percent leads to an increase in labour productivity by 0.06 percent, accounting for cyclical and structural factors. The relationship between concentration and productivity is larger for the top 10 firms, rather than the top four firms, indicating that there could be some spill over benefits. When time-sector fixed effects are introduced, the coefficients become a lot larger, suggesting that the model is better explaining the economic structures in the economy. For example, a 10% increase in concentration of top 4 firms and top 10 firms lifts aggregate productivity by 1% and 1.5%. Across all measures and fixed effects, the coefficient on concentration is low relative to findings in Autor et al. (2017) and Covarrubias et al. (2019). This provides *some* support for superstar mechanisms, although small.

Appendix Table E.9 reports the results of regressing concentration with labour productivity dispersion and concentration measures. The results indicate a small but positive relationship with concentration. Appendix Table E.10 reports the results with total factor productivity dispersion. Across all measures, total factor productivity dispersion and concentration are positively correlated. Together, the two tables suggest that an increase in concentration increases the productivity divergence of leading and laggard firms, while the gap decreases with declining concentration. Labour productivity dispersion and concentration are only significant with industry fixed effects, while total factor productivity is significant with concentration only when there are fixed effects at the industry level. Even still, the magnitude is very small – an increase in 10% concentration of the top four firms would increase LP divergence by 0.3% and TFP divergence by 0.2%. Across all measures, there is a positive and significant but weak correlation with productivity dispersion, supporting the previous findings that while there is some evidence of superstar mechanisms, it is small.

Chapter 8
Conclusion

Using a novel firm level data set, this thesis answers two important questions regarding the share of income accruing to labour: What are the trends in labour shares in Australia and what is driving them, with a focus on competition as the most significant driver. The following sections gives an overview of the answers to these questions, identifying key knowledge contributions made to theory and practice, implications for theory and policy making, and avenues for future research.

8.1 Trends in Labour Share

The first practical contribution is the construction of labour shares using firm level data, which has been done for the first time in Australia. The results include identifying individual firms which are likely to have self-employed individuals or businesses owners using SISCA classification, dividing gross mixed income to self-employed on a firm-to-firm basis and understanding the difference between corporate and non-corporate labour shares. Such detailed construction of measures as well as detailed levels of decomposition have not been possible due to the way ABS National Accounts is set up (see e.g. Trott and Vance, 2018). [67]

Second, this analysis provides useful insights and practical contribution into labour share trends in Australia, which is a topic of international interest and domestic interest given recent weak wage growth and declining global labour share trends. The finding of stable labour shares at the aggregate level [68] is reversed after measurement issues and heterogeneity at the firm level are considered. Once depreciation is accounted for, net labour shares have fallen by 6 percentage points between 2001-02 and 2016-17, reversing the direction of the movements in the labour share. This places Australia next to countries like Japan who have also experienced this decline in net labour shares (e.g. Bridgman, 2018).

Moreover, this thesis also finds that the long-term trend of stability in labour shares reflects approximately a fifty-fifty split of industries and firms experiencing a net decline

[67] BLADE estimates of aggregate labour shares do not match up with ABS published measures of labour shares; however, this is because BLADE canvases administrative data for 99% of all firms in Australia, rather than relying on ABS collected survey data. Hence, BLADE estimations for the sample are more representative of the economy. That said, there are several limitations in the estimation of BLADE including the way value added is constructed.

[68] This refers to labour shares for the market sector, excluding financial and insurance services. When financial and insurance services are included, labour shares decline is prominent since 2002.

and increase in labour shares, which gets cancelled out at the aggregate level. Moreover, this thesis documents that labour share growth is driven by a reallocation of value added to high labour share firms and increase in the number of high-labour share firms. Low labour shares firms, by contrast, have fallen both in number and contribution to value added. As high labour share firms are less productive, this thesis demonstrates that the reallocation of value added to high labour share firms could reflect a declining in allocative efficiency. Moreover, it calls into question the conclusion that a stable aggregate labour share is an efficient outcome.

A key implication of this finding is that labour share decline is real in Australia, although it may not be identifiable at the gross level. Declining net labour shares suggest an increasing gap between workers and capital owners, carrying implications for wealth and income inequality. Given the current context of stagnating wage growth, the finding of declining labour shares carries policy implications. Furthermore, the industry division analysis shows an uneven distribution of labour share changes. Further can be done to understand how this empirical finding of uneven distribution affects macroeconomic models, such as the Cobb Douglas production function, and stylised macroeconomic facts proposed by Kaldor (Kaldor, 1957). Having said that, this measure of net labour share could be subject to more robustness tests. Depreciation is sensitive to the level of capital stock, which could be mismeasured in BLADE, not only due to the construction of the data set but also because it may not consider intangibles and unmeasured investment flows into organisational capital (Basu, 2019; Karabarbounis and Neiman, 2019b).

Though several specifications to capital stock and cost of capital were considered a further improvement would be to measure capital stock and capital costs estimating equity and debt costs, as well as tax rates as this forms the basis of gross mixed income measures and net labour share results. Another future avenue for research could be to estimate income for self-employed using a hedonic regression, estimating hourly compensation of employees based on census data, cross-tabulated by industry, sex, age and educational attainment level (Jorgenson et al., 2012; Young, 1995). This is arguably the best method to measure the income for self-employed (Jorgenson et al., 2012), even though it may be limited in how it considers entrepreneurial activity (Gollin, 2002). While it was not within the remit of this thesis to do this, access to linked employee-employer data can facilitate a future research opportunity.

8.2 Competition is a key driver of labour share trends

To understand the drivers of labour share at the detailed 4-digit industry level, this thesis provides reduced form empirical evidence that labour share trends can be explained by competition, measured using concentration and mark-ups. This thesis tests for other prominent hypotheses in the literature, like monopsony power, capital-labour substitution or the decline in the price of capital by constructing empirical proxies but doesn't find support for them at the economy level. This is consistent with international literature such as Gutierrez (2018), Autor et al. (2019) and (Barkai, 2016). Such a thorough examination of key hypotheses in the literature using firm level data is the third empirical contribution this thesis makes to Australian research. While Weir (2018) and La Cava (2019) provide several useful insights into what is driving the labour share trend, there is little conclusive evidence. Nonetheless, this thesis is not complete either. Firm level data on import competition and union membership would have been useful to test for the role of import competition and declining unionisation on labour share, as both are key features in the Australian economy.

As concentration and mark-ups are endogenous to competition, a key theoretical contribution this thesis makes is to understand how competition affects labour shares. To do this, Diewert and Fox (2010) productivity dynamic decomposition method is uniquely applied to labour shares to understand whether reallocation or within-industry effects dominate. The second theoretical contribution is to propose a two-fold decomposition method which combines Melitz and Polanec (2015) and Diewert and Fox (2010) decompositions to understand the components of labour share and how they respond to competition. This builds and improves the identification strategy and econometric specification proposed by Autor et al. (2019), but also brings into question some of the robustness in their findings.

The new framework applying DF decomposition of labour shares overturns the findings however, and gives evidence that within industry changes dominate, not a reallocation effect. DF results aligns with previous research in Australia by of Statistics (2017) and Weir (2018) and international literature by Kehrig and Vincent (2017), Autor et al. (2019) and Barkai (2016), which give evidence that labour share change is driven primarily by within-industry change. Comparatively, Melitz and Polanec decomposition identifies that superstar mechanisms are the key drivers of labour share changes in Australia, however. It gives evidence for declining allocative efficiency for industries that are experiencing a superstar mechanism. This questions the robustness of Autor et al's strategy, and suggests that analysis of the Autor et al paper using the DF methodology might bring different results.

Although Diewert and Fox has been identified in the literature as a superior decomposition method (e.g. Balk, 2016; Riley and Bondibene, 2016), this thesis did not seek to contest the Autor et al methodology and focus solely on DF analysis. A future research application could be to see whether the MP or DF method is better at identifying the superstar mechanism. At present, however, this thesis views MP and DF as complementary, and uses DF as a tool to further decompose the MP 'covariance' term and understand its drivers.

Combining these two competing views by decomposing the MP covariance term into DF components, the analysis finds that a fall in concentration has resulted in the reallocation of value added to high labour share firms (MP covariance term), but also an increase in the number of high labour share firms (DF within change). Overall, this results suggest the presence of 'fading superstars' industries, where a fall in concentration and increase in labour shares reflects a reallocation of value added to low productive high labour share firms. This is an empirical finding that is unique to Australia, but builds on Autor et al model. Divisions include Manufacturing, Construction, Mining and Agriculture. Within the service industries, a lot of the covariance, however, is driven by a within industry change as well, suggesting that labour shares of the large firms have increase proportionally more. This could reflect increased price competition according to Barkai (2016) or an inelastic demand curve, where a decline in market shares cause firms to lower mark-ups and hence increase labour share (Edmond et al., 2018). While Autor et al indicate that this is a decline in allocative efficiency, further decomposition using the Diewert and Fox finds suggest a pro-competitive outcome. There are also a few superstar firms but this is mostly concentrated to a few 4-digit industries, mostly in Retail Trade. However, there is evidence to suggest that these superstar firms may be engaging in rent-seeking behaviour.

The implication of these findings in terms of competition is very dependent on the interpretation of the DF 'within' component change in labour share, that is an industry wide increase in labour share. For example, an industry wide decrease (increase) in the labour share represents an increase (fall) in rent seeking behaviour according to Barkai (2016) - firms raise (drop) prices relative to marginal costs, causing profit shares to increase (decrease) and labour shares to fall (increase). This thesis finds ancillary evidence such as increased profit share, and a positive coefficient with concentration and profit. Globally, increasing rent-seeking and declining investment has also been documented (e.g. Gutiérrez and Philippon, 2017). Conversely, Edmond et al. (2018) describes an inelastic demand function where the increase in market share causes all firms in the industry to increase mark-ups, and hence experience a fall in labour shares. This is a pro-competitive outcome, and reaffirms Autor et al. (2019) initial superstar model.

The possibility of a pro-competitive and anti-competitive outcome reflect the difficulty in identifying competition and it is well understood in this thesis as well. This thesis tries examining features of exiting and entering firms, and regressing concentration with other measures, though it is still inconclusive (see Section 7.5). Hence, while this thesis provides an improved strategy to the method proposed by Autor et al. (2019) and gives a more nuanced understanding to how concentration is affecting labour share, further investigation is still needed to confirm whether the decrease (increase) in concentration has caused labour share to increase (fall) for anti-competitive or pro-competitive reasons.

In addition, it is important to not overstate the role of fading superstar industries and superstar industries in Australia. As figure 7.9 showed, there were many industries that did not experience either effects. The fact that the covariance term was still significant after controlling for industry heterogeneity and cyclical factors suggest that there has been a reallocation of value added which is significant, but that there could also be other drivers like the price of capital or productivity dispersion which are manifesting at the aggregate level. Similarly, the changes in labour share are not only explained by the change in concentration and labour share. Subsample analysis in Chapter 5 also showed that the role of capital was significant and more apparent in goods, trade-intensive sectors and primary divisions, like mining and agriculture.

Nonetheless, the finding that concentration and mark-ups are driving labour shares is significant and is something needs to be addressed. The results suggest that improvements in economic performance are not translating into effective reallocation of resources, and that it is instead shifting away from productive firms. Without intervention, it implies a growing level of inefficiency in the economy, where labour shares may be increasing but it is decoupled form productivity growth (Schwellnus et al., 2017). This suggests that better market institutions, regulations and enforcement mechanisms need to be put in place to support the level of competition within the economy. Moreover, this could also be another indicator for declining business dynamisms, which has been a core focus in Australian literature recently.

A positive take is that lessons can be learnt from industries that are identified as 'superstar firms'. The benefit of micro-level data is the ability to look at the changes in competition and labour share at a granular industry level and identify features that have led to an increase in its competitiveness, despite a fall in labour share and increase in concentration. An example of this is Retail Sector.

8.3 Conclusion

A large body of work has documented labour share trends and drivers globally and in the United States. There has been little systematic assessment in Australia, however. Hence, to fill the knowledge gap, this thesis combines several key movements in the literature and uses a rich firm level panel dataset to compute labour shares in the Australia economy. Though the results find that labour shares have remained stable in Australia over the past fifteen years, stability of the results conceal the fact that net labour shares have been declining, which indicates that the distribution of income to labour is falling. This has welfare and income distribution implications. Moreover, stability at the aggregate level conceals heterogeneity at the industry and firm level, where there are indications that labour share has been increased because of a reallocation of value added to high labour share firms and increase in number of high labour share firms, which are unproductive.

The firm level data enables the use of industry-time fixed effect modelling techniques and detailed subsample analysis to identify competition as a key driver of labour share trends. The thesis also contributes to theory by proposing a novel identification strategy to determine whether labour share trends reflect an increase or decrease in competition. Complementing Autor et al. (2019), the strategy applies Diewert and Fox (2010) productivity dynamic decomposition to the novel situation of labour shares and finds that there has been a reallocation of value added to high labour share firms, with the largest increases in labour shares by highly productive firms. Overall, the analysis points to a fall in allocative efficiency in the economy and the presence of 'fading superstars', as opposed to 'superstars'.

Appendix A
Business Longitudinal Analytical Data Environment

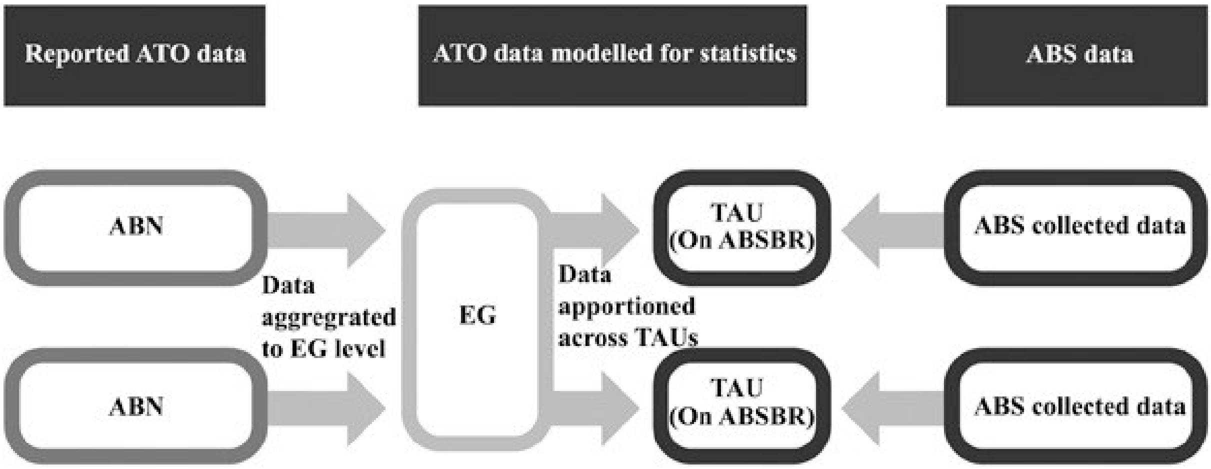
The data for this study comes from a novel micro-level panel dataset called Business Longitudinal Analysis Data Environment (BLADE). This is provided by the Australian Bureau of Statistics, in collaboration with the Australian Taxation Office (ATO) and other governmental agencies. BLADE combines multiple firm-level panel datasets including annual government administrative data from ATO, such as Business Activity Statements (BAS), Business Income Tax Filings (BIT) and Pay as You GO Summarises (PAYG), as well as ABS Survey data, like Business Characteristic Surveys (BCS) and Economic Activity Survey (EAS), for an individual firm. Together, this provides a rich and complete set of characteristics for more than two-million actively trading observations in Australia between 2001-02 to 2016-17.

A.1 Nature of the data

The following information has been provided through Hansell and Rafi (2018). According to Hansell and Rafi (2018), these datasets can be merged using an integrating spine, known as the Australian Bureau of Statistics Business Register (ABSBR). Each individual firm is recorded on the ABSBR as an ABS activity unit. For firms with simple business structure, the ABS activity unit is the same as their Australian Business Number. Hence, their data across multiple data sets is merged according to their ABN. Such businesses are grouped together as the 'non-profiled' population and accounts for 99% of ABS activity units each year (around 8.9 million). For firms with complex business structures, such as an enterprise group, they contain multiple units of activity. Often these are large firms which operate over multiple industries as well as multiple jurisdictions. Hence, the enterprise group appears in the ABSBR split up according to its Type of Activity Units (TAU). Such firms are classified as the 'profiled' population and only represent about 1% of the sample per year (around 800,000); although they account for 60% of gross output (Hansell and Rafi, 2018). Overall, the ABS activity unit referred to as a 'firm' in this study consists of ABNs from the non-profiled population and TAUs from the profiled population.

The process of integrating the ABS survey data and the ATO data is complex for the profiled population. As ATO data is provided for the ABNs related to the enterprise group, ABS aggregates the ATO data for related ABNs to the enterprise group and then disaggregates it into TAUs using the relative share of employment of each TAU in the enterprise group as a weight (Hansell and Rafi, 2018). This process enables the ABS data and the ATO data to be integrated as shown in Figure A. The consequence is that head count and FTE are a fractional level, which can make things difficult for interpretation.

Figure (A.1) Process of compiling BLADE



Source: Hansell and Rafi (2018)

A.2 Data Confidentiality

The data included in the BLADE dataset is highly confidential. The ATO data provides profit and loss information, business activity statements and labour data of individual firms within Australia.

Because of the confidential nature of the data, the ABS have a duty to protect the confidentiality of individuals and businesses in these datasets, under *Census and Statistics Act 1905 (Cth)*. The ABS is responsible for ensuring that individual firms cannot be identified and fulfil this duty in three key ways: First, users do not have access to the full dataset of all firms within Australia. ABS provide users with 99.97% of total observations across the 16 years across all industries. The removal of these observations has been done to protect against spontaneous identification of firms. Regardless, the dataset is still highly representative of the population. Second, firms are anonymised by a random firm identification number, so that users are not able to identify a firm by name. Third, users must follow a strict access control protocol, so that only authorised people can view the data. Access to the datasets includes audit trails and is limited on a need to know basis. All ABS officers are legally bound to secrecy under the *Census and Statistics Act 1905 (Cth)*. Officers sign an undertaking of fidelity and secrecy as well as complete training to ensure that they are aware of their responsibilities. Lastly, the disclosure of results to the public must maintain the confidentiality of individuals and organisations. Hence, the study only reports aggregate results to ensure unlikely identification of a worker or a firm. Moreover, the results have been cleared by the ABS, before publication.

A.3 Disclaimer

The results of these studies are based, in part, on Australian Business Registrar (ABR) data supplied by the Registrar to the ABS under A New Tax System (Australian Business Number) Act 1999 and tax data supplied by the ATO to the ABS under the Taxation Administration Act 1953. These require that such data is only used for the purpose of carrying out functions of the ABS. No individual information collected under the Census and Statistics Act 1905 is provided back to the Registrar or ATO for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes, and is not related to the ability of the data to support the ABR or ATO's core operational requirements.

Legislative requirements to ensure privacy and secrecy of these data have been followed. Source data are de-identified and so data about specific individuals or firms has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

A.4 Variable Construction

This section will explore how value added, capital stock, rental rate of return and user costs of capital were created.

A.4.1 Output Measures

The main output measure provided by BAS is turnover. Hence, output measures of interest like value added and gross output that are used in the literature are constructed from firm-level data on turnover and goods and services tax data.

Value added is constructed as the difference between gross output and intermediate inputs. Negative values of value added can and do appear in the data. This is because there are periods where a firm may be experiencing a loss, where turnover is low, but the firm must pay for intermediate products like labour and capital. In BLADE, this occurs about 1/5th of the observations over the sample period. Division A, E, M, N G are the industries with the most negative value added, with around 21% negative value added coming from Division A and 9% from Division G.

There are multiple methods to deal with negative terms. However, for the purpose of this study, I retain negative value-added observations to reflect the methodology of ABS. Two measures of robustness tests I undertake include replacing the observation with negative value added with zero or using gross output instead of value added entirely.

The results are robust to alternative methods of dealing with negative value added like replacing negative value added with zero. Ultimately, I have chosen to keep negative value added to aggregate macroeconomic level labour shares. While it is common in the literature to replace negative values with a zero or drop them (e.g. Barkai, 2016), the decision to keep negative value added was to reflect the methodology of the ABS when they calculate labour shares in National Accounts, as they also aggregate from firm level. This approach was also adopted by Kehrig and Vincent (2017). Gross output is an alternative measure that could have been used, as it has a zero bound. It has been used multiple times for a robustness check in this thesis.

A.5 Division Level Labour Shares

The following section provides a graphical representation of labour shares at the Division level for the market sector of the economy between 2001-02 and 2016-17. Each division level measure of labour share has been aggregated from firm-level data as a weighted average as in Equation 3.6.

Sources include *ABS BLADE 16-17, ABS 5620.*

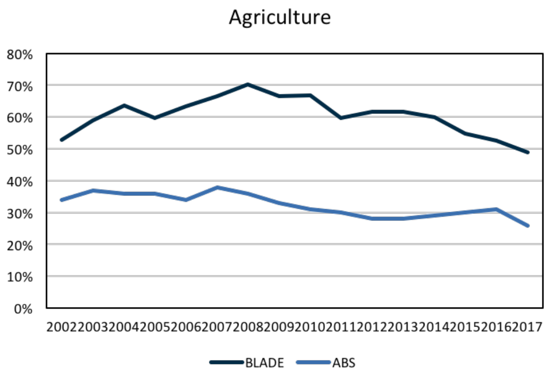
Divisions listed include:

- A AGRICULTURE, FORESTRY AND FISHING
- B MINING
- C MANUFACTURING
- D ELECTRICITY, GAS, WATER AND WASTE SERVICES
- E CONSTRUCTION
- F WHOLESALE TRADE
- G RETAIL TRADE
- H ACCOMMODATION AND FOOD SERVICES
- I TRANSPORT, POSTAL AND WAREHOUSING
- J INFORMATION MEDIA AND TELECOMMUNICATIONS
- K FINANCIAL AND INSURANCE SERVICES

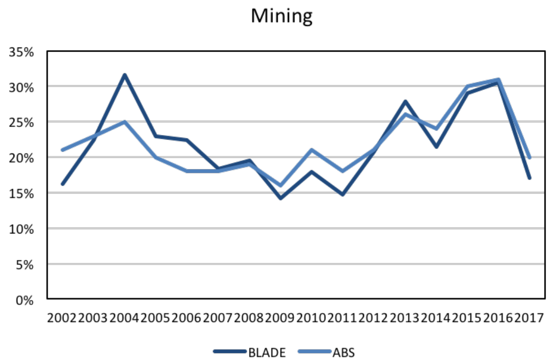
- L RENTAL, HIRING AND REAL ESTATE SERVICES
- M PROFESSIONAL, SCIENTIFIC AND TECHNICAL SERVICES
- N ADMINISTRATIVE AND SUPPORT SERVICES
- O PUBLIC ADMINISTRATION AND SAFETY
- P EDUCATION AND TRAINING
- Q HEALTH CARE AND SOCIAL ASSISTANCE
- R ARTS AND RECREATION SERVICES
- S OTHER SERVICES

Figure (A.2) Labour Shares, Division A - F

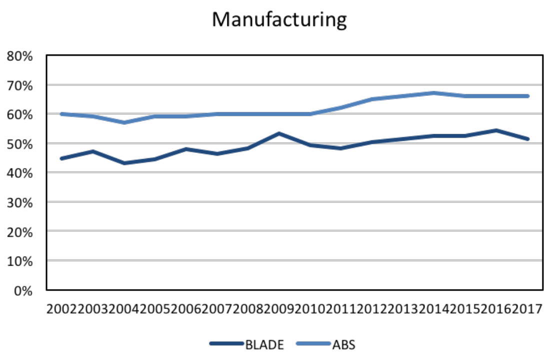
(a) Division A



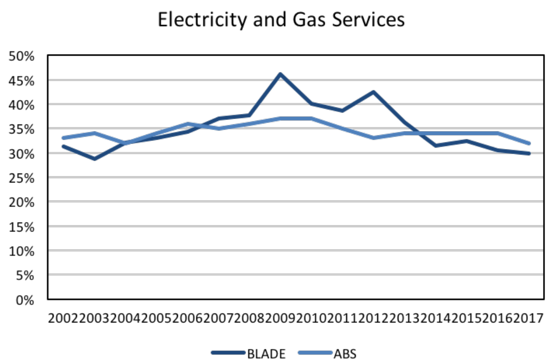
(b) Division B



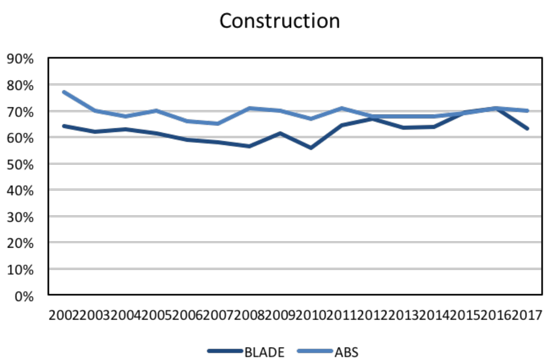
(c) Division C



(d) Division D



(e) Division E



(f) Division F

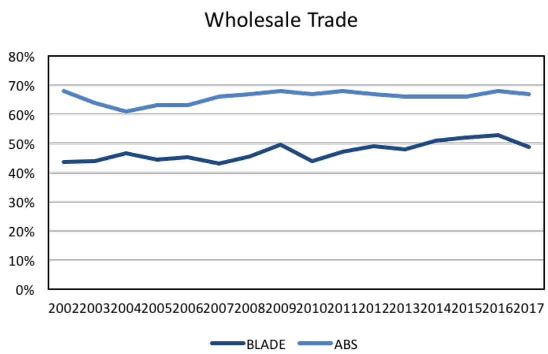
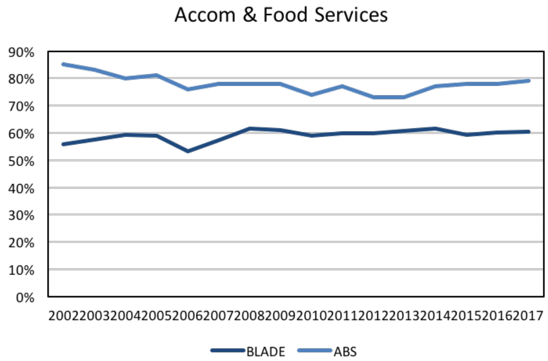


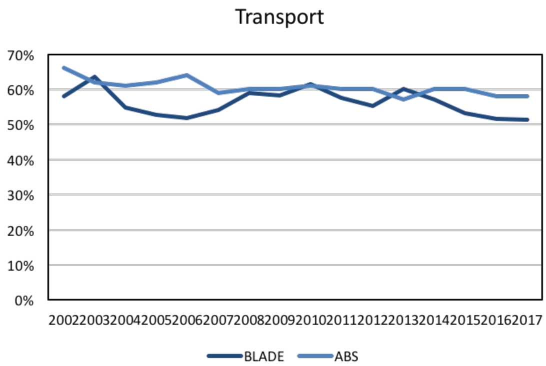
Figure (A.3) Labour Shares, Divisions G - M

(a) Division G

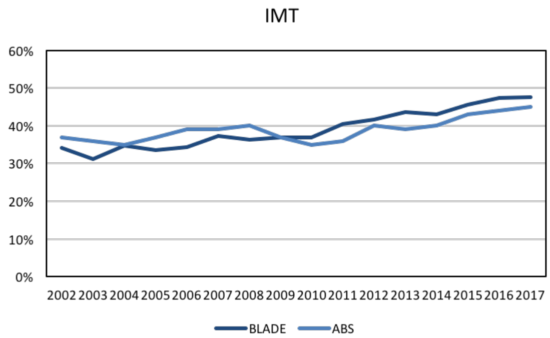
(b) Division H



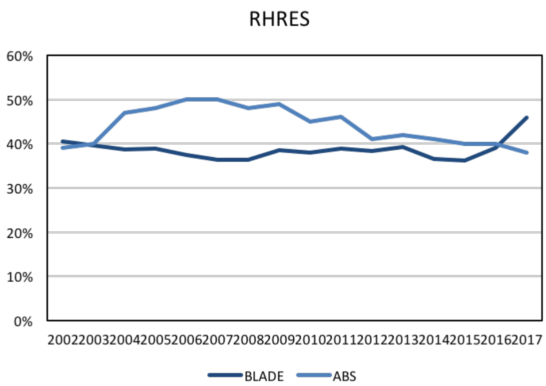
(c) Division I



(d) Division J



(e) Division L



(f) Division M

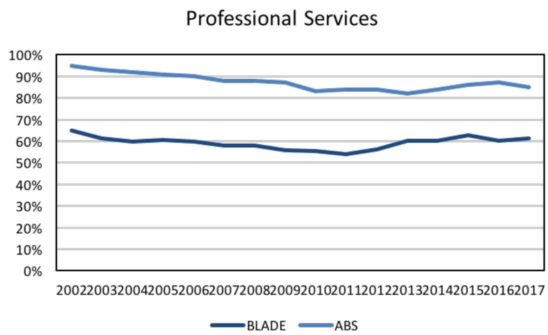
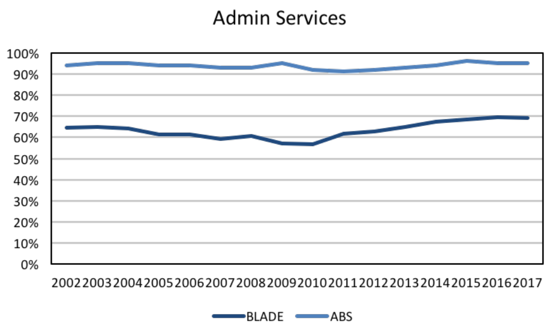
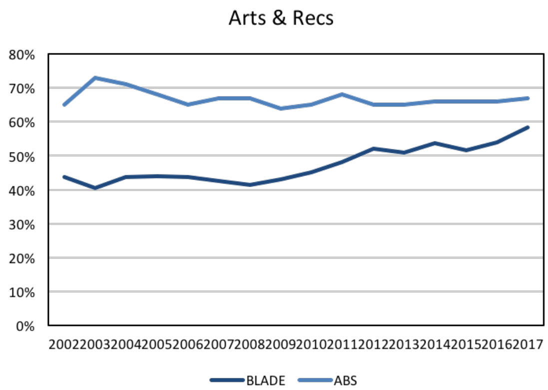


Figure (A.4) Labour Shares, Divisions N - S

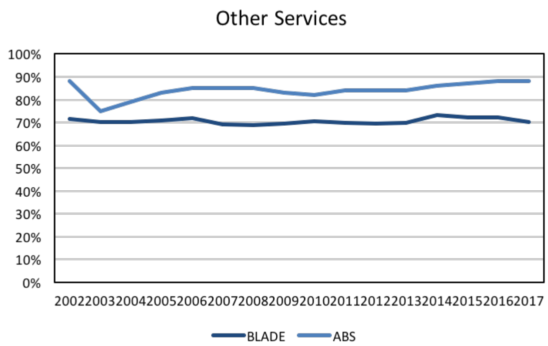
(a) Division N



(b) Division R



(c) Division R



Appendix B
Construction of Variables

Althought BLADE is a very rich dataset, there are several missing variables. This paper will outline the construction of key proxies used in Chapter 6, limitations in their estimation and future options for research.

B.1 Labour Shares

Aggregate shares are calculated as a weighted average of individual firms in the group. For example, 4-digit industry-level labour share, λ_{jt}, is the sum of total salary, wages and other payments reported by firms in their Business Activity Statement and imputed wages of self-employed workers over the industry's gross value added (see Equation B.1). It can be also calculated by aggregating the labour share of individual firms, weighted by the value-added of the firm. Here, $\omega_{it} = \frac{Y_{it}}{Y_t}$ reflects the value-add weight of firm i. These are mathematically similar.

$$\lambda_{jt} = \sum_{i} {}_{it}\lambda_{it} = \frac{\sum W_{it} L_{it}}{\sum Y_{it}} \tag{B.1}$$

Labour compensation is the sum of total salary, wages and other payments reported by firms in their Business Activity Statement and imputed wages of self-employed workers as well. The imputation is based on the average compensation of salaried workers in the corresponding 4-digit ANZSIC industry. This methodology broadly follows lot of literature and is outlined in detail in the next section.

B.2 Concentration Ratios and Herfindahl-Hirschman Index

Concentration ratios and the Herfindahl-Hirschman Index (HHI) are the two most common measures of concentration. The concentration ratio is the share of an industry or market accounted by the top firms, such as the top 4, top 10 or top 20 firms. It can be calculated as:

$$C_n = \sum_{i=1}^{n} \frac{Y_{it}}{Y_t} \tag{B.2}$$

where n represents the number of top firms, Y_{it} is the value added of the top nth firm, Y_t is the sum of value added for all firms within an industry in a particular year, t.

The Herfindahl-Hirschman Index (HHI), the sum of the squares of the market shares for all firms in a market, is a non-linear version of the concentration ratio.

$$HHI = \sum_{i=1}^{N} (\frac{Y_{it}}{Y_t})^2 \tag{B.3}$$

The results for these concentration ratios can be found in Appendix Section C.0.2

B.3 Mark-Ups

Mark-ups are a more direct measure of market power as it reflects the ability of firms to raise prices above marginal costs (Basu, 2019; Syverson, 2017; Tirole, 1988). However, mark-ups are notoriously difficult to measure, due to limited information available on a firm's marginal cost. However, De Loecker and Warzynski (2012) have developed a mark-up estimation method which does not require marginal cost information and has become widely used in subsequent literature. The advantages of this method are that it relies on the assumption that firms are cost minimisers and that labour is fully flexible, but does not require any assumptions about the specific price-setting mechanisms employed by the firm and hence marginal cost information (Autor et al., 2019; Basu, 2019; Hambur and La Cava, 2018).

Formally, De Loecker and Warzynski show that for a cost-minimizing firm, the optimal mark-up, μ, is the ratio of output elasticity for a variable input, such as labour, $(\frac{\delta Y_{it}}{\delta L_{it}} \frac{L_{it}}{Y_{it}})$ and share of expenditure on that input, relative to sales, such as $\frac{w_{it} L_{it}}{P_{it} Y_{it}}$:

$$\mu_i t = \frac{\delta Y_{it}}{\delta L_{it}} \frac{L_{it}}{Y_{it}} / w_{it} L_{it} P_{it} Y_{it} \tag{B.4}$$

While expenditure shares are readily available in the data, output elasticities are difficult to estimate. De Loecker and Warzynski suggests estimating output elasticity with a production function approach using various methods proposed in literature. Generally,

$$y_{it} = f(l_i, k_{it}, \beta) + \omega_{it} + \epsilon_{it} \tag{B.5}$$

Where y_{it} represents value added, the function $f(.)$ represents a production function, with a scalar Hicks-neutral productivity term, ω_{it}, and common technology parameters common across the set of producers, β. For example, the production function could be a Cobb Douglas function or translog function with labour, and capital, as inputs, and represents the productivity of each firm. There is a simultaneity issue as the firm's choice of input (will be correlated with the unobserved productivity term)

B.3.1 Capital Stock

Capital stock, K_t, is calculated using the perpetual inventory method, which is used by multiple insitutitions like OECD (Berlingieri et al., 2017), ONS (Groves, 2018), and ABS. The perpetual inventory method (PIM) calculates the beginning-of-period capital stock by accumulating real gross investment, subject to a constant depreciation rate:

$$K_t = (1 - \delta_j) K_{t-1} + I_{t-1} \tag{B.6}$$

where

- δ_t is the depreciation rate of gross capital, estimated using National Accounts Data (ABS)
- I_{t-1} is investment of a firm, calculated as total assets minus current assets and deflated using a capital deflator. This is estimated using BIT data.
- K_{t-1} is the capital stock of the previous year which is calculated based off investment data, but also ABS data on capital stock. Details are provided below.

Due to limitations of the data, PIM cannot be run for different types of capital assets, such as plant and machinery, buildings and vehicles. Similarly, different depreciation rates cannot be applied, so we use a singular depreciation rate to capture the whole process.

Moreover, in order to run PIM, it is necessary to have a starting value or an initial estimate of capital stock for each firm. This will provide a complete time series to calculate PIM. While firms report information on investment in their balance sheets, around 99% of firms do not. Hence, we need a consistent method of estimating initial capital stock.

I allocate a share of total industry capital stock to a firm using a proxy to calculate the firm's share of total capital stock (Groves, 2018).[69] The proxy to determine a firm's share of total capital stock is intermediate inputs and employment, which is positively correlated with unobserved firm-level capital and are observed at the firm and aggregate level. To test for this, I test firm-level investment provided by BIT and employment by BAS and find a correlation of 0.43; a similarly, intermediate inputs provides me with a correlation of 0.56. Hence, my ultimate proxy is 0.56.

There are other methods for allocating starting capital stock to a firm; while they were test for robustness, they have not been provided in this thesis.One, for example, involves allocating the book value of capital goods as the starting value to initialize PIM, as BLADE contains book value of capital goods. i.e. $K_1 = K^{BV}$. There is a large number of empirical studies which use this approach. However, the main drawback of this is that book value does not necessarily reflect the productive capital stocks of firms. Age efficiency profiles

[69] Groves (2018) shares are firstly estimated at (1) subdivision level by looking at subdivision's share of total purchases (seen to be highly correlated with capital stock - others are energy consumption, material demand) and then (2) firm level by look at share of employment.

are not considered, also firms may have accelerated depreciation profiles to compute book values for fiscal purposes. Moreover, corporations will report book value assets as part of their balance sheets, and not non-corporations. Hence, this will lead to an ex ante difference in capital share between corporation and non-corporations. This creates an upward bias for corporations and downward bias for non-corporations. Berlingieri et al. (2017)) estimate the starting value of initial capital stock as average firm investment in all years divided by the depreciation rate and the long run growth rate of investment, sourced from the ABS National Accounts (Berlingieri et al., 2017). However, when this was attempted, this lead to a dramatic decline in capital shares, which seemed to be misaligned with capital share data provided by the ABS. Ultimately, the intermediate input proxy approach was most sensible.

B.3.2 User Cost of Capital

The main specification for the required rate of return, R_t is calculated according to Hall and Jorgenson (1967):

$$R_t = \ i^D - \pi_s + \ \delta_t(1 + \pi_s) \tag{B.7}$$

where

- i^D is the cost of debt to finance capital, measured using a nominal business lending indicator rate
- δ_t is the depreciation rate of capital, estimated using National Account Data
- $E[\pi_s]$ is expected inflation, measured using the Consumer Price Index

For the purpose of this thesis,

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Profit

Profit represents retained earnings after labour and capital costs are deducted from value added (Barkai, 2016). Because it is calculated as the residual of labour share and capital share, profit share is very sensitive to measurement issues of capital share and labour share. Within Australia, the research of profit share has been non-existent to date. In the USA, Barkai (2016) shows profits have increased dramatically over the past 3 decades, from approximately 2.2% of gross value added in 1984 to 15.7% of gross value added in 2014 - a more than six-fold increase of 13.5 percentage points. This has supported the argument that decline in labour shares reflects anti-competitive reasons.

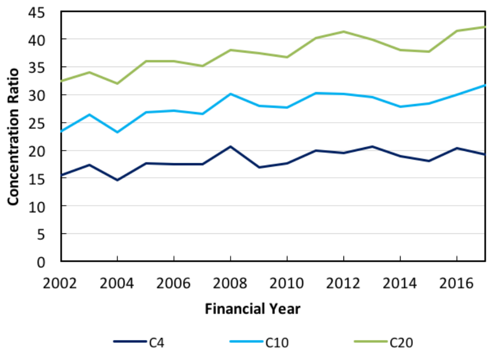
Appendix C
Empirical Proxies

C.0.1 Concentration Ratios of Divisions (Market Sector Only)

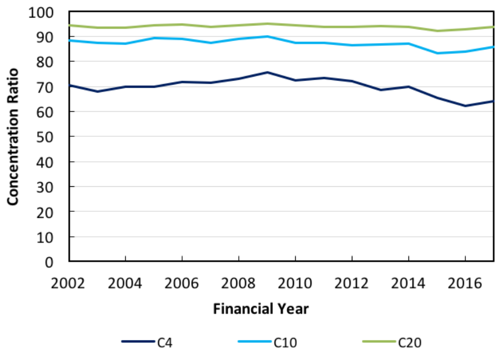
This section provides a graphical representation of concentration ratios for at the division level for the market sector of the economy between 2001-02 and 2016-17. Three concentration ratios are presented, including concentration ratio of top 4 firms, concentration ratio of top 10 firms, and the HHI index. They have been calculated at the 4-digit level and then aggregated to the division level using the median.

Figure (C.1) Concentration Ratios - Median of 4-digit ANZSIC Industry Concentration - Div A - F

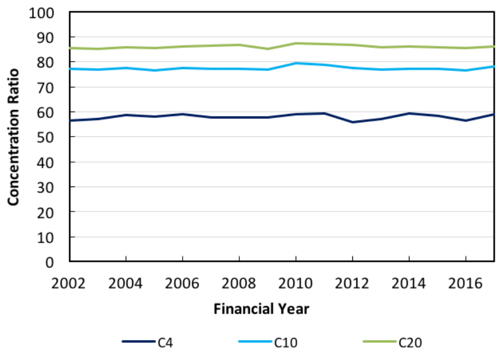
(a) Division A



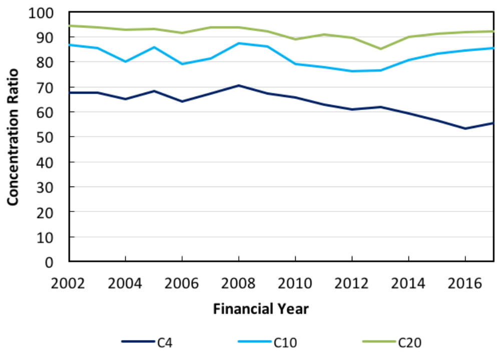
(b) Division B



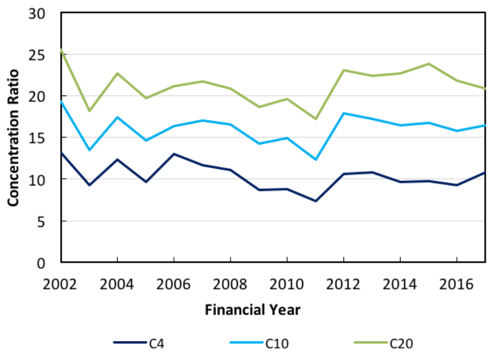
(c) Division C



(d) Division D



(e) Division E



(f) Division F

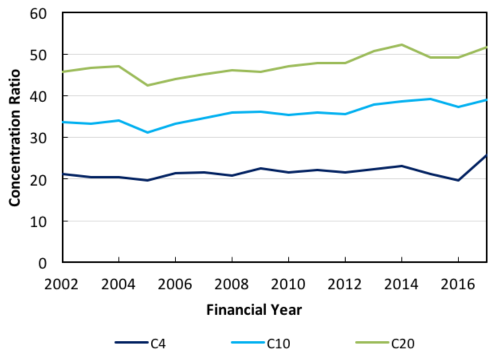
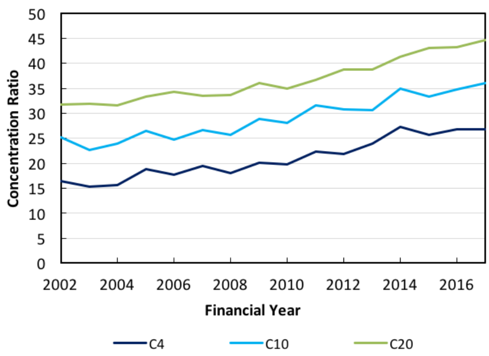
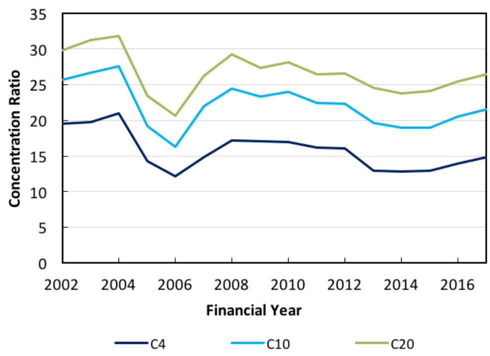


Figure (C.2) Concentration Ratios - Median of 4-digit ANZSIC Industry Concentration - Div G - M

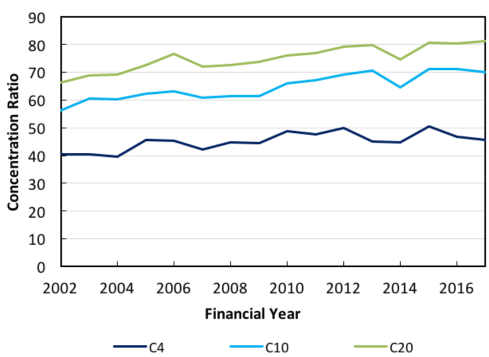
(a) Division G



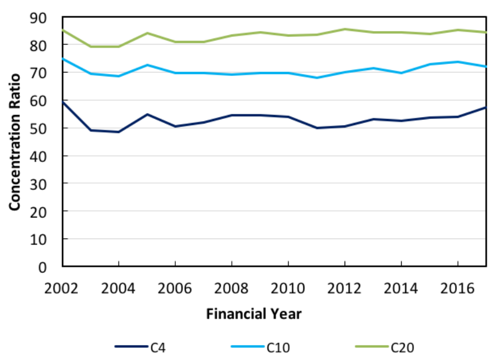
(b) Division H



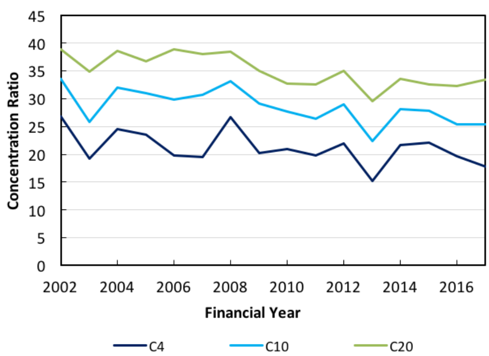
(c) Division I



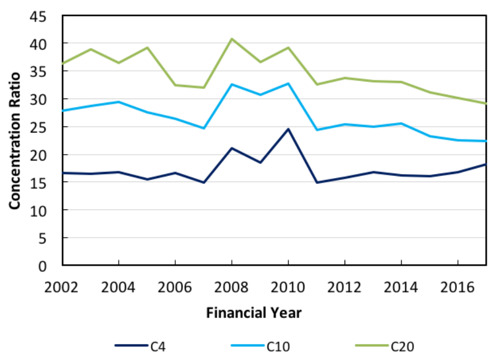
(d) Division J



(e) Division L



(f) Division M

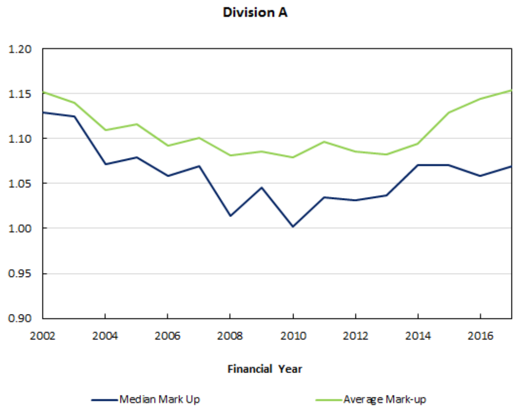


C.0.2 Mark-ups, Division Level)

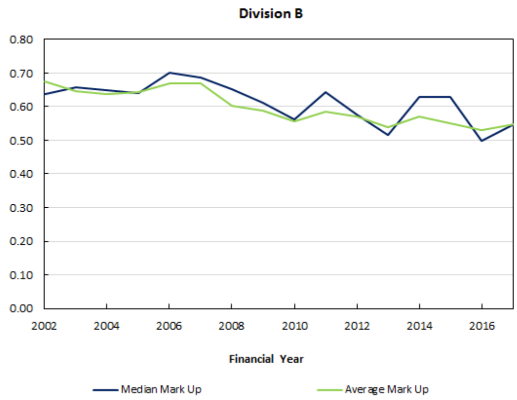
This section provides a graphical representation of mark-ups for at the division level for the market sector of the economy between 2001-02 and 2016-17.

Figure (C.3) Mark-ups, Division Level A -F

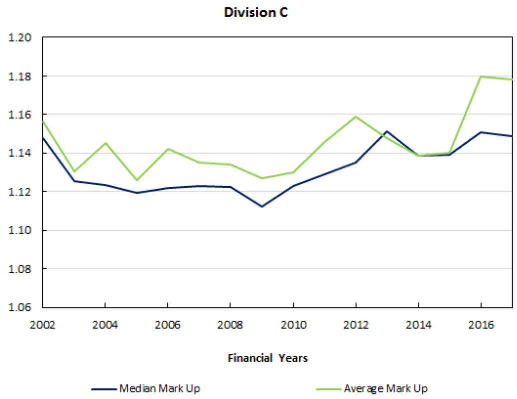
(a) Division A



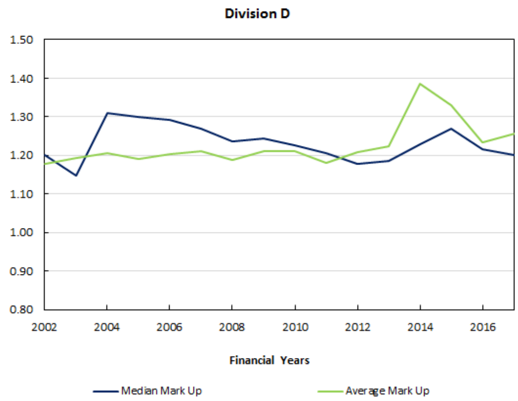
(b) Division B



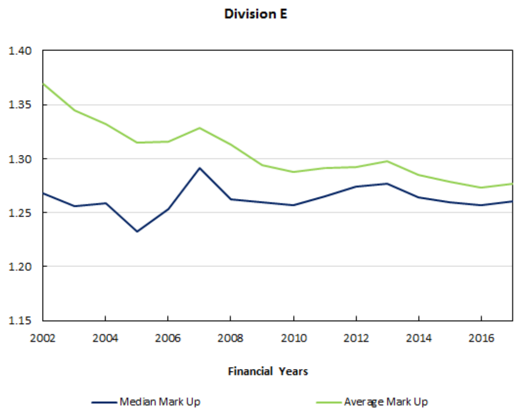
(c) Division C



(d) Division D



(e) Division E



(f) Division F

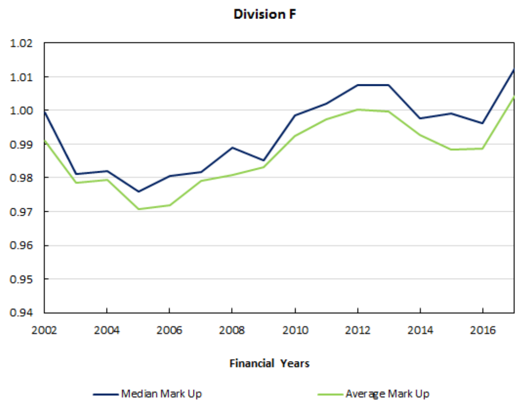
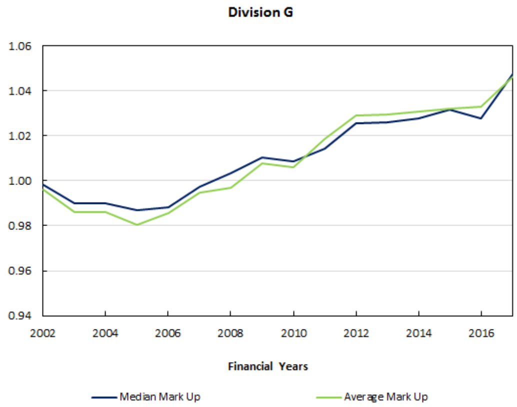
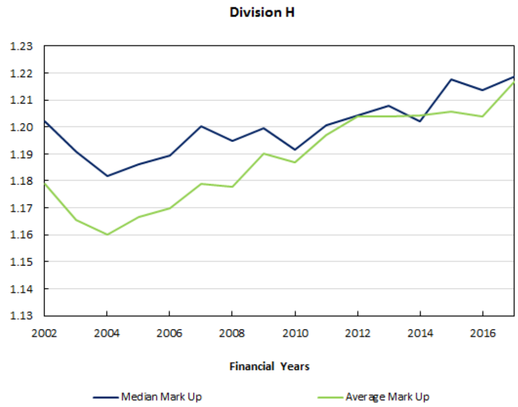


Figure (C.4) Mark-ups, Division Level G - M

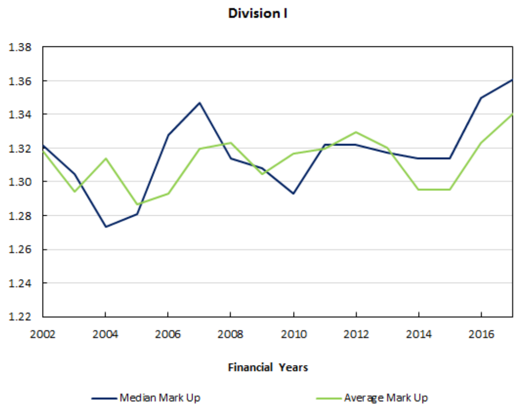
(a) Division G



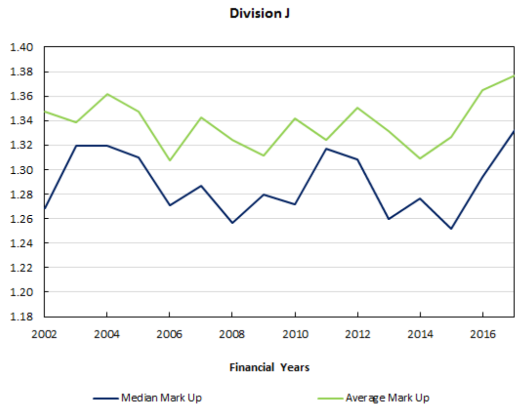
(b) Division H



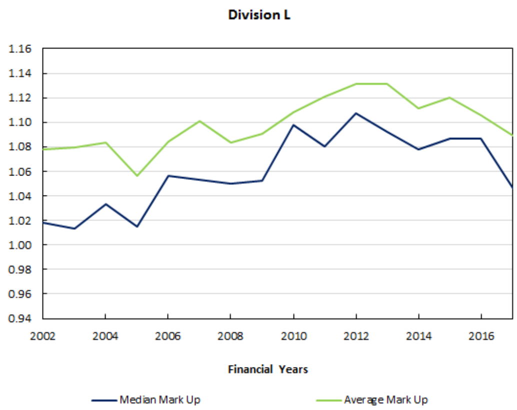
(c) Division I



(d) Division J



(e) Division L



(f) Division M

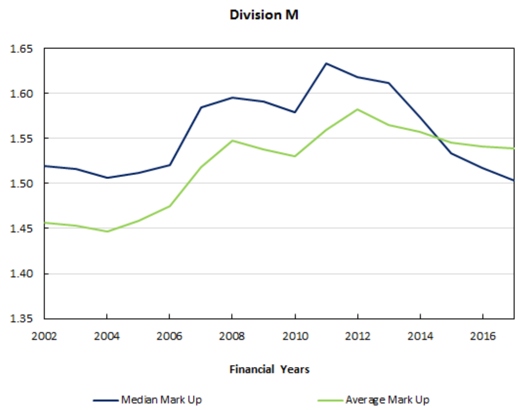
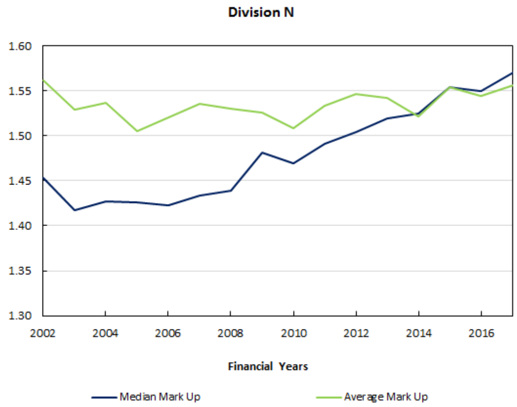
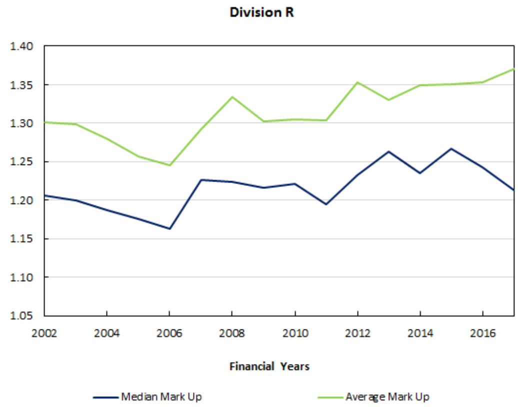


Figure (C.5) Markups, Division Level N - R

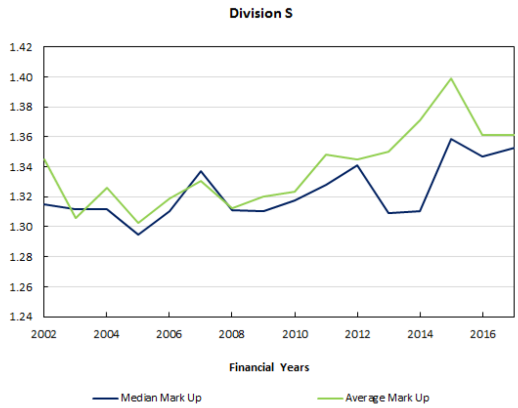
(a) Division G



(b) Division R



(c) Division R



Appendix D

Drivers of Labour Shares - Regression Tables

D.0.1 Alternate Specifications

Table (D.1) Quantile Regression Specification

	(1) Log(C4)	(2) Log (LpIQR)	(3) Log (tf-pIQR)	(4) Log(μ_{jt})	(5) KY	(6) Rel Price	(7) Log(Rental Rate)	(8) Log(UC)
log(λ_{jt})	-1.645***	-0.177***	-0.0827*	-0.0144*	0.00153***	0.294**	0.194+	0.728***
	(0.0232)	(0.0157)	(0.0398)	(0.00578)	(0.0000498)	(0.0976)	(0.116)	(0.148)
Constant	3.450***	-1.453***	-1.841***	-1.819***	-1.804***	-1.808***	-2.330***	-2.595***
	(0.139)	(0.167)	(0.130)	(0.133)	(0.131)	(0.129)	(0.185)	(0.253)
Observations	7193	7188	7182	7190	7193	7193	7193	7193
R^2	0.228	0.042	0.04	0.04	0.073	0.038	0.039	0.038
Adjusted R^2	0.226	0.04	0.038	0.037	0.071	0.036	0.037	0.035
Pseudo R^2								
AIC	17619.7	19026.3	19019.4	19182.8	18935.5	19200.8	19193.5	19202.7
BIC	17729.8	19136.4	19129.5	19292.8	19045.6	19310.9	19303.6	19312.8
F	38.11	8.032	5.723	5.644	6.582	5.194	5.333	5.217
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001
The table reports results of quantile regression of the log of labour shares on empirical proxies, with industry and time fixed effects. Standard errors are clustered by 4-digit ANZSIC industry. Each column represents a separate quantile regression with the proxy. Proxies include concentration ratio of top four firms (logC4), labour productivity dispersion (logLPIQR), total factor productivity dispersion (logTFPIQR), mark ups (logMARKUPS), capital intensity (KY), relative price of capital (rel price), Price of capital, Rental rate of return (Rt) and Usercost of capital (LogUC). It takes The unit of observation is at the 4-digit industry level, where firm level data has been weighted by their industry's share of sales. Data for all variables, except relative price of capital, rental rate of return and user cost of capital, come from BLADE.

D.0.2 Sub-sample Analysis

D.0.3 Concentration and Robustness Tests

This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient represents the results of regressing a measure of concentration on a measure of labour share. Measures of labour shares tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentration ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calculated as wages over value added and concentration are gross output measures.

Table (D.12) Labour Share and Markups

	1	**2**	**3**	**4**	**5**
Mark-up (log)	-0.471	-0.494	-0.532	-0.52	-0.381
	0.00	0.00	0.00	0.00	0.00
Year FE		X	X	X	X
Division FE			X		
Industry FE				X	
Firm FE					X
R2	0.1798	0.1888	0.235	0.2147	0.1881
N	17396314	17396314	17396314	17396314	17396314

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This is a firmlevel annual fixed effects regression of the concentration ratio of top 4 firms in an industry j on firm-level mark-ups. Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.

Source: ABS BLADE 16-17, Author's calculations

Table (D.2) Non-parametric Regression Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(C4)	Log (LpIQR)	Log (tfpIQR)	Log (μ_{jt})	KY	Rel Price	Log(Rental Rate)	Log(UC)
log(Labour Share)	-0.742	-0.742	-0.725	-0.751	-0.825	-0.743	-0.759	-0.726
Effect	-2.365	-6.211	-1.073	-0.951	0.00435	-6.097	-0.360	-1.032
Observations	7193	7188	7182	7190	7193	7193	7193	7193
R^2	0.644	0.084	0.04	0.04	0.073	0.038	0.039	0.038
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

The table reports results of non-parametric regression of the log of labour shares on empirical proxies, with industry and time fixed effects. Standard errors are clustered by 4-digit ANZSIC industry. Each column represents a separate non-parametric regression with the proxy. Proxies include concentration ratio of top four firms (logC4), labour productivity dispersion (logLPIQR), total factor productivity dispersion (logTFPIQR), mark ups (logMARKUPS), capital intensity (KY), relative price of capital (rel price), Rental rate of return (Rt) and Usercost of capital (LogUC). The unit of observation is at the 4-digit industry level, where firm level data has been weighted by their industry's share of sales. Data for all variables, except relative price of capital, rental rate of return and user cost of capital, come from BLADE.

Table (D.3) OLS Reduced Form Regression, By Sector

	(1) **Log(C4)**	(2) **Log (LpIQR)**	(3) **Log (tfpIQR)**	(4) **Log (Mark-up)**	(5) **KY**	(6) **Rel Price**	(7) **Log(Rental Rate)**	(8) **Log(UC)**
log(Labour Share)	-3.014***	-1.522***	-0.953***	0.622***	0.00530***	1.345	0.210	-2.862***
	(0.08)	(0.233)	(0.246)	(0.0572)	(0.00160)	(5.957)	(0.701)	(0.563)
D_corporate	-1.974***	-0.573***	-0.562***	-0.486***	-0.717***	-0.554***	-0.555***	-0.564***
	(0.0934)	(0.122)	(0.121)	(0.120)	(0.118)	(0.122)	(0.122)	(0.122)
Constant	9.003***	-0.969***	-6.208***	-2.682***	-1.901***	7.036***	-8.007***	-1.901***
	(0.257)	(0.187)	(0.635)	(0.132)	(0.118)	(0.770)	(1.194)	(0.116)
Observations	7193	7188	7182	7190	7193	7193	7193	7193
R-squared	0.228	0.042	0.04	0.04	0.073	0.038	0.039	0.038
Adjusted R-squared	0.226	0.04	0.038	0.037	0.071	0.036	0.037	0.035
Pseudo R-squared								
AIC	17619.7	19026.3	19019.4	19182.8	18935.5	19200.8	19193.5	19202.7
BIC	17729.8	19136.4	19129.5	19292.8	19045.6	19310.9	19303.6	19312.8
F	38.11	8.032	5.723	5.644	6.582	5.194	5.333	5.217
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

The table reports results of OLS regression of the log of labour shares on empirical proxies, with industry and time fixed effects. There is a dummy variable, which is equal to 1 if the firms are within the corporate sector. Standard errors are clustered by 4-digit ANZSIC industry and industry controls used include size (measured through employment) and capital intensity. Each column represents a separate regression with the proxy. Proxies include concentration ratio of top four firms (logC4), labour productivity dispersion (logLPIQR), total factor productivity dispersion (logTFPIQR), mark ups (logMARKUPS), capital intensity (KY), relative price of capital (rel price), Price of capital, Rental rate of return (Rt) and Usercost of capital (LogUC). It takes The unit of observation is at the 4-digit industry level, where firm level data has been weighted by their industry's share of sales. Data for all variables, except relative price of capital, rental rate of return and user cost of capital, come from BLADE.

Table (D.4) Labour Share on Empirical Proxies, OLS Regression, By Size

	(1) Log(C4)	(2) Log (LpIQR)	(3) Log (tfpIQR)	(4) Log (Mark-up)	(5) KY	(6) Rel Price	(7) Log(Rental Rate)	(8) Log(UC)
log(Labour Share)	-3.209***	-1.109***	-0.766***	0.738***	0.00334***	-6.279***	-2.403***	-6.093***
	(0.04)	(0.17)	(0.21)	(0.07)	(0.00)	(0.63)	(0.41)	(0.63)
Small	-1.684***	-1.473***	-1.455***	-1.543***	-1.436***	-1.445***	-1.437***	-1.445***
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Medium	-2.032***	0.427***	0.576***	0.209+	0.467***	0.531***	0.505***	0.532***
	(0.09)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Medium Large	-3.394***	1.029***	1.256***	0.717***	1.042***	1.136***	1.114***	1.138***
	(0.10)	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)	(0.16)	(0.16)
Large	-3.684***	1.130***	1.342***	-0.149	0.993***	1.234***	1.204***	1.236***
	(0.11)	(0.18)	(0.18)	(0.22)	(0.17)	(0.18)	(0.18)	(0.18)
Constant	10.27***	-7.061***	-4.495***	-3.645***	-3.942***	2.277***	-1.517***	-4.003***
	(0.21)	(0.50)	(0.16)	(0.11)	(0.10)	(0.64)	(0.41)	(0.10)
Observations	7193	7188	7182	7190	7193	7193	7193	7193
R-squared	0.228	0.042	0.04	0.04	0.073	0.038	0.039	0.038
Adjusted R-squared	0.226	0.04	0.038	0.037	0.071	0.036	0.037	0.035
Pseudo R-squared								
AIC	17619.7	19026.3	19019.4	19182.8	18935.5	19200.8	19193.5	19202.7
BIC	17729.8	19136.4	19129.5	19292.8	19045.6	19310.9	19303.6	19312.8
F	38.11	8.032	5.723	5.644	6.582	5.194	5.333	5.217
Industry Controls	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

This table presents the OLS annual fixed effects regression of labour shares on empirical proxies, with dummy variables for firm sizes. Standard errors are clustered at the 4-digit level. Year and industry fixed effects apply, with industry controls. Firms which are micro, small medium, medium large and large are grouped and then aggregated to 4-digit level to account for their heterogeneity.

Table (D.5) Labour Share on Concentration - Annual Fixed Effects

	Unadjusted Labour Shares log(LS)	Adjusted Labour Shares (Non Corporate) log(LS)	Adjusted Labour Shares (Corporate and Non Corporate) log(LS)
log(c4)	-0.326***	-0.357***	-0.357***
	(0.02)	(0.02)	(0.02)
log(c10)	-0.440***	-0.482***	-0.483***
	(0.02)	(0.02)	(0.02)
log(c20)	-0.556***	-0.608***	-0.609***
	(0.02)	(0.02)	(0.02)
log(HHI)	-0.183***	-0.199***	-0.198***
	(0.02)	(0.02)	(0.02)
N	7085	7085	7085
Year Dummies	Yes	Yes	Yes
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes

Table (D.6) Labour Share on Concentration - Regression in First difference (6YR)

	Unadjusted Labour Shares LS(t) - LS(t-5)	Adjusted Labour Shares (Non Corporate) LS(t) - LS(t-5)	Adjusted Labour Shares (Corporate and Non Corporate) LS(t) - LS(t-5)
C4(t) - C4(t-5)	-0.119***	-0.204***	-0.203***
	(0.00013)	(0.00020)	(0.00020)
C10(t) - C10(t-5)	-0.153***	-0.263***	-0.263***
	(0.00013)	(0.00021)	(0.00021)
C20(t) - C20(t-5)	-0.182***	-0.310***	-0.310***
	(0.00013)	(0.00022)	(0.00022)
HI (t) - HHI(t-5)	-0.00115***	-0.00187***	-0.00186***
	(0.000)	(0.000)	(0.000)
N	4953	4953	4953
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes

Table (D.7) Labour Share on Concentration - Annual Fixed Effects - Gross Output Measure

	Unadjusted Labour Shares log(LS)	Adjusted Labour Shares (Non Corporate) log(LS)	Adjusted Labour Shares (Corporate and Non Corporate) log(LS)	Net Labour shares log(LS)
log(c4)	-0.145***	-0.157***	-0.157***	
	-0.0171	-0.0167	-0.0166	
log(c10)	-0.250***	-0.276***	-0.276***	
	-0.0303	-0.0295	-0.0295	
log(c20)	-0.336***	-0.375***	-0.375***	
	-0.0426	-0.0412	-0.0414	
log(HHI)	-0.414***	-0.463***	-0.464***	
	-0.0561	-0.0539	-0.0541	
N	7085	7085	7085	
Year Dummies	Yes	Yes	Yes	
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes	

Notes: Standard errors are in parentheses. P-values * $p<0.1$ ** $p<0.05$ *** $p<0.01$

This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient reprresents the results of regressing a measure of concentraiton on a measure of labour share. MEasures of labour sahres tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentraiton ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calcualted as wages over gross output and concentration are gross output measures.

Table (D.8) Labour Share on Concentration - Value Added Based Measure- Annual Fixed Effects

	Unadjusted Labour Shares log(LS)	Adjusted Labour Shares (Non Corporate) log(LS)	Adjusted Labour Shares (Corporate and Non Corporate) log(LS)	Net Labour shares log(LS)
log(c4)	-0.0370***	-0.0392***	-0.0391***	
	-0.00892	-0.00845	-0.00844	
log(c10)	-0.0846***	-0.0897***	-0.0898***	
	-0.018	-0.0172	-0.0172	
log(c20)	-0.0828***	-0.0895***	-0.0897***	
	-0.0213	-0.0205	-0.0206	
log(HHI)	-0.0715**	-0.0787***	-0.0789***	
	-0.023	-0.0223	-0.0224	
N	7198	7085	7085	
Year Dummies	Yes	Yes	Yes	
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes	

Notes: Standard errors are in parentheses. P-values * p<0.1 ** p<0.05 *** p<0.01

This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient reprresents the results of regressing a measure of concentraiton on a measure of labour share. MEasures of labour sahres tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentraiton ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calcualted as wages over value added and concentration are value-added measures.

Table (D.9) Labour Share on Concentration - Turnover Based Measure- Annual Fixed Effects

	Unadjusted Labour Shares	Adjusted Labour Shares (Non Corporate)	Adjusted Labour Shares (Corporate and Non Corporate)	Net Labour shares
	log(LS)	log(LS)	log(LS)	log(LS)
log(c4)	-0.0165**	-0.0178***	-0.0180***	
	-0.00524	-0.00493	-0.00494	
log(c10)	-0.0352**	-0.0401***	-0.0405***	
	-0.0121	-0.0113	-0.0113	
log(c20)	-0.0545**	-0.0656***	-0.0658***	
	-0.0178	-0.0163	-0.0164	
log(HHI)	-0.0879***	-0.109***	-0.109***	
	-0.0251	-0.0233	-0.0233	
N	7198	7085	7085	
Year Dummies	Yes	Yes	Yes	
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes	

Notes: Standard errors are in parentheses. P-values * p<0.1 ** p<0.05 *** p<0.01
This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient reprresents the results of regressing a measure of concentraiton on a measure of labour share. MEasures of labour sahres tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentraiton ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calcualted as wages over value added and concentration are turnover measures.

Table (D.10) Labour Share on Concentration -Full Time Equivalent Measure- Annual Fixed Effects

	Unadjusted Labour Shares log(LS)	**Adjusted Labour Shares (Non Corporate) log(LS)**	**Adjusted Labour Shares (Corporate and Non Corporate) log(LS)**	**Net Labour shares log(LS)**
log(c4)	0.0552*	0.011	0.0118	
	-0.0244	-0.0243	-0.0241	
log(c10)	0.0446	-0.0245	-0.0227	
	-0.0316	-0.0293	-0.0289	
log(c20)	0.051	-0.0433	-0.043	
	-0.0384	-0.0374	-0.0375	
log(HHI)	0.0389	-0.0719	-0.0723	
	-0.0475	-0.0492	-0.0493	
N	7198	7085	7085	
Year Dummies	Yes	Yes	Yes	
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes	

Notes: Standard errors are in parentheses. P-values * $p<0.1$ ** $p<0.05$ *** $p<0.01$

This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient reprresents the results of regressing a measure of concentraiton on a measure of labour share. MEasures of labour sahres tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentraiton ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calcualted as wages over value added and concentration are full time equivalent measures.

Table (D.11) Labour Share on Concentration -Headcount Measure- Annual Fixed Effects

	Unadjusted Labour Shares log(LS)	Adjusted Labour Shares (Non Corporate) log(LS)	Adjusted Labour Shares (Corporate and Non Corporate) log(LS)	Net Labour shares log(LS)
log(c4)	0.0552*	0.011	0.0118	
	-0.0244	-0.0243	-0.0241	
log(c10)	0.0446	-0.0245	-0.0227	
	-0.0316	-0.0293	-0.0289	
log(c20)	0.051	-0.0433	-0.043	
	-0.0384	-0.0374	-0.0375	
log(HHI)	0.0389	-0.0719	-0.0723	
	-0.0475	-0.0492	-0.0493	
N	7198	7085	7085	
Year Dummies	Yes	Yes	Yes	
4-digit ANZSIC Industry Fixed Effects	Yes	Yes	Yes	

Notes: Standard errors are in parentheses. P-values * $p<0.1$ ** $p<0.05$ *** $p<0.01$

This table reports the OLS regression of labour shares on concentration, using annual fixed effects and standard errors clustered at the 4-digit industry level. Each coefficient reprresents the results of regressing a measure of concentraiton on a measure of labour share. MEasures of labour sahres tested include non-adjusted labour shares, Labour shares adjusted for household sectors, adjusted for household and corporate sector and net labour shares. Concentration measures include Concentraiton ratio of top 4 firms (logC4), ratio of top 10 firms (logC10), ratio of top 20 firms (logC20) and the Heifl-Hirschman Index (logHHI). Labour shares are calcualted as wages over value added and concentration are full time equivalent measures.

Appendix E

Results - Regression Tables

E.1 Diewert and Fox Results - Regression Tables

E.1.1 Robustness and Further Analysis Regressions

Table (E.1) Industry (4-Digit) Regression of the components of a DF Labour Share Decomposition on the change in C10, C20, HHI and Mark ups

	(A) C10				**(B) C20**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Within	-0.0106***	-0.0110**	-0.0126***	-0.0159***	-0.00926**	-0.00941**	-0.0112**	-0.0154***
	(0.00316)	(0.00331)	(0.00313)	(0.00258)	(0.00349)	(0.00358)	(0.00342)	(0.00215)
Between	0.00170	0.00163	0.00373	0.000957	0.00127	0.00128	0.00295	0.000634
	(0.00268)	(0.00266)	(0.00410)	(0.00488)	(0.00234)	(0.00233)	(0.00372)	(0.00452)
Exit	0.0150	0.0149+	0.0130	0.0205++	0.0142	0.0143+	0.0125	0.0194++
	(0.0120)	(0.0115)	(0.0112)	(0.0109)	(0.0115)	(0.0109)	(0.0107)	(0.0110)
Entry	-0.0258	-0.0244	-0.0290	-0.00321	-0.0217	-0.0207	-0.0242	-0.00202
	(0.0264)	(0.0238)	(0.0256)	(0.00662)	(0.0224)	(0.0202)	(0.0221)	(0.00578)
N	437	437	437	437	437	437	437	437
Industry Control	X				X			
1-digit ANZSIC Industry FE		X				X		
2-digit ANZSIC Industry FE			X				X	
3-digit ANZSIC Industry FE				X				X

	(C) HHI				(D) Mark Up			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Within	-0.000888*	-0.000919*	-0.000744+	-0.00111+	-0.0219	-0.0292	-0.0618+	0.0242
	(0.000445)	(0.000467)	(0.000467)	(0.000735)	(0.0460)	(0.0490)	(0.0448)	(0.0587)
Between	0.000158	0.000190	0.000106	-0.0000683	-0.0148	-0.0206	-0.0280+	-0.0216
	(0.000203)	(0.000200)	(0.000244)	(0.000309)	(0.0173)	(0.0186)	(0.0210)	(0.0296)
Exit	-0.000484	-0.000550+	-0.000550+	-0.000686+	-0.0148	-0.0206	-0.0280+	-0.0216
	(0.000383)	(0.000390)	(0.000389)	(0.000514)	(0.0173)	(0.0186)	(0.0210)	(0.0296)
Entry	-0.000788++	-0.000814++	-0.000865++	-0.00114*	0.0424+	0.0507+	0.0710+	0.0603++
	(0.000468)	(0.000454)	(0.000461)	(0.000578)	(0.0320)	(0.0362)	(0.0439)	(0.0361)
N	437	437	437	437	448	448	448	448
Industry Control	X				X			
1-digit ANZSIC Industry FE		X				X		
2-digit ANZSIC Industry FE			X				X	
3-digit ANZSIC Industry FE				X				X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This table presents the results of regressing the DF decomposition of labour shares with the concentration ratio of top 4 firms in a 15 -year long difference regression. There are four different concentration measures assessed including C10, C20, HHI and Markups, with increasingly strict industry fixed effects.

Source: ABS BLADE 16-17, Author's Calculations

Table (E.2) Sub-sample Analysis - Goods v Services, Tradeable v Non Tradeable, Primary v Non Primary. Regression of the components of DF Labour Share Decomposition on the Change in Concentration

	Goods v Services		Tradeable v Non Tradeable		Primary v Non-primary	
	(1) Goods	(2) Services	(1) Trade	(2) Non Trade	(1) Primary	(2) Non-primary
Within	-0.0342	-0.205**	-0.0135	-0.0905++	0.00727	-0.143***
	(0.0388)	(0.0642)	(0.0552)	(0.0525)	(0.0501)	(0.0411)
Between	-0.0231	-0.00439	-0.0241	-0.0382+	-0.0264	-0.0126
	(0.0210)	(0.0452)	(0.0308)	(0.0289)	(0.0278)	(0.0256)
Exit	0.0326	-0.119++	-0.0750+	0.143	0.0921	-0.0877*
	(0.0916)	(0.0680)	(0.0543)	(0.223)	(0.139)	(0.0394)
Entry	-0.0570+	-0.165+	-0.0167	-0.171*	-0.0119	-0.146*
	(0.0373)	(0.117)	(0.0443)	(0.0707)	(0.0379)	(0.0634)
N	324	97	214	207	198	226
Industry Controls	X	X	X	X	X	X
2-digit Industry FE	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001
Notes: This table presents the results of regressing the DF decomposition of labour shares with the concentration ratio of top 4 firms in a 15 -year long difference regression. The sub samples include Goods Division, Services Division, Tradeable Division, Non Tradeable Division, Primary Division and Non Primary Division. Standard errors are clustered at the 4-digit industry level, and industry controls as well as 2-digit Industry Fixed Effects have been applied.
Source: ABS BLADE 16-17, Author's Calculations

E.1.2 Understanding the Results - Tables and Figures

Figure (E.1) Top Rent Seeking Industries, by Value Added

4-Digit ID	Description	No firms in 2017	Total Value Added in 2017	Change in C4	Change in Labour Share	Change in Labour productivity	Labour Share in 2017	Labour productivity in 2017
4530	Clubs (hospitality)	6669	5,404	0.015	-0.011	0.045	0.48	0.110
4400	Accommodation	18352	7,935	0.011	-0.061	0.040	0.52	0.096
7291	Office Administrative Services	12499	10,337	0.023	-0.037	0.065	0.66	0.136
6720	Real Estate Services	50813	14,115	0.033	-0.086	0.052	0.53	0.120
4110	Supermarket and Grocery Stores	12594	16,039	0.124	-0.044	0.037	0.61	0.081
Rent seeking Industry Average			**2289**	**0.12**	**-0.10**	**0.10**	**0.49**	**0.16**
Industry Average			**2292**	**-0.02**	**0.02**	**0.07**	**0.52**	**0.17**

Figure (E.2) Top Non-Rent Seeking Industries, by Value Added

4-Digit ID	Description	No firms in 2017	Total Value Added in 2017	Change in C4	Change in Labour Share	Change in Labour Productivity	Labour share in 2017	Labour Productivity in 2017
6931	Legal Services	28545	11895	-0.44	0.277	-0.033	0.49	0.13
4511	Cafes and Restaurants	43950	12006	-0.09	0.0376	0.023	0.67	0.07
5802	Other Telecommunications Network Operations	408	16689	-0.02	0.0539	0.094	0.28	0..35
6962	Management Advice and Related Consulting Services	73984	19539.54	-0.05	0.0475	0.05	0.58	0.12
600	Coal Mining	406	30989.66	-0.239	0.011	0.431987	0.16	0.77
801	Iron Ore Mining	90	36328.86	-0.036	0.024	0.472987	0.12	1.12
6712	Non-Residential Property Operators	116733	41962.4	-0.180	0.142	0.116711	0.38	0.26
Non-rent-seeking average			2765	-0.15	0.04	0.058	0.56	0.16
Industry Average			**2292**	**-0.02**	**0.02**	**0.07**	**0.52**	**0.17**

E.2 Melitz and Polanec Results - Regressions

E.2.1 Robustness and Further Analysis

Table (E.3) Industry (4-Digit) Regression of the components of a MP Labour Share Decomposition on the change in C10, C20, HHI and Mark ups

	C10				C20			
Mean	-0.0022	-0.00272	-0.00414+	-0.00242	-0.00251+	-0.00292+	-0.00427++	-0.00258
	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Covariance	-0.00792*	-0.00823*	-0.00628	-0.0126+	-0.00629+	-0.00643+	-0.00516	-0.0122+
	(0.004)	(0.004)	(0.006)	(0.008)	(0.004)	(0.004)	(0.005)	(0.008)
Exit	0.0207*	0.0206*	0.0192++	0.0215++	0.0192++	0.0193++	0.0178++	0.0205++
	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)
Entry	-0.004	-0.00351	-0.00397	-0.00268	-0.0027	-0.00241	-0.0025	-0.00135
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.006)
N	437	437	437	437	437	437	437	437
Industry Control	X				X			
1-digit ANZSIC Industry FE		X				X		
2-digit ANZSIC Industry FE			X				X	
3-digit ANZSIC Industry FE				X				X

	HHI				Mark Up			
Mean	0.000124	0.0000742	0.000187	-0.000122	-0.0135	-0.0237	-0.0646+	0.00231
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0416)	(0.0423)	(0.0413)	(0.0545)
Covariance	-0.000789*	-0.000717++	-0.000629+	-0.00102++	-0.0255	-0.0303	-0.0322	-0.0522+
	(0.000)	(0.000)	(0.000)	(0.001)	(0.0372)	(0.0375)	(0.0349)	(0.0405)
Exit	-0.000498	-0.000583+	-0.000617+	-0.000724	-0.0230	-0.0259	-0.0308	-0.0214
	(0.000)	(0.000)	(0.000)	(0.001)	(0.0260)	(0.0286)	(0.0324)	(0.0363)
Entry	-0.000363	-0.000382	-0.000406	-0.000642+	0.0424+	0.0507+	0.0710+	0.0603++
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0320)	(0.0362)	(0.0439)	(0.0361)
N	437	437	437	437	448	448	448	448
Industry Control	X				X			
1-digit ANZSIC Industry FE		X				X		
2-digit ANZSIC Industry FE			X				X	
3-digit ANZSIC Industry FE				X				X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This table presents the results of regressing the MP decomposition of labour shares with the concentration ratio of top 4 firms in a 15 -year long difference regression. There are four different concentration measures assessed including C10, C20, HHI and Markups,with increasingly strict industry fixed effects.

Source: ABS BLADE 16-17, Author's Calculations

Table (E.4) **Sub-sample Analysis - Goods v Services, Tradeable v Non Tradeable, Primary v Non Primary. Regression of the components of MP Labour Share Decomposition on the Change in Concentration**

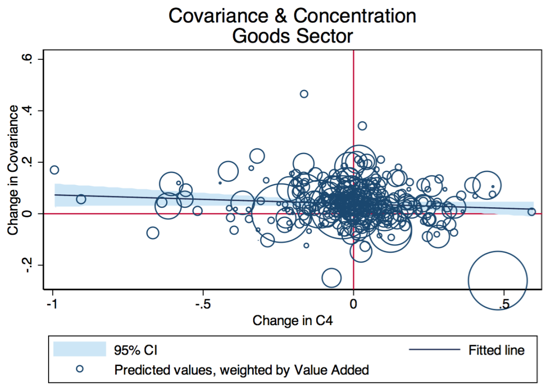
	Goods v Services		Tradeable v non tradeable		Primary	
	(1) Goods	**(2) Services**	**(1) Trade**	**(2) Non Trade**	**(1) Primary**	**(2) Non-primary**
Covariance	-0.0712*	-0.146*	-0.0322	-0.149*	-0.0337	-0.144***
	(0.0357)	(0.0727)	(0.0514)	(0.0618)	(0.0457)	(0.0423)
Mean	0.0100	-0.0307	0.0157	0.00670	0.0146	-0.0104
	(0.0232)	(0.0303)	(0.0316)	(0.0391)	(0.0302)	(0.0239)
Exit	0.0326	-0.119++	-0.0750+	0.143	0.0921	-0.0877*
	(0.0916)	(0.0680)	(0.0543)	(0.223)	(0.139)	(0.0394)
Entry	-0.0570+	-0.165+	-0.0167	-0.171*	-0.0119	-0.146*
	(0.0373)	(0.117)	(0.0443)	(0.0707)	(0.0379)	(0.0634)
N	324	97	214	207	198	226
Industry Controls	X	X	X	X	X	X
2-digit Industry FE	X	X	X	X	X	X

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001
Notes: This table presents the results of regressing the MP decomposition of labour shares with the concentration ratio of top 4 firms in a 15 -year long difference regression. There are four different concentration measures assessed including C10, C20, HHI and Markups,with increasingly strict industry fixed effects.
Source: ABS BLADE 16-17, Author's Calculations

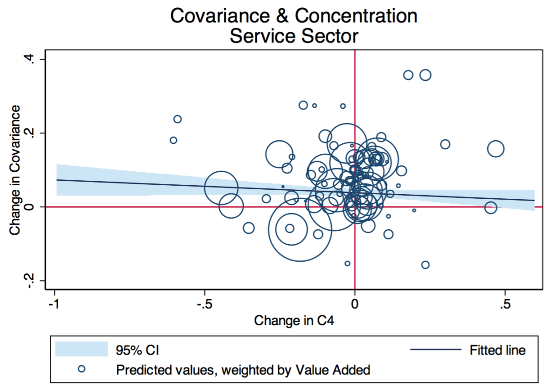
E.2.2 Understanding Results

Figure (E.3) Predicted Values of Sub-sample regressions, using Diewert and Fox decomposition

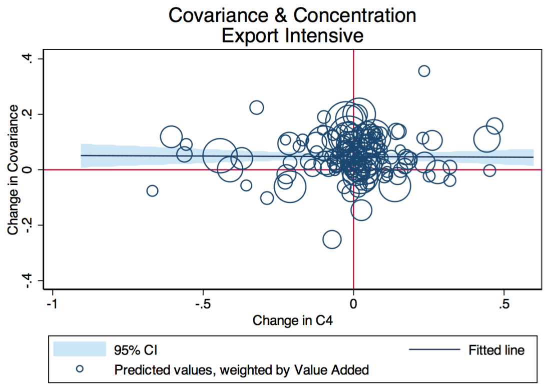
(a) Goods Sector



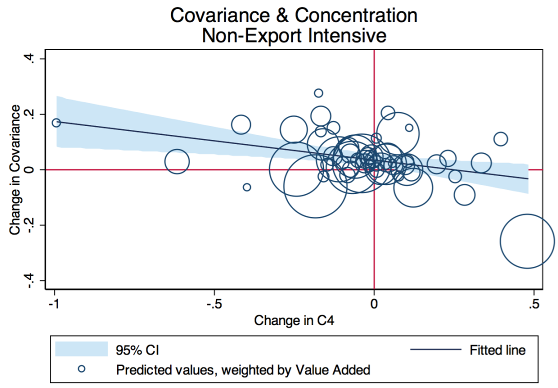
(b) Services Sector



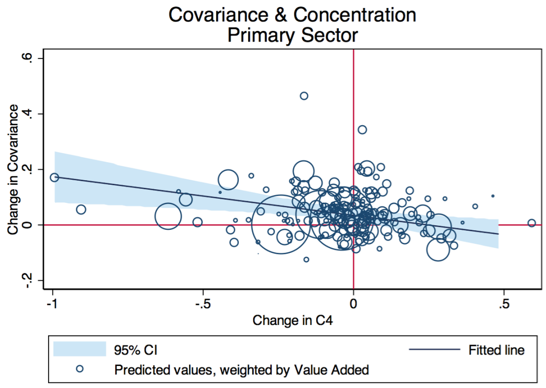
(c) Export Intensive Sector



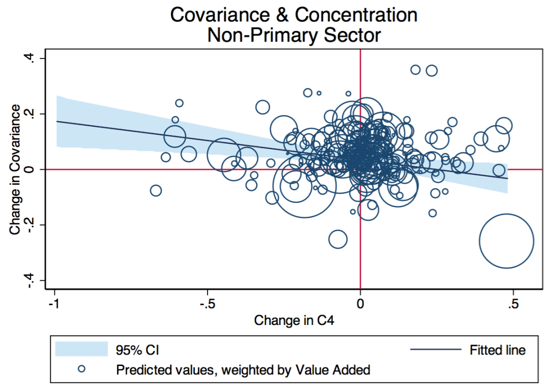
(d) Non-Export Intensive Sector



(e) Primary Sector



(f) Non-Primary Sector



E.2.2.1 Superstar Firms

This section explores some of the industries that can be classified as 'superstar' to gain better understanding of the results. Splitting the chart into four quadrants, industries that are experiencing a superstar phenomenon akin to Autor et al. (2017, 2019)'s model are in the bottom right quadrant. The superstar phenomenon implies a growing gap between leading firms and other firms, leading to an increase concentration due to the reallocation of value added to highly productive low labour share firms. This accounts for 12% of four-digit industries, and only 15% of total value added. Hence, they make a small contribution in our economy.

Majority of these industries are in the Retail Trade sector, Wholesale Trade sector and Construction sector. The largest industries, in terms of total value added, are listed in the table below and are likely to be the industries with the largest 'superstar' effect. These include supermarket, fuel retailing, grain sheep and grain beef cattle farming, electricity distribution, and accommodation, who have labour shares lower than the economy average. The level of labour productivity in 2017 and change in labour productivity from 2002 to 2017 for the superstar quadrant is higher than the economy-wide industry average. This supports the superstar model that industries that have had the largest increase in concentration, have the lowest labour shares but also the largest growth in productivity.

E.2.2.2 Fading Superstar Industries

Industries that are experiencing the characteristics of a fading superstar (see Section 5.1.1 for the discussion surrounding fading stars) are found in the top left quadrant, where there is declining concentration and increasing labour share. More than a third of total industries and 40% in terms of value added exist in this quadrant, indicating that 'fading superstars' outweigh 'superstars'. Figure x demonstrates the composition of the fading superstar industries by number, share of value added and share of employees. While more than a third of these industries are in the Manufacturing division and one-fifth come from Wholesale Trade, the largest industries in terms of value added are in the Construction sector, Professional Scientific and Technological Services and Mining sector. The largest industries in terms of employment are Retail trade and the service divisions.

Table **??** below presents some of the top 4-digit industries contributing to this cluster. All of them have experienced a decline in concentration and an increase in labour share, resulting in labour shares which are higher than the economy industry average. According to Autor's model then, the reallocation of value added to high labour shares indicates a decline in allocative efficiency and declining competition. Labour productivity and aggregate productivity growth is also small in comparison to the economy, supporting the idea that resources have shifted towards low productive firms. In Legal Services, for example, there has been a decline in the labour productivity, while labour shares have increased significantly. The number of industries that are experiencing a decline in allocative efficiency as 'fading superstars', rather than an increase in allocative efficiency, as superstars is concerning. Understanding 'fading superstars' from a policy point of view is important as it implies obsolescence and declining efficiency in the economy.

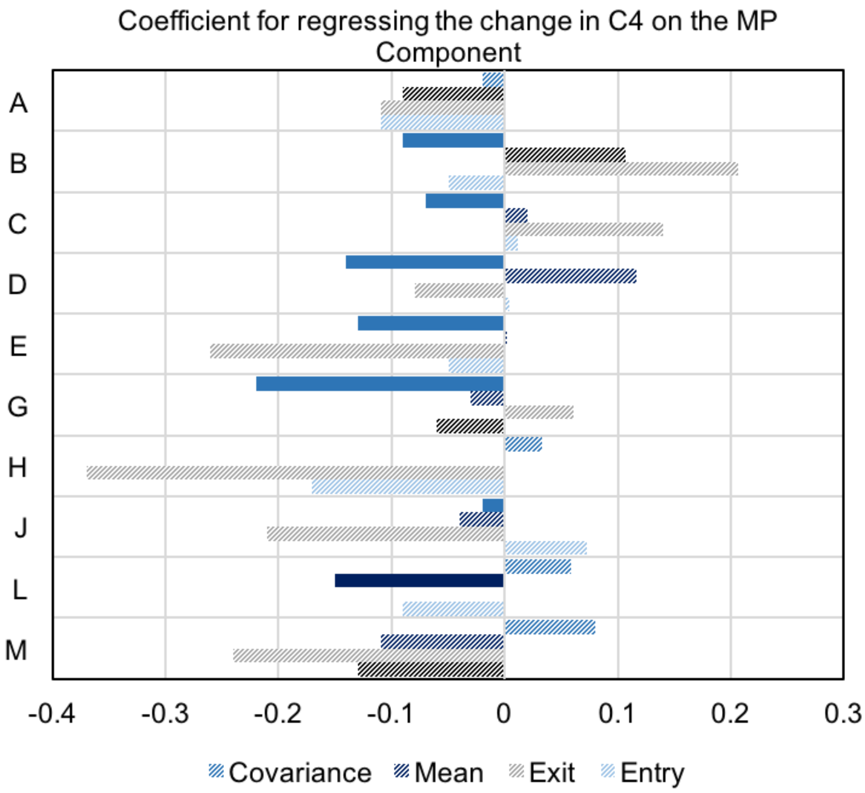
4-Digit ID	Description	No firms in 2017	Total Value Added in 2017 ($m)	Change in C4	Change in Labour Share	Change in Labour Productivity	Labour share in 2017	Labour Productivity in 2017
4520	Pubs, Taverns and Bars	8904	6248	-0.41	0.254	-0.037	0.51	0.35
4900	Air and Space Transport	1574	10391	-0.15	0.026	0.12	0.39	0.25
3211	Land Development and Subdivision	14844	5337	-0.21	0.043	0.068	0.24	0.32
3020	Non-Residential Building Construction	15009	9678	-0.02	0.011	0.07	0.56	0.12
3212	Site Preparation Services	23502	6834	-0.005	0.072	0.058	0.54	0.12
6931	Legal Services	28228	11895	-0.442	0.259	-0.033	0.49	0.13
4511	Cafes and Restaurants	43532	12006	-0.09	0.094	0.023	0.67	0.07
7000	Computer System Design and Related Services	60135	28950	-0.065	-0.001	0.071	0.59	0.15
6962	Management Advice and Related Consulting Services	75031	19539	-0.057	0.095	0.053	0.58	0.12
Non-superstar Average		**-**	**2475**	**-0.14**	**0.03**	**0.05**	**0.57**	**0.16**
Economy -wide Industry Average		**-**	**2292**	**-0.02**	**0.02**	**0.07**	**0.52**	**0.17**

Table (E.5) Top Fading superstar industries, by value added (2017)

E.2.3 Division Analysis

Figure E.4 plots the coefficients from divison regression. For each industry, the top bar denotes the coefficient for regressing concentration on the within component of labour share; next, on the between component;and the last two on exit and entry component. Coefficients which are significant are shown in block colours, while coefficients which are insignificant are shown as dashed lines. Overall, there is evidence for covariance effects dominating.

Figure (E.4) Division Analysis of MP Labour Share Components and Concentration



E.3 Comparing superstars and fading superstars

This section compares the characteristics of superstar and fading superstar industries to understand what this means for the Australian economy.

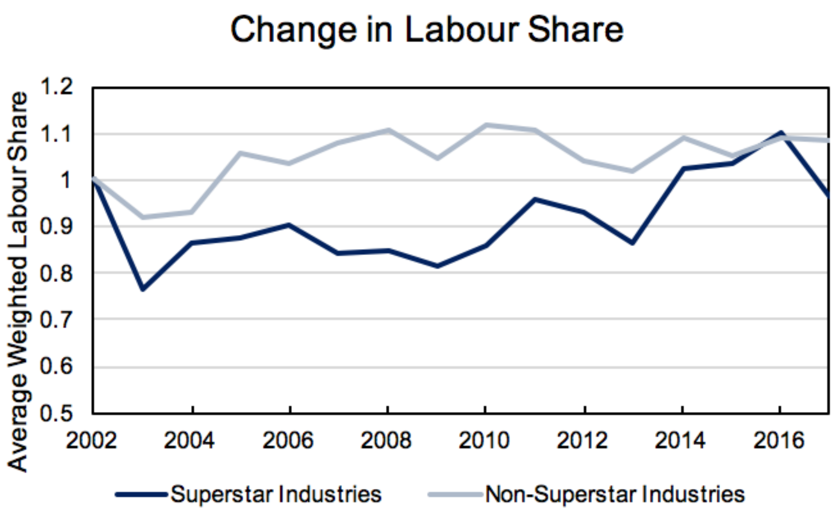
- Chart A plots the growth in labour productivity for superstar and fading superstars. Comparing the labour productivity of industries classified as 'superstar industries' and industries classified as 'non superstar industries', there is evidence that the labour productivity of fading superstar industries is falling as shown in the Figure A. However, there is declining aggregate productivity growth for superstar industries, the reverse of what is expected according to Autor et al. (2019)

- Chart B and C plots productivity dispersion trends. Productivity dispersion is a key element of the superstar hypothesis. Panel A of Chart x plots median labour productivity dispersion of top 90% of firms over the bottom 10% percentile firms in industries that were identified as superstars in 2017. It is has overall remained flat, with no substantial growth for the superstar quadrant and the non-superstar quadrant.

- Chart D to F plots the dispersion in value added, profit and capital stock in the frontier and non-frontier firms for the superstar and non-superstar sectors. In the superstar segment, frontier firms are leaps ahead of the rest of firms in terms of value added, profit and capital stock; in the non-superstar segment, the gap between frontier firms and the rest of firms is shrinking significantly.

- • Chart G plots the dispersion in capital investment. In the superstar hypothesis, one would expect capital intensity dispersion to increase, as large firms invest heavily in technology and capital to experience increased returns to scale. In non-superstar firms, other firms are catching up to leading firms or leading firms are declining in investment, causing the dispersion to fall. Interestingly, while capital investment dispersion in superstar segments was large up until 2014, it has since fallen. For non-superstar segments, the dispersion has remained relatively flat. This supports the idea behind 'fading superstars', as there has not been a larger change in capital investment by small firms to bridge the gap between frontier and other firms.

Overall, there appears to be a tension between superstar and fading superstar industries as explained by Autor et al. (2017). Empirically, many stylized facts of fading superstars are explained in the data including increased labour shares, declining productivity, capital investment, profit and sale dispersion. On the other hand, key stylized facts of superstar firms are not explained. While labour shares are falling, and there is increasing profit and sales dispersion, productivity dispersion and capital investment dispersion has not increased. In fact, in some measures it has fallen. This supports the idea that superstar firms are engaging in 'rent-seeking behaviour'.



E.4 Confirming Competition in the Economy - Regression Tables

Table (E.6) Regression of Concentration on Profit Share

	Profit Share											
Concentration	**Top 4 firms (log)**			**Top 10 firms (log)**			**Top 20 firms (log)**			**HHI (log)**		
Profit Share	0.938+	0.892+	0.659+	0.822+	0.806+	0.651+	0.962+	0.962+	0.709+	0.349+	0.345+	0.278+
	0	0	0	0	0	0	0	0	0	0	0	0
Industry Controls	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X		X			X			X		
Industry FE		X			X			X			X	
Year X Industry FE			X			X			X			X
R2	0.114	0.152	0.114	0.112	0.149	0.112	0.122	0.159	0.122	0.2147	0.107	0.151
N	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601	5601

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001
Notes: This is a 4-digit industry level annual fixed effects regression of the concentration ratio of top 4 firms on profit ratios. Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.
Source: ABS BLADE 16-17, Author's calculations

Table (E.7) Regression of Concentration on Mark-ups

Concentration	**Top 4 firms (log)**			**Top 10 firms (log)**			**HHI (log)**		
Mark-ups	0.101+	0.0992+	0.0616***	0.137+	0.134+	0.0768***	0.0560+	0.0551+	0.0376+
	-0.001	-0.001	-0.013	-0.001	-0.002	-0.02	-0.001	-0.001	-0.007
Industry Controls	X	X	X	X	X	X	X	X	X
Year FE	X	X		X			X		
Industry FE		X			X			X	
Year X Industry FE			X			X			X
R2	0.034	0.04	0.041	0.033	0.039	0.039	0.041	0.048	0.049
N	7190	7190	7190	7190	7190	7190	7190	7190	7190

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001
Notes: This is a 4-digit industry level annual fixed effects regression of the concentration ratio of top 4 firms on mark-ups. Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.
Source: ABS BLADE 16-17, Author's calculations

Table (E.8) **Regression of Concentration on Labour Productivity**

Concentration	**Top 4 firms (log)**			**Top 10 firms (log)**			**HHI (log)**		
Labour Productivity	0.0679+	0.0392+	0.101+	0.0145	0.0508+	0.153+	0.0306+	0.00599	0.0197***
(log)	-0.002	-0.009	0	-0.547	-0.01	0	-0.009	-0.535	-0.017
Industry Controls	X	X	X	X	X	X	X	X	X
Year FE	X	X		X			X		
Industry FE		X			X			X	
Year X Industry FE			X			X			X
N	7182	7182	7182	7182	7182	7182	7182	7182	7182
R2	0.022	0.349	0.35	0.023	0.349	0.412	0.023	0.349	0.349

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This is a 4-digit industry level annual fixed effects regression of the concentration ratio of top 4 firms on labour productivity . Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.

Source: ABS BLADE 16-17, Author's calculations

Table (E.9) **Regression of Concentration on LP Dispersion**

	Labour Productivity Dispersion								
Concentration	**Top 4 firms (log)**			**Top 10 firms (log)**			**HHI (log)**		
Labour Productivity (log)	0.0679+	0.0158	0.0388+	0.109+	0.0145	0.0517+	0.0306+	0.00599	0.0190***
	-0.002	-0.388	-0.006	0	-0.547	-0.006	-0.009	-0.535	-0.019
Industry Controls	X	X	X	X	X	X	X	X	X
Year FE	X	X		X			X		
Industry FE		X			X			X	
Year X Industry FE			X			X			X
R2	7182	7182	7182	7182	7182	7182	7182	7182	
N	0.022	0.349	0.433	0.023	0.347	0.481	0.021	0.349	0.418

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This is a 4-digit industry level annual fixed effects regression of the concentration ratio of top 4 firms on labour productivity dispersion. Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.

Source: ABS BLADE 16-17, Author's calculations

Table (E.10) Regression of Concentration on TFP Dispersion

	Total Factor Productivity Dispersion								
Concentration	**Top 4 firms (log)**			**Top 10 firms (log)**			**HHI (log)**		
Labour Productivity	0.00223	0.0101	0.0201***	0.00237	0.00237	0.0100*	0.00308	0.00643	0.00965**
	-0.835	-0.327	-0.04	-0.682	-0.682	-0.105	-0.58	-0.233	-0.067
Industry Controls	X	X	X	X	X	X	X	X	X
Year FE	X	X		X			X		
Industry FE		X			X			X	
Year X Industry FE			X			X			X
R2	7182	7182	7182	7182	7182	7182	7182	7182	7182
N	0	0.042	0.123	0	0.042	0.114	0	0.042	0.099

Notes: Standard errors are in parentheses. P-values = ++p<0.2 +p<0.1 *p<0.05 **p<0.01 ***p<0.001

Notes: This is a 4-digit industry level annual fixed effects regression of the concentration ratio of top 4 firms on total factor productivity dispersion. Standard errors are clustered at the 4-digit level, with various levels of fixed effects including time fixed effects, industry fixed effects and time-industry fixed effects.

Source: ABS BLADE 16-17, Author's calculations

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