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The drivers of labour share and impact on pay inequality: A firm-level investigation

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Abstract

Income inequality and labour share have followed divergent trends in Australia. Empirical studies have attempted to explain their movement and their relationship using macro data. However, what is lacking is a firm-level study to capture the determinants of labour share specific to the firm's production technology and market structures with an investigation into the impact on pay inequality inside firms. Hence, we conduct the first Australian firm-level study using a sample of Australian listed firms over the period 2004-2019. First, we examine the impact of technological progress, product market power and labour market power on the labour share. The results show that the decline in Australian labour share is mainly driven by technological progress and increasing product market power. However, labour market power does not have a significant impact on labour share. These findings are robust to an array of sensitivity tests. Second, we examine the impact of labour share on pay inequality within firms. We find robust evidence that declining labour share is a significant driving force in the evolution of pay inequality. Moreover, a 10 per cent decline in labour share rises pay inequality by 4.19 per cent. Additional tests show that technological progress and product market power can moderate the negative impact of labour share on pay inequality.

Keywords

Income Distribution
Mark-up
Labour Share
Pay Inequality
Total Factor Productivity

JEL Classification

D33
J31
D42

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1. Introduction

The worldwide shift in the functional distribution of income between significant factors of production (capital and labour) and the rise in income inequality has been observed in many countries. For example, several studies have documented a decline in aggregate labour share (e.g., Dao et al., 2019; Karabarbounis and Neiman, 2014) and an increase in inequality (e.g., OECD, 2015) in most countries. This divergent trend between labour share and income inequality has also been emphasised in Australia in recent decades. Regardless of the measurement method, Australian labour share has substantially declined since the mid-1970s (Gianni, 2019), while income inequality has increased and now exceeds the OECD average (Sila and Dugain, 2019).

The decline in the labour share and the rise in income inequality has led to a growing literature on personal and functional income distribution drivers. Several potential explanations for the declining labour share have been proposed, including technological progress (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014), market concentration (Autor et al., 2020; De Loecker et al., 2020; Kehrig and Vincent, 2021), labour market institution (Piketty, 2014) and globalisation (Elsby et al., 2013). Some studies go a step further and argue that declining labour share is a driver of income inequality. Atkinson (2009) proposes a theoretical framework and shows that the transition from labour share to capital share can increase income inequality under plausible characterisations of capital and labour incomes. The negative association between labour share and income inequality has been illustrated in few empirical studies (Daudey and García-Peñalosa, 2007; Erauskin, 2020; IMF, 2017; Jacobson and Occhino, 2012; Sauer, Rao, Pachauri, et al., 2020)

Despite the surge of interest in the determinants of labour share and its link with personal income distribution, there has not been enough investigation at firm-level. In fact, existing research on the drivers of declining labour share relies heavily on country or industry aggregate macro data and downplays the importance of firm-level data. In addition, there is little clear guidance about the link between functional and personal income distribution inside firms. However, firm-level study is essential for two main reasons. First, most economic activities are organised within firms, where production and compensation decisions are taken that eventually impact the functional distribution of income and pay inequality between those who provide services in the form of labour and those whose contribution is primarily tied to capital. Second, studying the labour share at the firm-level allows us to overcome important measurement issues confronted by most of the labour share literature such as the treatment of capital depreciation (Bridgman, 2018), self-employment (Elsby et al., 2013; Gollin, 2002), intangible capital (Koh et al., 2018) and business owners taking capital instead of labour income (Smith et al., 2019). Nevertheless, only a few studies (e.g., D. Autor et al., 2020; De Loecker et al., 2020; Growiec, 2012; Guschanski and Onaran, 2018; Siegenthaler and Stucki, 2015) have investigated the firm-level determinants of labour share. Furthermore, the impact of a firm's labour share on the pay inequality between CEO, whose compensation is linked to capital income, and employees (pay inequality) as one of the drivers of income inequality [1] has not been investigated. Therefore, what is lacking is a firm-level analysis of factors determining Australian labour share, and the impact of labour share on pay inequality within firms. Therefore, this paper aims to address these gaps by examining two related questions: (i) What factors explain a firm's labour share? and (ii) Is there a relationship between labour share and pay inequality within firms?

To fulfil our aim, we analyse a sample of Australian listed firms over the period 2004-2019. Our empirical analysis is divided into two parts. In the first part, we examine the underlying determinants of labour share at the firm level. We consider three leading channels: technological progress, product market power and labour market power, which have been proposed in the literature as the main drivers of labour share movement. We find that technological progress and product market power are salient factors in explaining the level of labour share. Employees in firms with higher technological progress and product market power gain a lower proportion of these firms' value added. In the second part, we investigate the impact of labour share on pay inequality within firms. Our finding indicates a significant negative association between labour share and pay inequality. Lastly, we conduct further analysis to explore how potential drivers of labour share may affect the relationship between labour share and pay inequality.

This study contributes to the academic literature on labour share and pay inequality and has implications for policymakers. First, to the best of our knowledge, this study is the first that documents the firm-level determinants of labour share in Australia. Our findings thus contribute to the debate that has been dominated by evidence from the United States. Second, it extends the empirical study of the firm-level determinants of labour share by considering the impact of three leading channels: technological progress, product market power and labour market power. Third, our study provides novel insight into the link between labour share and pay inequality within firms. Investigating this link within firms help us detect a determinant of pay inequality and, more importantly, sheds light on possible way of overcoming the pay inequality problem. Finally, our findings can help policymakers limit further declines in labour shares and increases in pay inequality in Australia.

The article proceeds as follows. Section 2 reviews the related literature and develops the key hypothesises. Section 3 explains our methodology in this study. The data source, sample selection, measurement and descriptive statistics are discussed in section 4, followed by our empirical analysis and findings in section 5. Finally, section 6 provides concluding remarks.

[1] The high CEO compensation relative to average employee at the firm level can eventually lead to higher income inequality at macro level. For example, (Bakija et al., 2012), using information reported on U.S. individual income tax returns, find that executives, managers, supervisors, and financial professionals account for about 60 percent of the top 0.1 percent of income earners in recent years, and can account for 70 percent of the increase in the share of national income going to the top 0.1 percent of the income distribution between 1979 and 2005.

2. Literature review and hypothesis development

This section, first, reviews the existing theoretical and empirical literature on the drivers of declining labour share to shape our first hypothesis about firm-level causes of the fall in Australia's labour share. Second, it reviews the related literature about the linkage between functional and personal income distribution at the macro level. Thereafter it extends the literature into the relationship between labour share and pay inequality within firms and develops our second hypothesis.

2.1. Determinant of labour share: a short review and hypothesis

There is an ongoing debate about the underlying causes of the declining labour share. One stream in the literature points to technological progress as a primary reason (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014). Karabarbounis and Neiman (2014) hypothesise that the fall in the cost of capital relative to labour encourages firms to replace one factor of production with another. However, the type of capital and labour can complicate this substitution. For example, equipment substitutes differently with regard to labour than to buildings and structures (Eden and Gaggl, 2019; Hubmer and Restrepo, 2021) and some employees may benefit from technical changes, while others suffer as a result (Acemoglu and Autor, 2011). Furthermore, Bentolila and Saint-Paul (2003) propose a theoretical model to illustrate the relationship between technological progress and labour share. Their model implies that, under specific assumptions, the variation of labour share may be due to different values of the capital-output ratio, the elasticity of substitution and capital-augmenting technical progress. According to their model, the impact of capital intensity and capital-augmenting on labour share can be either positive or negative depending on the elasticity of substitution between capital and labour. Hence, a common element in these papers is the elasticity of substitution between capital and labour. While some studies find an elasticity of substitution of below one (Chirinko, 2008; Chirinko and Mallick, 2017; Oberfield and Raval, 2021), Grossman et al. (2021) show that a slowdown in labour productivity growth or capital-augmenting technological progress can eventually result in declining labour shares even if capital and labour are gross complements.

Another stream of literature points to rising product market power, measured by mark-up or industry concentration, as a potential cause of declining labour share (e.g., Autor et al., 2020; De Loecker et al., 2020). In the absence of competition, firms gain market power and price their goods above their marginal cost, leading to higher mark-up (De Loecker et al., 2020). Bentolila and Saint-Paul (2003) theoretically and empirically show that the increase in mark-up is associated with a lower labour share. In addition, some studies show that an increase in the US aggregate mark-up, driven by the reallocation of economic activity toward large and high-mark-up firms with lower labour share, decreases the aggregate labour share (Baqaee and Farhi, 2020; De Loecker et al., 2020). Similarly, Autor et al. (2020) present evidence that the rise in the US industry concentration positively impacts the decline in the labour share across industries.

Furthermore, some researchers assert that a decline in labour market power leads to a shift in functional income distribution (e.g., Farber et al., 2021; Gouin-Bonenfant, 2018). Declining labour market power may have allowed firms to exercise greater monopsony, and, as a result, stronger wage markdowns (Grossman and Oberfield, 2021). Kehrig and Vincent (2021) theoretically show that a higher wage markdown leads to a lower labour share. A stronger wage markdown may result from labour market deregulation, such as de-unionisation or increasing labour market concentration. Many authors point to de-unionisation as an explanation for the decline in labour market power (Stansbury and Summers, 2020). For example, Farber et al. (2021) document a positive correlation between state-level labour share and state union membership rates. In addition, increasing a firm's labour concentration in the relevant labour markets could account for stronger markdowns of wages relative to marginal revenue productivity and perhaps to a smaller labour share. Gouin-Bonenfant (2018) shows that a higher dispersion of productivities, which implies a greater concentration of employment, results in a lower aggregate labour share. Azar et al. (2020) use data from online job postings to show an inverse correlation between real wages and market concentration. Similarly, Benmelech et al. (2020) show that the negative correlation is stronger in the presence of low unionisation rates.

Empirical studies of labour share have used different levels of analysis. Most studies are based on country-level data (e.g., Checchi and García-Ieñalosa, 2010; Hogrefe and Kappler, 2013; Young and Lawson, 2014; Young and Tackett, 2018) and industry-level data (e.g., Alvarez-Cuadrado et al., 2018; Elsby et al., 2013; Hutchinson and Persyn, 2012; Pianta and Tancioni, 2008; Young and Zuleta, 2017). Only a few studies (e.g., Autor et al., 2020; De Loecker et al., 2020; Growiec, 2012; Guschanski and Onaran, 2018; Siegenthaler and Stucki, 2015) have focused on firm-level labour share. For example, Siegenthaler and Stucki (2015) examine the firm-level determinants of labour share in Switzerland. They find that the growth in the firm's share of workers using information and communication technology is the primary cause of the declining labour share. Similarly, Growiec (2012) investigate the sources of labour share variations in Poland using quarterly firm-level panel data. They show that changes in the ownership structure and human capital accumulation explain the downward trend in the labour share. In addition, Guschanski and Onaran (2018) provide international evidence for the negative impact of financialisation on firm-level labour share due to increased shareholder value orientation. The result of these studies emphasises the importance of firm-level analysis in investigating the movement in labour share. Hence, In this paper, first, we examine the impact of the three channels previously described – technological progress, product market power, and labour market power – on Australian firms' labour share. Given the related literature, our first hypothesis is as follows:

H1: *A firm's labour share decreases with technological progress and product market power and increases with labour market power.*

2.2. Labour share and pay inequality: a conceptual framework and hypothesis

The decline in labour share has been associated with the debate on rising income inequality. As argued by (Glyn, 2011; Morrisson, 2000; Piketty, 2014), capital income tends to be more unequally distributed than labour income and hence a transfer from labour income to capital income leads to an increase in income inequality. For example, (Wolff, 2010) shows that capital ownership (e.g., stock ownership, bonds, trust, and business equity) is mainly concentrated among the top of income distribution in the U.S. during the period 2001–2007. Furthermore, (Atkinson, 2009) proposes a standard approach for analysing the relationship between functional income distribution (labour/capital share) and income inequality. His study asserts that the positive linkage between capital share and income inequality is possible under plausible characterisations of capital and labour incomes.

An empirical relationship between labour share and income inequality has been investigated by a few studies using macro-level data. For example, using a sample of 39 developed and developing countries between 1970 and 1994, (Daudey and García-Peñalosa, 2007) find that a larger labour share is associated with a lower Gini coefficient. Similarly, (Jacobson and Occhino, 2012) show that a one per cent decreases in the U.S. labour share is associated with 0.15 to 0.33 per cent increase in the Gini index. A recent (IMF, 2017) report suggests that lower labour share is associated with higher Gini coefficients for 49 countries (mostly advanced countries) between 1991 and 2014. (Sauer, Rao, and Pachauri, 2020) find that the most robust factor behind rising income inequality is declining labour share for 73 countries (mostly observations from advanced OECD countries) between 1981 and 2010. Similarly, using a sample of 62 developed and developing countries for the period 1990-2015, (Erauskin, 2020) shows that the declining labour share is strongly associated with a smaller income share for the lowest two quintiles and a larger income share for the highest quintile.

The current literature on the relationship between functional income distribution and personal income distribution has focus mostly on macro-level data and obscured the relationship inside firm. However, the linkage between labour share and income inequality at the macro level can be extended into the firm level. At macro level, individuals' income comes from two main sources, capital and labour. Since the distribution of capital income is more concentrated on the top of income distribution (Piketty, 2014; Wolff, 2010), declining labour share (increasing capital share) rises income inequality. The same argument can be implicitly applied at the firm level. Individual remuneration package inside firms consists of short-term pay (e.g. salary and fees, accrued bonus), post-employment benefits (e.g., superannuation) and share-based payments. Among them, share-based payments (such as stock options and stock appreciation rights), which is a type of compensation based on the share of the company, is an effective mechanism to align the divergent interests of executives and shareholders (Jensen and Meckling, 1979). In another word, the part of employee's compensation, share-based payment, is linked with shareholder wealth (capital share) inside a firm. Similar to capital income, share-based payment is not equally distributed among all individuals inside the firm and this inequality is more pronounced among individuals at different hierarchical levels in an organisation. For example, (Cheffins and Thomas, 2004) assert that CEOs receive vastly higher stock options in comparison with other counterparties. Empirical studies in Australia show that long-term incentives, such as share-ownership or share-option schemes, comprise the largest percentage of Australian CEO compensation (Little, 2021) and an increase in shareholder wealth leads to an increase in CEO compensation (Merhebi et al., 2006). Since the distribution of share-based payment is not equal and mainly contributes to the top executives' compensation, we expect that a fall in labour share, resulting in a transfer from labour share to capital share, leads to a rise in pay inequality between CEO and average employee. This conceptual framework, though simple, provides a lens through which we can interpret the firm-level evidence on labour shares and pay inequality. Hence, our second hypothesis is as follows:

H2: *Labour share is negatively associated with pay inequality within firms.*

3. Methodology

This section consists of two parts. The first part explains our empirical model to examine the impact of three main channels: technological progress, product market power, and labour market power on labour share. The second part describes the model for examining the impact of labour share on pay inequality within firms.

3.1. Determinants of the Labour Share

Based on empirical studies that examine the impact of technological progress, product market power, and labour market power on labour share within firms (e.g., Autor et al., 2020; Bentolila and Saint-Paul, 2003;), we model the impact of these channels as follows:

$$LnLabourShare_{i,t} = \alpha_0 + \alpha_1 LnLabourShare_{i,t-1} + \beta_1 LnCapital/VA_{i,t} + \beta_2 TFP_{i,t} + \beta_3 LnMarkup_{i,t} + \beta_4 HHIEmp_{j,t} + \beta_5 Union_{k,t} + \beta_6 delta.LnEmpNum_{i,t} + \beta_7 BTM_{i,t} + \beta_8 LnAge_{i,t} + \beta_9 LnRevenue_{i,t} + \beta_{10} Leverage_{i,t} + u_{i,j,k,t} \quad (1)$$

In the above equation, labour share is our dependent variable measured as labour expenses divided by value added in each firm year. The model includes a lagged dependent variable to reflect the persistence of labour share over time (Bentolila and Saint-Paul, 2003). Subscript *i* is the firm identifier, *j* is the industry identifier, defined using a two-digit Global Industry Classification Standard (*GICS*) code, *k* is the region identifier, *t* is the fiscal year, and u is an error term that contains region, industry, firm and year fixed effect.

$$u_{i,j,k,t} = \theta_{k,j,i,t} + \varepsilon_{i,t} = \gamma_k + \delta_j + \mu_i + \tau_t + \varepsilon_{i,t}$$

Where $\varepsilon_{i,t}$ assumed to be independent and identically distributed with mean zero and constant variance.

Three main labour share drivers in our equation are technological progress, product market power and labour market power. Technological progress is included into our model by using two proxies, capital to value-added ratio ($LnCapital/VA_{i,t}$) and Total Factor Productivity ($TFP_{i,t}$). Following Bentolila and Saint-Paul (2003) and Autor et al. (2020), $LnCapital/VA_{i,t}$ is measured as the natural logarithm of gross property, plant and equipment to value-added ratio.

Based on Bentolila and Saint-Paul's (2003) model, *LnCapital/VA*$_{i,t}$ and *TFP*$_{i,t}$ can be negatively or positively associated with labour share. If labour and capital are complements (negative elasticity of substitution), increasing *LnCapital/VA*$_{i,t}$ or *TFP*$_{i,t}$ increases labour share. The converse applies if labour and capital are substitutes.[2] Therefore, we would expect a lower labour share in firms with higher technological progress if labour and capital are substitutes. Regarding product market power, we include firm-level mark-up (*LnMarkup*), measured by De Loecker et al.'s (2020) approach, in our equation. Lastly, labour market power is included using two proxies, labour market concentration (*HHIEmp*) and union membership (*Union*).

In addition to these three channels, we control the effect of labour adjustment cost (*delta.LnEmpNum*) by the growth rate of the number of employees, following Bentolila and Saint-Paul (2003). Firm size (*LnRevenue*), firm age (*LnAge*) and book to market ratio (*BTM*) are included to measure the complexity of a firm's operation and growth opportunities. The capital structure (*Leverage*), measured by total debt scaled by total assets, is also included. *Leverage* may be negatively associated with compensation because it decreases companies' ability to make their payroll. However, leverage can be positively correlated with compensation since potential bankruptcy costs arising from high leverage should be compensated by higher pay.

A potential problem arises when estimating the above equations. As discussed in the literature, the inclusion of the lagged dependent variable in the empirical model implies a correlation between the regressors and the error term, since lagged labour share depends on $u_{i,j,k,t-1}$, a function of the region, industry, and firm fixed effect, which could bias the coefficient estimates. In addition, region, industry, and firm fixed effect are potentially correlated with our explanatory variables. As a result, the lag dependent variable endogeneity consideration, using standard two-stage least squares regressions and instruments for labour share, may bias our estimation since it does not control for the endogeneity of other explanatory variables. Therefore, the appropriate way to control the endogeneity problem is to use instrument variables that are not subject to reverse causality for all variables of interest. However, this method seems hardly possible since this would require exogenous variables for all the potentially endogenous drivers of the labour share.

Thus, the preferred estimator in this case, following other studies in this stream of literature (e.g., Bentolila and Saint-Paul, 2003), is the “system generalised method of moments (*SGMM*)” (Arellano and Bond, 1991; Arellano and Bover, 1995) with a robust standard error. The econometrics literature shows that the two-step *SGMM* estimator is the most widely used technique to deal with potential endogeneity (Windmeijer, 2005). In addition, *SGMM* controls

[2] The effects of TFP and k on LS should have the same sign. If TFP shifts the Labour share-LnCapital/VA curve but violates that condition, it is neither labour- nor capital-augmenting (Bentolila and Saint-Paul (2003)).

for unobserved heterogeneity and dynamics in the system since there is the possibility of persistence in labour share and mismeasurement of variables that may bias estimates.

SGMM estimates a system of equations that express labour share as a function of the covariates in both levels and first differences. We treat the labour share and all right-hand side variables except *Union* as potentially endogenous variables. Regarding the first differences equation, since differencing induces a first-order moving average of the residuals, we use the second and third, rather than first, lagged values of endogenous variables as instruments. Turning to level equations, we use the first and second lagged first differences of all endogenous variables. The identification assumption in this model are as follows. In the level equation, If there is a variable, say $Z^L_{i,j,k,t}$, satisfying the condition E($Z^L_{i,j,k,t}\ \varepsilon_{i,t}$)=0 and we can assume that E($Z^L_{i,j,k,t}\ \theta_{k,j,i,t}$) does not depend on t, then we have E($\Delta Z^L_{i,j,k,t}\ u_{i,j,k,t}$)= 0, i .e. $\Delta Z^L_{i,j,k,t}$ is a valid instrument for the level equation. Similarly, for the equation estimated in the first difference $Z^D_{i,j,k,t}$ is a valid instrument. The specification is checked using the Hansen statistic, a test of over-identifying restrictions for the validity of the instrument set. We also report a statistic for the absence of second and third-order serial correlation in the first-differenced residuals. This is based on the standardized average residual autocovariance, which are asymptotically N(0, 1) variables under the null of no autocorrelation, and should not be significantly different from zero if the residuals in levels are serially uncorrelated (note that, due to differencing, first-order autocorrelation is expected ex-ante).

3.2. Labour Share and Pay Inequality

In order to examine our second hypothesis, we assume a log-linear relation between the two variables of interest, labour share and pay inequality using the following equation:

$$\begin{aligned}
LnPayInequality_{i,t} &= \alpha_0 + \alpha_1 LnPayInequality_{i,t-1} + \beta_1\, LnLaborShare_{i,t} + \beta_2\, LnRevenue_{i,t} \\
&+ \beta_3\, BTM_{i,t} + \beta_4\, LnAge_{i,t} + \beta_5\, ROA_{i,t} + \beta_6\, Ret_{i,t} + \beta_7\, STDRet_{i,t} \\
&+ \beta_8\, Leverage_{i,t} + \beta_9\, IsCEOChair_{i,t} + \beta_{10}\, BoardTenure_{i,t} \\
&+ \beta_{11}\, IndCommittee_{i,t} + \beta_{12}\, PPEIntensity_{i,t} + \beta_{13}\, RDIntensity_{i,t} \\
&+ \beta_{14}\, IndConcentration_{j,t} + \beta_{15}\, Education_{k,t} + \beta_{16}\, Union_{k,t} \\
&+ \beta_{17}\, UnemploymentRate_{k,t} + \beta_{18}\, VacantJobRatio_{j,t} \\
&+ \ u_{i,j,k,t} \qquad (2)
\end{aligned}$$

In the above equation, pay inequality is calculated using the ratio of the total CEO compensation to the mean employee pay during the fiscal year. We also consider the persistence of pay inequality over time. The coefficient of interest, β_1, captures the association between the labour share and pay inequality. Subscript i is the firm identifier, j is the industry identifier, defined using a two-digit Global Industry Classification Standard (GICS) code, k is the region identifier, and t is the fiscal year, and u is an error term that contains region, industry, firm, year fixed effect and $\varepsilon_{i,t}$ assumed to be independent and identically distributed with mean zero and constant variance.

Similar to prior studies (Core et al., 1999; Faleye et al., 2013; Taherifar et al., 2021), we control firm and labour market characteristics that can potentially affect pay inequality and may also be related to labour share. Hence, we include the firm's operation and growth opportunity proxies such as firm size (*LnRevenue*), firm age (*LnAge*), book to market ratio (*BTM*), return on asset (*ROA*), annual stock return (*Ret*), the standard deviation of common stock returns (*STDRet*), and capital structure (*Leverage*). Furthermore, executives' bargaining power over board members is controlled by including CEO chair duality (*IsCEOChair*), Board tenure (*BoardTenure*) and the percentage of independent board members on the compensation committee (*IndCommittee*). Finally, labour bargaining power, measured by employees' skills and labour market characteristics, is also controlled. Employees' skills are measured by R&D intensity (*RDIntensity*), physical capital intensity (*PPTIntensity*), and workforce education (*Education*). Labour market characteristics, such as industry concentration (*IndConcentration*), employee unionisation (*Union*), unemployment rate (*UnemploymentRate*), and vacant job ratio (*VacantJob),* are included. All variables are explained in Appendix B.

The most critical concern in the estimation of equation 2 is the simultaneity problem because compensation decisions jointly impact labour share and pay inequality inside firms. Therefore, the causality may run in both directions, from labour share to pay inequality and vice versa. Similar to the previous section, we address this endogeneity problem using two-step *SGMM* with robust standard errors. For the level equation, the second lagged first differences in pay inequality, labour share, firm performance and firm risk are used as instruments in our estimation. The level equation also uses the lagged values of all other right-hand side firm-level ratios as its instrument. The first differences equation uses the third lagged values of pay inequality, labour share, and firm performance. It also uses the second lagged first differences of all other right-hand side firm-level ratios as their instrument. Similarly, the specification is checked using the Hansen statistic. The first-order autocorrelation, second-order autocorrelation, third-order autocorrelation for testing the absence of serial correlation are reported.

4. Sample and Data, and Measurement

The financial data for this research are obtained from the Thomson Reuters DataStream database (*TRD*).[3] We start with all Australian listed firms covering all sectors of the economy over the period 2004–2019. In addition, Australian regional and industry-level data are collected from the Australian Bureau of Statistics (*ABS*). In order to merge *TRD* and *ABS* databases, industry groups and the region of incorporation are required for all firms. However, there are two issues. First, the state of incorporation for all companies and the *GICS* codes are not available in *TRD*. To address this problem, the country of incorporation, registered office region and *GICS* for all companies are retrieved from MorningStar DatAnalysis (*MD*). Then,

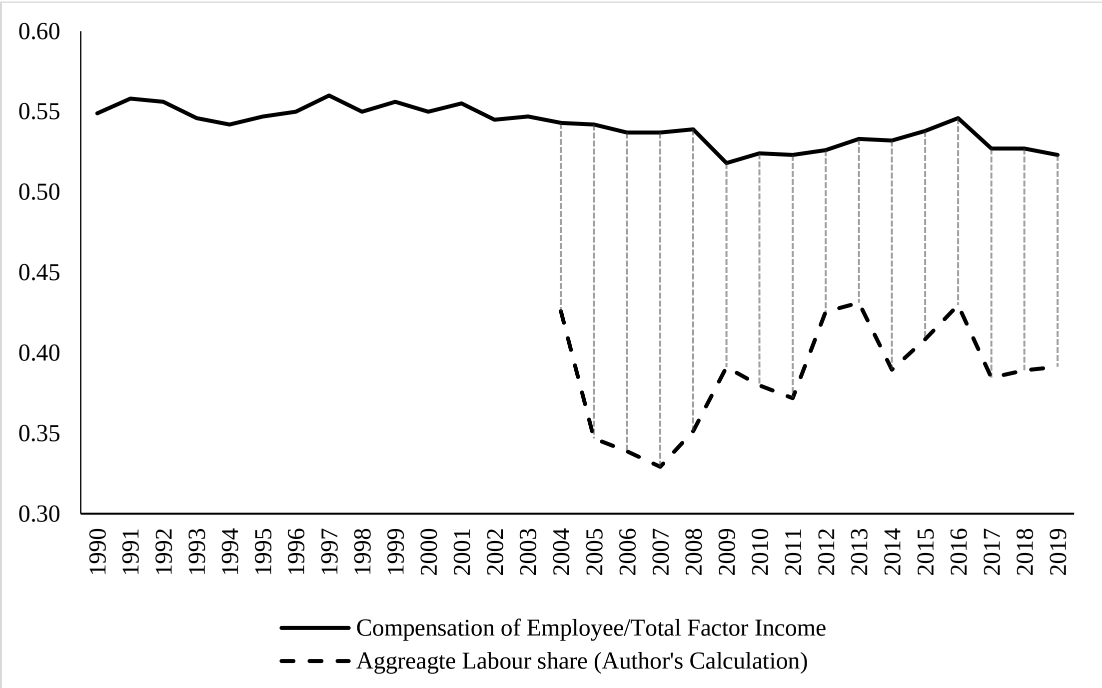
[3] To our knowledge, TRD is the only data source that provides financial data for Australian firms which has been widely used in the literature on compensation, pay inequality, and labour share (e.g., Guschanski and Onaran 2018)

the missing values of the country of incorporation and registered office region in *TRD* are completed using data from *MD*. Second, the industry identifiers differ in *MD* and *ABS*; the former uses *GICS* and the latter uses Australian and New Zealand Standard Industrial Classification (*ANZSIC*). To overcome this problem, we relate each two-digit *GICS* industry code to a two-digit *ANZSIC* code. If an exact match is not possible for the two-digit *ANZSIC* code, we use the broadest level of the *ANZSIC* code that potentially maps to the *GICS* industry code (Appendix C illustrates the industry map). Using these steps, our primary required dataset, including firm-level, industry-level, and region-level data, is constructed.

Our primary variable of interest is the firm-level labour share. Following Hartman-Glaser et al. (2019) and Donangelo (2021), labour share is defined as labour cost divided by value added in each firm at the end of the fiscal year. Labour cost is proxied by staff expenses, including wages and benefits such as health insurance and contributions to pension plans. In addition, value-added is defined as earnings before interest, tax, depreciation, and amortisation plus labour cost. We follow Hartman-Glaser et al. (2019) and exclude firm-year observations with negative sales, negative number of employees, negative total assets, and negative staff expenses from our primary analysis. In addition, we eliminate firm-year observations with zero asset turnover. We also exclude firms that do not report a sector code. Consistent with the literature (Autor et al., 2020; Donangelo, 2021; Donangelo et al., 2019), all observations in which labour share is negative or greater than one are excluded from the sample. Our final sample of firm-level labour share includes 8,515 firm-year observations and 1,592 unique firms.

Figure 1 demonstrates a correspondence between the aggregate firm-level labour share and the national account labour share. The aggregate labour share is calculated as the weighted average of labour share based on the share of value added in our sample, and the national account labour share is the ratio of employee compensation to total factor income, which is equal to GDP less net taxes on production and imports. Figure 1 shows that the aggregate labour share and national account labour share movement is quite similar. However, the national account labour share is larger and smoother than the aggregate labour share from 2004 to 2019. As De Loecker et al. (2020) discussed, listed firms are larger, older, more capital-intensive, and involve a more significant role for multinationals, which may cause a lower labour share among listed firms than in the whole economy. Generally, this correspondence provides some confidence that our estimation is a robust proxy of the aggregate labour share and can be employed to shed some light on the determinants of the labour share over the period 2004 - 2019.

Figure 1. The relationship between firm-level aggregate labour share and national account's labour share



Source: https://www.abs.gov.au/statistics/economy/national-accounts/australian-system-national-accounts/2019-20

In addition to labour share, other financial variables are also calculated based on data availability in the *TRD* database. The second variable of interest, pay inequality, is calculated as the ratio of total CEO compensation to the mean employee expenses during the fiscal year. CEO's compensation is defined in the *TRD* database as the highest remuneration within a firm.[4] Employees' average compensation is calculated as the ratio of employee expenses minus the highest remuneration to the number of employees minus one.[5] Appendix A details the measurement of all significant variables such as *LnCapital/VA*, *TFP*, *LnMarkup*, and *HHIEmp*. For all variables, we exclude observations with missing values, resulting in a sample of 3292 firm-year observations with 659 unique firms. In addition, all continuous financial variables are winsorised at the 1% level in each two-digit GICS to reduce the influence of possible outliers.

Table 1 provides descriptive statistics for all variables in the sample of 3292 observations. On average, the proportion of Australian firms' value-added paid to labour is 55 per cent over the period 2004-2019. Fifty per cent of the labour share in our sample lies between 37.7% and

[4] CEO compensation, reported in TRD, is based on the US dollar. Therefore, we collect the USD/AUD currency rate from TRD and we calculate CEO compensation in AUD by multiplying CEO compensation in USD by the currency rate in the fiscal date of each firm-year

[5] If the number of employees is missing, we use the employee numbers from the previous year.

73.3%. In addition, the average mark-up in our sample is 1.48 (*LnMarkupOP* is equal to 0.395), which means that the average mark-up charged is 48% over marginal cost. Moreover, our further primary analysis shows that none of variables are highly correlated, and the signs of the correlations are consistent with our expectations. Technological progress and product market power are negatively correlated with labour share, while a negligible positive correlation exists between Union and labour share. In addition, there is a negative correlation between labour share and pay inequality.

Table 1. Summary statistic of all variables

Variable	Obs.	Mean	SD.	1st quartile	Median	3rd quartile
LabourShare	3,292	0.550	0.243	0.377	0.593	0.733
LnPayInequality	1,352	3.223	1.096	2.458	3.234	3.928
LnCapital/VA	3,292	0.000	1.305	-0.875	0.099	0.949
TFPOLS	3,292	0.034	0.656	-0.336	0.030	0.420
LnMarkupOLS	3,292	0.408	0.649	0.044	0.281	0.596
TFPOP	3,292	0.745	1.848	-0.433	0.739	2.022
LnMarkupOP	3,292	0.395	0.643	0.037	0.256	0.568
TFPWRDG	3,292	0.652	1.711	-0.354	0.600	1.857
LnMarkupWRDG	3,292	0.415	0.652	0.020	0.297	0.620
IndHHIEmp	3,292	0.181	0.134	0.099	0.150	0.190
Union	3,292	15.081	2.446	12.924	15.372	16.674
LnEmployeeNumber	3,292	6.433	2.079	5.187	6.460	7.770
BTM	3,292	0.825	0.763	0.375	0.629	1.053
LnAge	3,292	2.540	0.904	2.036	2.618	3.130
LnRevenue	3,292	5.729	1.886	4.474	5.677	6.977
Leverage	3,292	2.651	1.374	2.334	3.067	3.495
ROA	3,284	8.578	7.850	4.165	7.225	11.510
Ret	3,260	0.057	0.477	-0.185	0.086	0.322
STDRet	2,717	0.126	0.067	0.081	0.111	0.154
IsCEOChair	1,425	0.103	0.304	0.000	0.000	0.000
BoardTenure	1,413	6.684	3.168	4.560	6.130	8.050
IndCommittee	1,389	84.013	22.079	67.000	100.000	100.000
PPEIntensity	3,292	2.286	16.679	0.023	0.087	0.340
RDIntensity	3,292	0.447	2.461	0.000	0.000	0.000
IndConcentration	3,292	0.093	0.070	0.044	0.069	0.125
Education	3,292	18.509	3.224	16.124	18.107	20.831
Unemployment	3,292	5.174	0.728	4.761	5.143	5.747
VacantJob	3,292	1.898	1.084	1.143	1.516	2.282

Notes: Table 1 presents summary statistics for the main variables in our samples. Firm characteristic Continuous variables are winsorised at 1 per cent and 99 per cent in each two-digit GICS.
All variables are defined in Appendix B.

5. Empirical analysis

This section starts by examining the firm-level determinants of labour share. It then follows the relationship between labour share and pay inequality within firms.

5.1. Determinants of Labour Share

Table 2 illustrates the impact of three leading channels, technological progress, product market power and labour market power on labour share. In all columns, our dependent variable is the natural logarithm of labour share. The first three columns report the estimation of our regression model in equation 1 using SGMM including region, industry, firm and year-fixed effects with robust standard error. For robustness check, we also estimate the static linear regression using the ordinary least squares (*OLS*) method, including region, industry, and year fixed effects. The result is shown in columns 4, 5, and 6. In all columns, robust standard errors clustered at the firm level are reported in parentheses.

Table 2 shows that technological progress significantly negatively impacts labour share. The negative and significant coefficient of *LnCapital/VA* across all columns, shown in the second row, indicates that capital and labour are substitutes. Therefore, a capital increase is associated with a decline in labour share. The next three rows illustrate the estimated coefficient of *TFP*, calculated based on the estimation of the Cobb-Douglas production function by Olley and Pakes' (1996) method (*TFPOP*), the Ordinary Least Squares method (*TFPOLS*) and the one-step GMM (Wooldridge, 2009) method (*TFPWDRG*). Regardless of our estimation method, we find a negative and significant association between *TFP* and labour share. Bentolila and Saint-Paul (2003) point out that the similar coefficient sign of *LnCapital/VA* and *TFP* shows that total factor productivity captures strictly capital-augmenting technological progress. Hence, Australian firms with higher capital-output ratios and capital-augmenting technological progress have lower labour share, consistent with our first hypothesis.

Turning to product market power, we investigate the relationship between *LnMarkup* and labour share. To calculate firm-level mark-up, we need to estimate the Cobb-Douglas production function for each two-digit GICS industry. Similar to *TFP* estimation, we employ three different methods of estimating a Cobb-Douglas production function. Hence, *LnMarkupOP*, *LnMarkupOLS* and *LnMarkupWRDG* present the natural logarithm of mark-up, in which the Cobb-Douglas production function is estimated by the methods of Olley and Pakes (1996), OLS, and Wooldridge (2009), respectively. Rows 6, 7 and 8 report a negative and significant association between mark-up and labour share across all columns. In other words, 10% increase in the firm's mark-up decrease the labour share by 0.55% to 0.67% based on two-step *SGMM and* 2.1% to 2.4 % based on OLS estimation. Although the coefficient of the mark-up differs across our estimation method, the broad pattern is quite similar. In sum, we find firm-level evidence of a direct inverse relation between mark-up and labour share, consistent with our first hypothesis.

Table 2. Determinants of labour share

Variable	LnLabourShare					
	SGMM-OP (1)	SGMM-OLS (2)	SGMM-WDRG (3)	OP (4)	OLS (5)	WDRG (6)
Lag.LnLabourShare	0.608***	0.603***	0.609***			
	(0.044)	(0.043)	(0.043)			
LnCapital/VA	-0.056**	-0.094***	-0.062**	-0.173***	-0.273***	-0.186***
	(0.023)	(0.028)	(0.024)	(0.022)	(0.025)	(0.022)
TFPOP	-0.163***			-0.175***		
	(0.028)			(0.029)		
TFPOLS		-0.209***			-0.429***	
		(0.041)			(0.048)	
TFPWRDG			-0.180***			-0.214***
			(0.030)			(0.032)
LnMarkupOP	-0.066**			-0.245***		
	(0.031)			(0.036)		
LnMarkupOLS		-0.055**			-0.215***	
		(0.027)			(0.035)	
LnMarkupWRDG			-0.067**			-0.243***
			(0.028)			(0.035)
IndHHIEmp	0.086	0.171	0.193	0.225	0.288*	0.308*
	(0.145)	(0.159)	(0.149)	(0.156)	(0.159)	(0.164)
Union	0.001	-0.003	0.002	0.023	0.017	0.024
	(0.011)	(0.01)	(0.011)	(0.016)	(0.016)	(0.016)
D.LnEmployeeNumber	-0.029	-0.046	-0.029	-0.072***	-0.111***	-0.077***
	(0.038)	(0.035)	(0.039)	(0.028)	(0.028)	(0.027)
BTM	0.057**	0.061***	0.057**	0.111***	0.092***	0.107***
	(0.024)	(0.023)	(0.024)	(0.025)	(0.023)	(0.024)
LnAge	-0.039**	-0.043***	-0.042***	-0.033*	-0.049***	-0.034*
	(0.015)	(0.014)	(0.015)	(0.019)	(0.018)	(0.019)
LnRevenue	0.033**	0.021	0.035**	0.040***	0.053***	0.045***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.012)	(0.014)
Leverage	-0.002	0.006	-0.002	0.020*	0.023**	0.019*
	(0.014)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
Constant	-0.085	-0.306	-0.066	-1.151***	-1.422***	-1.082***
	(0.199)	(0.197)	(0.207)	(0.335)	(0.333)	(0.336)
Observation	3292	3292	3292	3292	3292	3292
Firm	659	659	659	659	659	659
Adjusted R2				0.45	0.495	0.455
Root MSE				0.523	0.501	0.52
Number of Instrument	576	576	576			
Hansen test of over-identification	0.387	0.369	0.371			
Arellano-Bond test for AR(1)	0	0	0			
Arellano-Bond test for AR(2)	0.093	0.081	0.093			
Arellano-Bond test for AR(3)	0.503	0.452	0.511			

Notes: Table 2 reports the determinants of labour share. Labour share is measured as labour cost divided by the sum of earnings before interest, tax, depreciation, and amortisation (*EBITDA*) and labour cost. Each regression includes region, industry, and year fixed effects. Continuous variables are winsorised at 1 per cent and 99 per cent. Robust standard errors clustered at the firm level are reported in parentheses.
*, **, *** Indicate significance at the 10%, 5% and 1% levels, respectively. All variables are defined in Appendix B.

We also examine how labour market power impacts labour share. Row 9 shows the impact of *IndHHIEmp* on labour share. The *SGMM* estimates reported in columns 1, 2 and 3 indicate an insignificant relationship between *IndHHIEmp* and labour share. Similarly, the OLS estimates, column 4, 5 and 6, does not show a significant relationship at 5% level. While this finding is not consistent with our first hypothesis, it is close to the result achieved by Lipsius (2018) which shows that labour market concentration is an implausible driver of the falling labour share. In addition, row 10 illustrates that *Union* does not significantly impact labour share. In all columns, we also control for the possible effect of other factors on labour share. Among them, *BTM* and *LnAge* are strongly related to labour share. Table 2 shows that labour share decreases with a decrease in *BTM* and an increase in *LnAge*. This is consistent with Donangelo et al. (2019). High labour share firms are more exposed to systematic risk and less productive.

As a preliminary robustness check, Table 3 shows the impact of each driver, including technological progress, product market power and labour market power, separately on labour share. The coefficients in all columns are estimated by two-step *SGMM* with robust standard error in which labour share and all right-hand side variables except *Union* are treated as potentially endogenous variables. We use the first and second lagged first differences of endogenous variables as instruments for the level equation and the second and third lagged values of endogenous variables as instruments for the first differences equation. The first three columns show that firms with a higher *LnCapital/VA* and *TFP* have a lower labour share. The next three columns provide evidence of the negative relationship between *LnMarkup* and labour share. A 1% increase in mark-up leads to around a 0.08% decrease in the labour share across all the Cobb-Douglas production function estimation methods. The last column shows that labour market power, measured by *IndHHIEmp* or *Union*, is not related to firm-level labour share, at least in our sample. Overall, the Australian firm-level evidence on the potential drivers of labour share is in line with previous studies. Our result shows that technological progress and product market power are the most critical factors in explaining the level of labour share.

Table 3. The determinants of labour share (robustness check)

	LnLabourShare						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L.LogLabourShare	0.604***	0.605***	0.604***	0.569***	0.568***	0.567***	0.599***
	(0.048)	(0.046)	(0.047)	(0.043)	(0.043)	(0.043)	(0.045)
LnCapital/VA	-0.075***	-0.111***	-0.078***				
	(0.023)	(0.029)	(0.023)				
TFPOP	-0.167***						
	(0.033)						
TFPOLS		-0.196***					
		(0.047)					
TFPWRDG			-0.180***				
			(0.037)				
LnMarkupOP				-0.083**			
				(0.037)			
LnMarkupOLS					-0.084**		
					(0.037)		
LnMarkupWRDG						-0.086**	
						(0.037)	
IndHHIEmp							0.123
							(0.135)
Union							0.007
							(0.009)
D.LnEmployeeNumber	-0.059	-0.074*	-0.059	-0.074	-0.075	-0.075	-0.088*
	(0.041)	(0.04)	(0.042)	(0.049)	(0.049)	(0.05)	(0.049)
BTM	0.073***	0.069***	0.072***	0.029	0.029	0.029	0.026
	(0.027)	(0.025)	(0.026)	(0.029)	(0.029)	(0.029)	(0.027)
LnAge	-0.033**	-0.028**	-0.032**	-0.043***	-0.043***	-0.043***	-0.024**
	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.012)
LnRevenue	0.039**	0.024	0.042**	-0.007	-0.007	-0.007	-0.02
	(0.018)	(0.016)	(0.018)	(0.014)	(0.014)	(0.014)	(0.016)
Leverage2	-0.004	0.007	-0.004	-0.011	-0.011	-0.011	0.004
	(0.013)	(0.014)	(0.013)	(0.011)	(0.012)	(0.012)	(0.011)
_cons	-0.125	-0.427***	-0.125	-0.222*	-0.214*	-0.205*	-0.355*
	(0.120)	(0.122)	(0.113)	(0.123)	(0.123)	(0.124)	(0.189)
Observation	3443	3443	3443	3722	3722	3722	4175
Firm	681	681	681	715	715	715	775
Number of Instrument	467	467	467	444	444	444	422
Hansen test of over-	0.424	0.276	0.429	0.383	0.383	0.385	0.288
Arellano-Bond test for AR(1)	0	0	0	0	0	0	0
Arellano-Bond test for AR(2)	0.061	0.053	0.061	0.082	0.081	0.081	0.087
Arellano-Bond test for AR(3)	0.469	0.456	0.471	0.404	0.403	0.403	0.622

Notes: Table 3 reports the impact of each leading channel: technological progress, product market power and labour market power, on labour share. Labour share is measured as labour cost divided by the sum of earnings before interest, tax, depreciation, and amortisation (*EBITDA*) and labour cost. Each regression includes region, industry, and year fixed effects. Continuous variables are winsorised at 1 per cent and 99 per cent. Robust standard errors clustered at the firm level are reported in parentheses.
*, **, *** Indicate significance at the 10%, 5% and 1% levels, respectively.
All variables are defined in Appendix B.

5.1.1. Further Empirical Results

This section presents several robustness tests seeking to test the stability of our result among different subsamples.[6] First, the primary regression model, table 2, considers year heterogeneity by including year dummies and imposes a common coefficient for all three channels over time. Table 4 Panel A reports the regression coefficients that result from separate period by period estimation of equation (1). All columns include region, industry, and year fixed effects and standard error are clustered at the firm-level. In all periods, technological progress and product market power have a significant and negative impact on labour share. However, the magnitude of the impacts is quite different. In addition, there is no evidence of a relationship between labour market power and labour share. The sign of the coefficient estimation is in line with the total sample result (Table 2).

Table 4. The determinants of labour share across years and sectors

Panel A: The determinants of labour share over time

Period	LnCapital/VA	TFPOP	LnMarkupOP	IndHHIEmp	Union	Obs	Firm	Adjusted R2
2004-2007	-0.165***	-0.207***	-0.391***	0.247	0.007	711	350	0.419
	(0.041)	(0.046)	(0.103)	(0.917)	(0.041)			
2008-2010	-0.208***	-0.165***	-0.195***	0.208	0.009	771	372	0.438
	(0.031)	(0.043)	(0.05)	(0.145)	(0.02)			
2011-2013	-0.152***	-0.162***	-0.274***	-1.452	-0.015	787	362	0.475
	(0.031)	(0.039)	(0.067)	(1.137)	(0.045)			
2014-2016	-0.167***	-0.215***	-0.194***	-1.583	0.099	512	255	0.52
	(0.033)	(0.046)	(0.048)	(1.201)	(0.09)			
2017-2019	-0.208***	-0.179***	-0.210***	0.955	0.029	511	229	0.476
	(0.039)	(0.055)	(0.046)	(0.633)	(0.04)			

[6] In all subsamples, the coefficients are estimated using the *OLS* method. The low number of observations in some subsamples and high numbers of instruments provided by *SGMM* restrict us to estimate coefficients using the two-step *SGMM* method. However, it appears that the *OLS* bias is limited since estimated coefficients using *OLS* and the *SGMM* method (Table 2) show a similar sign.

Panel B: The determinants of labour share across sectors

Sector	LnCapital/VA	TFPOP	LnMarkupOP	IndHHIEmp	Union	Obs	Firm	Adjusted R2
Communication	-0.104	-0.175*	-0.162***	0.701	0.049	251	44	0.358
	(0.063)	(0.099)	(0.057)	(0.821)	(0.038)			
Consumer	-0.042	-0.002	-0.088	-0.046	0.076**	576	106	0.123
	(0.043)	(0.036)	(0.075)	(0.194)	(0.032)			
Consumer Staples	-0.283***	-0.209	-0.431**	2.327*	-0.015	175	32	0.262
	(0.083)	(0.167)	(0.21)	(1.242)	(0.055)			
Energy	-0.434***	-0.980***	-0.03	5.748**	0.096	131	35	0.65
	(0.065)	(0.18)	(0.169)	(2.397)	(0.067)			
Financials	0.009	-0.761***	-0.19	-0.758	0.006	119	28	0.724
	(0.044)	(0.094)	(0.121)	(1.591)	(0.058)			
Health Care	0.082	-0.009	-0.016	-2.403	-0.040*	215	39	0.445
	(0.052)	(0.039)	(0.063)	(2.495)	(0.022)			
Industrials	-0.172***	-0.087	-0.272***	0.736	0.012	794	139	0.337
	(0.036)	(0.055)	(0.071)	(0.848)	(0.023)			
Information	-0.248***	-0.218	-0.017	-0.719	-0.002	283	75	0.242
	(0.059)	(0.153)	(0.045)	(3.323)	(0.031)			
Materials	-0.282***	-0.532***	-0.548***	-7.822	-0.011	526	123	0.368
	(0.062)	(0.145)	(0.161)	(7.866)	(0.058)			
Real Estate	-0.279***	-0.911***	-0.239	-46.673*	0.086	136	22	0.642
	(0.07)	(0.14)	(0.158)	(24.051)	(0.077)			
Utilities	-0.579***	-1.332***	0.001	0.106	-0.009	86	16	0.908
	(0.054)	(0.217)	(0.104)	(1.621)	(0.051)			

Notes: Table 4 presents the determinants of labour share over time and sectors. In each row, the dependent variable is the natural logarithm of labour share measured as the natural logarithm of labour cost divided by the sum of earnings before interest, tax, depreciation, and amortisation (*EBITDA*) and labour cost. Panel A reports the determinants of labour share in five periods between 2004 and 2019. Panel B reports the determinants of labour share across 11 sectors. Each regression includes control variables, region, industry, and year fixed effects. Continuous variables are winsorised at 1 per cent and 99 per cent. Robust standard errors clustered at the firm level are reported in parentheses.
*, **, *** Indicate significance at the 10%, 5% and 1% levels, respectively.
All variables are defined in Appendix B.

Second, the importance of industry heterogeneity in understanding declining labour share has been highlighted in several papers (e.g., Autor et al., 2020; Karabarbounis and Neiman, 2014). To explore this heterogeneity, we investigate sector differences by estimating equation (1) for 11 sectors, defined based on their one-digit *GICS*, including region, industry, and year fixed effects and clustered standard error at the firm-level (Table 4 panel B). The result shows that the coefficients of *TFP* and *LnMarkup* are negative in all sectors with a significance level of less than 10 per cent in 6 and 4 out of 11, respectively.[7] In addition, we do not find evidence of a significant impact of technological progress, *LnCapital/VA* and *TFP*, on labour share in high-tech sectors, including health care, information technology and Communication services,[8]

[7] Except the coefficient of the mark-up in Utilities, which is almost equal to zero.

[8] By following Abayadeera (2010), we consider health care, information technology and telecommunication services as sectors including most Australian high-tech firms.

with the exception of *LnCapital/VA* in the information technology sector. This result shows that firms operating in high-tech sectors are not significantly affected by technological progress. Since a high proportion of employees in high-tech firms are highly skilled, this result is consistent with a skilled-biased technological progress impact on labour share (e.g., Krusell et al., 2000). Moreover, our result shows that product market power has insignificant or a low significant impact on declining labour share in high-tech sectors. However, this contrasts with the findings of Autor et al. (2020) who posit that firm concentration predicts a larger fall in the labour share in high-tech sectors. One explanation could be that there is insufficient variation in the data of this sub-sample of companies to identify the impact of the product market.

Third, technological progress allows businesses to automate their routine and well-defined tasks and substitute their low-skilled workers in production. Therefore, we expect that labour share is unaffected by technological progress in firms that show a higher probability of skilled employees or are less capital-intensive. To evaluate this hypothesis, we focus on two subsets of firms. The first subset is firms with R&D expenditure, based on the argument that firms investing in R&D require highly skilled employees to execute R&D projects and increase the likelihood of successful innovation (Faleye et al., 2013). The second subset consists of firms where the capital intensity, the ratio of PPE to the number of employees, is less than the first quartile in the corresponding sector, based on the intuition that capital has a less significant role in production in lower capital intensity firms. As the first and third columns of Table 5 reveal, *LnCapital/VA* and *TFP* do not have a significant impact on labour share in both high R&D and low capital-intensive firms. Thus, labour share does not significantly decline with technological progress when employees have higher skill levels or greater roles in production.

Lastly, it is possible that labour share in firms with higher levels of external funds, measured by the ratio of total debt to total asset, is impacted differently by technological progress and product market power. One might expect that better access to external funds encourages firms to invest more in new technologies and automate their tasks. At the same time, leverage may decrease firms' ability to make their payroll and be negatively associated with compensation. Hence, we expect a more considerable decline in labour share by increasing technological progress and mark-up in high leverage firms. To test this hypothesis, we separate the subset of firms where the leverage is higher than the third quartile in the corresponding sector. Columns 5 and 6 in Table 5 shows that technological progress and product market power have a larger significant negative impact on labour share in a high leverage subsample compared to the rest of the observations.

Table 5. The determinants of labour share within different sub-groups

	LnLabourShare					
	R&D	Excluding R&D	PPE-Low	Excluding PPE-Low	Leverage-High	Excluding Leverage-High
LnCapital/VA	-0.064	-0.187***	-0.043	-0.105***	-0.146***	-0.161***
	(0.043)	(0.023)	(0.039)	(0.026)	(0.03)	(0.024)
TFPOP	-0.099	-0.206***	-0.037	-0.146***	-0.242***	-0.157***
	(0.061)	(0.032)	(0.048)	(0.034)	(0.062)	(0.027)
LnMarkupOP	-0.191**	-0.246***	-0.128**	-0.278***	-0.275***	-0.207***
	(0.087)	(0.038)	(0.049)	(0.045)	(0.066)	(0.036)
IndHHIEmp	-0.557	0.325*	-0.131	0.266	-0.191	0.174
	(0.499)	(0.166)	(0.206)	(0.186)	(0.284)	(0.183)
Union	0.002	0.027	0.018	0.017	0.023	0.033*
	(0.035)	(0.018)	(0.021)	(0.019)	(0.033)	(0.02)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observation	540	2752	637	2655	776	2516
Firm	139	596	216	560	262	576
Adjusted R2	0.305	0.481	0.203	0.47	0.534	0.452
Root MSE	0.451	0.527	0.348	0.538	0.533	0.499

Notes: Table 5 presents the determinants of labour share between different groups. In all Columns, the dependent variable is labour share, measured as the natural logarithm of labour cost divided by the sum of earnings before interest, tax, depreciation, and amortisation (*EBITDA*) and labour cost. The regression in the first column is estimated over firms with R&D investment. The second column is estimated over the total sample except for firms with R&D investment. The third column is estimated over firms where the ratio of PPE to the number of employees is less than the first quartile in the corresponding sector. The fourth column is estimated over firms where the ratio of PPE to the number of employees is greater than the first quartile in the corresponding sector. The fifth column is estimated over firms where the leverage is higher than the third quartile in the corresponding sector. The sixth column is estimated over firms where leverage is less than the third quartile in the corresponding sector. Each regression includes control variables, region, industry, and year fixed effects. Continuous variables are winsorised at 1 per cent and 99 per cent. Robust standard errors clustered at the firm level are reported in parentheses.
*, **, *** Indicate significance at the 10%, 5% and 1% levels, respectively.
All variables are defined in Appendix B.

5.2. The Relationship between Labour Share and Pay Inequality

This section estimates the regression of pay inequality on labour share Table 6, Column 1, reports the estimation result of the two-step *SGMM* method including region, industry, firm and year-fixed effects with robust standard error. As shown, we find a negative and statistically significant relationship (p-value less than 1%) between logged labour share and logged pay inequality. This coefficient in the log-log model can be interpreted as elasticities, thus suggesting that a 10 per cent rise in labour share is associated with a 4.19 per cent increase in the gap between CEO compensation and average employee pay. For a robustness check, we also estimate the static linear regression using the ordinary least squares (*OLS*) method, including region, industry, and year fixed effects with robust standard error clustered at the firm level. The estimation result is reported in column 2. Similarly, the result indicates that the coefficient for *LnPayInequality* is -0.477 and significant at the 1 per cent level. Hence, labour share appears to have a negative and significant impact on pay inequality in our sample, which is in line with our second hypothesis.

Furthermore, we examine whether the significant drivers of labour share, technological progress and product market power, are likely to affect the association between pay inequality and labour share. Technology allows businesses to automate their routine tasks, and it substitutes low-skilled employees in production. However, it benefits high-skill employees who are complementary to technological progress. Therefore, firms with higher technological progress employ more high-skill employees with higher average wages (AIIA, 2018; Bessen, 2015). Hence, technological progress may weaken the negative association between labour share and pay inequality. With regard to product market power, previous research (e.g., Baker and Salop, 2015; Comanor and Smiley, 1975; Creedy and Dixon, 1999) has argued that increasing product market power contributes to greater inequality. For example, using country-level data, Ennis et al. (2019) and Han and Pyun (2021) show that an increase in mark-up is associated with rising income inequality. Therefore, the negative impact of labour share on pay inequality is expected to be stronger in firms with higher product market power.

To perform our examination, we interact *LnPayInequality* with *TFP* (Table 6, column 3) and *mark-up* (Table 6, column 4). The coefficient in both columns is estimated using two-step *SGMM* with robust standard error. The *SGMM* equations are similar to column 1 with one more endogenous variable: in column 3 (column 4), the second lagged of differences in *TFP* (*LnMarkup*) and the third lagged values of *TFP* (*LnMarkup*) is used as an instrument in the level and differences equations, respectively. Column 3 reports a positive and significant coefficient for the interaction terms between labour share and *TFP* (0.075, p<5 per cent), suggesting that technological progress weakens the negative association between labour share and pay inequality. Conversely, column 4 shows a negative and significant coefficient for the interaction between labour share and *LnMarkup* (-0.179, p-value< 10 per cent), indicating that a higher product market power strengthens the negative relationship between labour share and pay inequity. These results suggest higher negative relationships between labour share and pay inequality in firms with lower technological productivity and higher product market power. This may indicate that a lower labour share driven by higher product market power has a more substantial negative impact on pay inequality than a low labour share driven by technological progress.

Table 6. The impact of labour share on pay inequality

	LnPayInequality			
	(2)	(2)	(3)	(4)
Lag.LnPayInequality	0.571***		0.542***	0.629***
	(0.088)		(0.086)	(0.089)
LnLabourShare	-0.419***	-0.477***	-0.549***	-0.239**
	(0.139)	(0.078)	(0.103)	(0.114)
TFPOP			-0.237*	
			(0.123)	
LogLabourShare * TFPOP			0.075**	
			(0.036)	
LnMarkupOP				-0.294**
				(0.142)
LogLabourShare * LnMarkupOP				-0.179*
				(0.107)
LnRevenue	0.148***	0.297***	0.258***	0.122**
	(0.04)	(0.035)	(0.06)	(0.049)
BTM	0.031	-0.175***	-0.082	-0.003
	(0.101)	(0.065)	(0.092)	(0.09)
LnAge	0.068	0.210***	0.061	0.075
	(0.056)	(0.064)	(0.059)	(0.052)
ROA	0.008	-0.011**	0.004	0.007
	(0.009)	(0.005)	(0.009)	(0.01)
Ret	0.209	-0.012	0.147	0.136
	(0.131)	(0.067)	(0.099)	(0.103)
STDRet	0.199	1.466*	-0.033	0.26
	(0.656)	(0.747)	(0.64)	(0.749)
Leverage	0.008	0.003	0.024	0.008
	(0.023)	(0.025)	(0.019)	(0.022)
IsCEOChair	-0.181*	-0.064	-0.167*	-0.131
	(0.11)	(0.146)	(0.09)	(0.082)
BoardTenure	-0.008	-0.02	-0.008	-0.009
	(0.012)	(0.013)	(0.01)	(0.01)
IndCommittee	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
PPEIntensity	-0.012***	-0.025***	-0.010***	-0.011***
	(0.004)	(0.006)	(0.002)	(0.003)
RDIntensity	-0.022*	-0.007	-0.003	-0.011
	(0.011)	(0.012)	(0.013)	(0.011)
IndConcentration	0.834	0.108	0.072	0.38
	(0.553)	(0.769)	(0.8)	(0.916)
Education	-0.114	-0.017	-0.057	-0.06
	(0.086)	(0.101)	(0.081)	(0.091)
Union	-0.043	-0.023	-0.021	-0.009
	(0.038)	(0.043)	(0.042)	(0.044)
Unemploymee	0.094**	0.150***	0.043	0.07
	(0.047)	(0.056)	(0.048)	(0.049)
VacantJobRatio	0.024	0.087*	0.022	-0.011
	(0.046)	(0.047)	(0.034)	(0.04)
Constant	2.442	0.368	1.415	1.109
	(2.156)	(1.912)	(2.004)	(2.337)
Observation	1247	1725	1031	1098
Firm	255	339	221	231
Adjusted R2		0.447		
Root MSE		0.826		
Number of Instrument	168		207	208
Hansen test of over-identification	0.634		0.823	0.727
Arellano-Bond test for AR(1)	0		0	0
Arellano-Bond test for AR(2)	0.051		0.168	0.054
Arellano-Bond test for AR(3)	0.739		0.577	0.969

Notes: Table 6 presents the relationship between labour share and income inequality. In all columns, the dependent variable is pay inequality measured as the natural log of the ratio of total CEO compensation to average employee pay. The first column estimates the coefficient of our model based on the OLS method. It includes region, industry, and year fixed effects. The second column estimates the coefficients of our model based on a two-step *SGMM* with robust standard error. The third column shows the moderation impact of TFP and is estimated based on a two-step *SGMM* with robust standard error. The fourth column shows the moderation impact of markup and is estimated based on a two-step *SGMM* with robust standard error. Continuous variables are winsorised at 1 per cent and 99 per cent. Robust standard errors clustered at the firm level are reported in parentheses.
*, **, *** Indicate significance at the 10%, 5% and 1% levels, respectively.
All variables are defined in Appendix B.

5. Conclusion

Following the fall in labour share and the rise in income inequality in recent decades in Australia, this article empirically examines the determinants of labour share and its impact on pay inequality using panel data from Australian listed firms between 2004 and 2019. First, we examine the impact of technological progress, product market power and labour market power on firms' labour share. We find that capital deepening and technological progress have a significant and negative impact on labour share. However, technological progress is not a significant driver of labour share in firms with highly skilled employees, such as firms with R&D investment, or those that are less capital intensive. In addition, firms with higher mark-up have significantly lower labour shares. Our findings do not support the hypothesis that labour market concentration and unionisation are associated with labour share. Our further analysis shows that technological progress and product market power have a more considerable negative impact on labour share in firms with a higher level of external funds, while they do not significantly affect labour share in high-tech sectors.

Second, we examine the impact of within-firm labour share on pay inequality between CEOs and employees. Our analysis shows that a decrease in a firm's labour share is significantly associated with increased pay inequality. In addition, our result asserts that the significant determinants of labour share, technological progress and product market power, can moderate the negative impact of labour share on pay inequality. We find that labour share has a larger negative impact on pay inequality in firms with lower technological productivity and higher product market power. In general, this study extends the current literature by documenting firm-level drivers of labour share in Australia, covering all sectors, and providing novel firm-level evidence on the relationship between labour share and pay inequality.

The findings from this study have several implications for policymakers who seek to mitigate the fall in labour shares and the rise in pay inequality in Australia. First, our study suggests that in the presence of highly skilled employees, technological progress does not have a significant negative impact on labour share. Therefore, investing in training and increasing the skill of workers may be the most important key for policy maker to prevent the further negative impact of technology on labour share. Second, the significant negative impact of product market power on Australian labour share recommends that government imposes further policies to prevent the concentration of market power and increase competition in the market.

Third, we find higher technological progress and lower product market power mitigate the negative impact of labour share on pay inequality. This finding recommends that policymakers should consider policies aimed at promoting innovation and deregulating the product market to prevent the further rise in pay inequality resulting from the decline in labour share.

Our research should be considered in the context of its limitations. First, our sample is limited to Australian listed firms, unlike the datasets commonly used in the micro-level analysis of labour share (e.g., Autor et al. 2020; Kehrig and Vincent 2021), while a proportion of economic activities take place in non-listed firms in Australia. Therefore, since listed and non-listed firms have different characteristics, one future avenue for research would be to investigate the determinant of labour share in non-listed firms. Second, a short-term data period (from 2004 to 2019) was employed for assessing the determinants and impact of labour share, which limits the possibility of grasping the underlying causes of the structural movements in Australian labour shares. Hence, another avenue for future research would be to investigate long-run underlying causes of declining labour share. A final limitation is the lack of publicly available data. Our study focuses on the impact of labour share on CEO-employee pay inequality. However, there are different types of pay inequality in organisations: pay differences between employees at the same level or pay differences across hierarchy levels. Therefore, future research might explore how labour share impacts different pay inequality types (i.e., vertical or horizontal pay disparity) rather than focusing on CEO-employee pay inequality. Considering these limitations, we believe that our study highlights the importance of firm-level analysis in understanding macroeconomic movements.

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Appendix

Appendix A: Measurement

I. Technological progress

As noted in the paper, we measure technological progress using two proxies: capital-output ratio (*LnCapital/VA*), and Total Factor Productivity (*TFP*). Following Bentolila and Saint-Paul (2003), *LnCapital/VA* is calculated as the ratio of gross capital stock to value-added. Gross capital stock is measured by the sum of net property, plant and equipment and accumulated depreciation.

TFP is calculated for each firm at time t in our sample based on the estimation of the Cobb-Douglas production function. Consider a log-linearised Cobb-Douglas production function for firm i in industry j:

$$y_{it} = \alpha_j + \theta_j^l l_{it} + \theta_j^k k_{it} + \epsilon_{it} \quad \text{i belongs to industry j} \quad (3)$$

Where y_{it} is value-added, l_{it} is the number of employees, k_{it} is the gross capital stock of firm i in industry j at time t, in log form. To ensure that our conclusions are robust, we apply a variety of approaches for estimating above equation.

One common approach to estimate the Cobb-Douglas production function is the Ordinary Least Squares (*OLS*) method. We estimate a separate regression for each two-digit *GICS* industry group to control industry heterogeneity. Following this approach, *TFP* based on *OLS* estimation (*TFPOLS*) is measured as the residual of equation 3. The challenge is that the *OLS* estimation suffers from simultaneity and selection biases. Simultaneity arises if firms decide the level of inputs consumed in the production process. In this case, inputs possibly are endogenous variables because the model's error term includes output determinants observed by the firm (Manjón and Mañez 2016). Selection bias results from the relationship between productivity shocks and the probability of exit from the market. If a firm's profitability is positively related to its capital stock, then a firm with a larger capital stock is more likely to stay in the market despite a low productivity shock than a firm with smaller capital stock because the firm with more capital can be expected to produce greater future profits. Therefore, we follow the literature by using a control function approach, which was first introduced by Olley and Pakes (1996) (*OP*), to overcome these challenges. Consider a log-linearised Cobb-Douglas production function for firm *i* in industry *j*

$$y_{it} = \alpha_j + \theta_j^l l_{it} + \theta_j^k k_{it} + \omega_{it} + \epsilon_{it} \quad \text{i belongs to industry j} \quad (4)$$

ω_{it} is unobserved productivity shock which refers for *TFP* and ϵ_{it} is measurement error. It is assumed that ω_{it} follows a first-order Markov process as below:

$$\omega_{it} = \mathrm{E}(\omega_{it} \mid \omega_{it-1}) + u_{it} = g(\omega_{it-1}) + u_{it} \quad (5)$$

u_{it} is a random shock component assumed to be uncorrelated with unobserved productivity shock, and our state variable k_{it}. In addition, the solution to the dynamic profit maximisation problem generates a demand function for the proxy variable (investment (i_{it}) in *OP*) that under certain assumptions can be inverted to define a firm's productivity as a function of observables as $\omega_{it} = \mathrm{h}(\mathrm{i}_{it}, k_{it})$. We measure investment as the per cent change in the capital; that is $i_{it} = k_{it} - k_{it-1}$. The estimation approach has two stages.

In the first stage, we plug the inverse of the demand function into the production function 4.

$$y_{it} = \alpha_j + \theta_j^l l_{it} + \theta_j^k k_{it} + \mathrm{h}(\mathrm{i}_{it}, k_{it}) + \epsilon_{it} = \theta_j^l l_{it} + \varphi(\mathrm{i}_{it}, k_{it}) + \epsilon_{it} \quad (6)$$

We non-parametrically estimate equation 6. This stage provides the estimate $\hat{\theta}_j^l$. In the second stage, assuming the Markovian nature of productivity process gives rise to the relevant moment condition which can be used to estimate the production function parameters, we parametrise the function φ and g using second-order polynomials. These two stages then allow us to estimate *TFP* based on *OP* (*TFPOP*) as:

$$\hat{\omega}_{it} = y_{it} - \hat{\alpha}_j - \hat{\theta}_j^l l_{it} - \hat{\theta}_j^k k_{it} \quad (7)$$

In addition to *OP*, we employ one-step *GMM* Wooldridge (Wooldridge 2009). The Wooldridge method allows us to estimate the two stages of *OP* jointly in a system of two equations, which relies on the set of assumptions. After estimation of the production function, *TFP* based on the Wooldridge method (*TFPWRDG*) is estimated using equation 7.

II. Firm-level mark-up

In an imperfect competitive product market, mark-up is commonly defined as the output price divided by the marginal cost (De Loecker and Warzynski 2012). Measuring mark-up is challenging since marginal cost data is not available. As recommended by De Loecker and Warzynski 2012, a measure of mark-up can be obtained for each firm at a given point in time as the wedge between inputs expenditure share in revenue (observed in data) and inputs output elasticity (obtained by estimating the associated production function). Their approach is based on the work of Hall (1988) to estimate mark-up from the firm's cost minimisation decision and does not require any assumptions on demand and how firms compete. Therefore,

$$\mu_{it} = \frac{\theta_i^v}{s_{it}^v} \qquad (8)$$

Where, θ_i^v is the output elasticity with respect to variables inputs v_{it} (labour, intermediate inputs, materials, …) and s_{it}^v is the share of variable inputs in the firm's revenue. A crucial component to measure mark-up is θ_i^v which is not observable and must be estimated from firm-level data. We consider an industry-specific Cobb-Douglas production function, with variables input (v_{it}) and capital (k_{it}) as inputs.

$$y_{it} = \alpha_j + \theta_j^l v_{it} + \theta_j^k k_{it} + \omega_{it} + \epsilon_{it} \quad \text{i belongs to industry j} \quad (9)$$

Following De Loecker et al. (2020), y_{it} is revenue, v_{it} is measured by the cost of goods sold (*COGS*), which includes all expenses directly attributable to the production of goods sold by the firm and includes material, intermediate inputs, labour cost, energy and so on,[9] and capital is measured by gross capital stock, in log form. ω_{it} is productivity shock, and ϵ_{it} captures measurement error in output. Following the similar approach for the estimation of *TFP*, we estimate θ_i^v using three methods – *OLS*, *OP* and Wooldridge, – and mark-up is calculated by substituting θ_i^v and s_{it}^v in equation 8.

III. Labour market concentration

We define the labour market as employees who work in the same industries. This means that firms within a labour market (same industry) compete for labour. With a definition of the labour market, labour market concentration can be calculated as the industry's Herfindahl-Hirschman index based on the number of employees (*HHIEmp*). *HHIEmp* is the sum of the squared shares of the labour market each firm hires. Therefore, for a market with N firms:

$$HHI = \sum \left(\frac{l_{i,j}}{L_j}\right)^2 \qquad (10)$$

Where $l_{i,j}$ is the number of employees at firm i in industry j, and L_j is total employment in industry j.

[9] The sample does not directly report a breakdown of the expenditure on variable inputs, such as labour, intermediate inputs, electricity, and others, and therefore we prefer to rely on the reported total variable cost of production.

Appendix B: Definition of Variables

Variables	Definition	Source
LabourShare	"Staff expenses" divided by "earnings before interest, tax, depreciation, and amortisation (EBITDA) plus staff expenses (WL)"	Author's calculation
PayInequality	The natural logarithm of (CEO Compensation / average employee compensation) in which CEO and employee compensation includes short-term pay (e.g. salary and fees, accrued bonus), post-employment benefits (e.g., superannuation) and share-based payment rights. Average employee compensation is calculated as Employee benefits minus CEO compensation divided by the number of employees minus one.	Author's calculation
LnCapital/VA	The natural logarithm of gross property, plant and equipment / Value-added	Author's calculation
TFPOLS	The residual of production function based on OLS	Author's calculation
TFPOP	$\ln \Omega_{it}$ productivity shocks based on Olly and Pakes (1996)	Author's calculation
TFPWRDG	$\ln \Omega_{it}$ productivity shocks based on Woordrige (2009)	Author's calculation
MarkupOLS	The output elasticity with respect to variables inputs (cost of goods sold) divided by "the share of variable inputs (cost of goods sold) in the firm's revenue". The production function is estimated using OLS for each industry	Author's calculation
MarkupOP	The output elasticity with respect to variables inputs (cost of goods sold) divided by "the share of variable inputs (cost of goods sold) in the firm's revenue". The production function is estimated using the Olly and Pakes (1996) method for each industry	Author's calculation
MarkupWRDG	The output elasticity with respect to variables inputs (cost of goods sold) divided by "the share of variable inputs (cost of goods sold) in the firm's revenue". The production function is estimated using the Wooldrige method for each industry	Author's calculation
IndHHIEmp	The industry's Herfindahl-Hirschman index based on the number of employees	Author's calculation
LnEmployeenum	The natural logarithm of the number of employees	Datastream
LnRevenue	The natural log of total sales in millions of dollars,	Datastream
BTM	Book value of equity /(share price * total shares outstanding)	Datastream
LnAge	Natural log of (current fiscal date – listing date) per year	Author's calculation
Ret	Log (return during the fiscal year)	Datastream
ROA	(Net Income + (Interest Expense on Debt-Interest Capitalized) * (1-Tax Rate)) / Average of Last Year's and Current Year's Total Assets * 100	Datastream
STDRet	Rolling 60-month standard deviation of returns	Author's calculation
STDROA	Rolling 5-year standard deviation of returns	Author's calculation
Leverage	Total debt scaled by the total assets	Datastream
BoardSize	The total number of board members at the end of the fiscal year	Datastream
IsCEOBoard	An indicator equal to 1 if the CEO is a board member and 0 otherwise	Datastream
IsCEOChair	An indicator equal to 1 if the CEO is the chairman of the board and 0 otherwise	Datastream
BoardTenure	The average number of years that each board member has been on the board.	Datastream
IndCommittee	Percentage of independent board members on the compensation committee as stipulated by the company	Datastream
RDIntensity	Research and development expenses scaled by total asset, assumed equal to zero when R&D is missing in Datastream.	Datastream
PPTIntensity	Net property, plant, and equipment per employee in millions of dollars.	Datastream
Education	The percentage of the population with at least a bachelor's degree in each region in each year.	ASB
IndConcentration	The sales-based Herfindahl index calculated based on all DataStream firms in the same industry. Revenue is trimmed at the 5^{th} and 95^{th} percentiles.	Author's calculation
Union	The percentage of employees who are members of trade unions in each region in each year.	ASB
UnemploymentRate	The percentage of those looking for a job in the labour force in each region in each year.	ASB
VacantJob	The ratio of vacant jobs to total jobs in each industry in each year.	ASB

Appendix C: Industry Map to Join GICS to ANZSIC

GICS Industry Group (two-digit)	ANZSIC code
Materials	Mining (B)
Energy	Oil & gas extraction (07)
Real Estate	Property operators & real estate services (67)
Software & Services	Computer system design & related services (70)
Capital Goods	Construction (E)
Diversified Financials	Finance (62)
Retailing	Retail trade (G)
Consumer Services	Accommodation and food services (H)
Commercial & Professional Services	Professional, scientific & technical services (except computer design) (69)
Health Care Equipment & Services	Health care and social assistance (Q)
Food, Beverage & Tobacco	Food product manufacturing (11)
Media & Entertainment	Information media and telecommunications (J)
Pharmaceuticals, Biotechnology & Life Sciences	Basic chemical & chemical product manufacturing (18)
Utilities	Electricity, gas, water, and waste services (D)
Transportation	Transport, postal and warehousing (I)
Banks	Finance (62)
Insurance	Insurance & superannuation funds (63)
Telecommunication Services	Telecommunications services (58)
Food & Staples Retailing	Food retailing (41)
Household & Personal Products	Other services (S)
Technology Hardware & Equipment	Information media and telecommunications (J)
Consumer Durables & Apparel	Textile, leather, clothing & footwear manufacturing (13)
Semiconductors & Semiconductor Equipment	Other services (S)
Automobiles & Components	Other services (S)