



# PRODUCTIVITY-ENHANCING LABOUR REALLOCATION IN AUSTRALIA

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  - 2 The views expressed in this paper are those of the authors and do not necessarily reflect those of The Australian Treasury or the Australian Government. The results presented here are based in part, on 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 the 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's core operational requirements. Legislative requirements to ensure privacy and secrecy of this data have been followed. Only people authorised under the *Australian Bureau of Statistics Act 1975* have been allowed to view data about any particular firm in conducting these analyses. In accordance with the *Census and Statistics Act 1905*, results have been confidentialised to ensure that they are not likely to enable identification of a particular person or organisation

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Productivity-Enhancing Labour Reallocation in Australia  
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## ABSTRACT

International evidence suggests that aggregate productivity growth is driven by the within-industry reallocation of inputs away from less productive firms and towards more productive firms, but little is known about this process in Australia. Accordingly, this paper exploits firm-level data to explore the nature of productivity-enhancing labour reallocation in Australia over the period 2002-2016. We first show that more productive firms on average account for a higher share of industry employment, particularly in sectors more exposed to competitive pressure via trade, and that this contributes positively to the aggregate level of productivity in Australia. Moreover, we show that the Australian economy is more successful at reallocating resources to high productivity firms than many other OECD countries, which is consistent with Australia's relatively sound structural policy environment that promotes economic flexibility. We then explore the extent to which labour is moving in the right direction over time. While high-productivity firms are more likely to expand and low-productivity firms are more likely to contract (or exit), the extent to which this is true has diminished over time. Counterfactual analysis shows that the weakening responsiveness of employment growth to firm productivity this decade is a significant drag on aggregate labour productivity growth, which motivates further analysis of structural policies that affect competition and labour mobility.

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# 1. INTRODUCTION

Australia's ability to sustain growth in living standards over the medium term will largely depend on our capacity to boost labour productivity growth (Gaetjens, 2018), either through capital deepening or multi factor productivity (MFP). While attention has been paid to the prospects for capital investment (Heads of Treasuries, 2017; Debelle, 2017), less is known about the drivers of MFP growth in Australia. This partly reflects historical constraints on access to firm-level data sources, which are essential to understand MFP performance given the widespread heterogeneity in firm productivity that exists even within narrowly defined sectors (see Syverson, 2011). While this heterogeneity reflects a number of complex within-firm factors – including the uneven diffusion of technology across firms (Andrews et al, 2016) – a more direct implication is that it creates scope for the reallocation of resources from low to high productivity firms to raise aggregate productivity. Indeed, international evidence suggests that the contribution of within-industry resource reallocation to aggregate productivity growth is significant (Bailey et al., 1992; Melitz and Polanec, 2015; Petrin et al., 2011), but little is known about this process in Australia.

Accordingly, this paper exploits comprehensive firm-level data from the Business Longitudinal Analysis Data Environment (BLADE) to provide new evidence on the nature of productivity-enhancing labour reallocation in Australia. A key starting point is that aggregate productivity is an increasing function of allocative efficiency, which measures the extent to which resources are allocated to their highest valued use. In this context, allocative efficiency can be measured in two ways (Haltiwanger, 2011), which we exploit in this study. First, static allocative efficiency implies that at any point in time, more productive businesses should command a larger share of aggregate resources. Second, dynamic allocative efficiency captures the extent to which resources are moving towards more productive businesses over time, which is accommodated via the downsizing or exit of less productive firms. These two concepts are clearly related: static allocative efficiency in a given period requires sufficient dynamic allocative efficiency in preceding periods. Moreover, these patterns are particularly sensitive to the structural policy environment, with differences in market regulations explaining a significant portion of the observed cross-country variation in allocative efficiency (Andrews and Cingano, 2014).

First, we exploit the workhorse Olley and Pakes (1996) decomposition to explore the nature of static allocative efficiency in the Australian business sector. Within industries, we find that more productive firms account for a higher share of employment on average over 2002-2016. As such, aggregate labour productivity in the Australian business sector is at least 20 per cent higher than it would be if labour were allocated randomly across firms. But important differences emerge across sectors, with the level of static allocative efficiency significantly higher in those sectors more exposed to competitive pressure via trade, such as manufacturing. Moreover, cross-country analysis shows that the level of static allocative efficiency is relatively high in Australia compared to many other OECD countries. This is broadly consistent with Australia's relatively sound structural policy environment and can be argued to be a reflection of the accumulated gains of past structural reforms, which have enhanced the capacity of the Australian economy to reallocate scarce resources to high-productivity firms.

Second, we model dynamic allocative efficiency by estimating the responsiveness of firm employment growth (and exit) to (lagged) firm labour productivity in a framework that carefully controls for a range of time-varying shocks at the national, state and industry level. Our results suggest that the process of dynamic labour reallocation has enhanced aggregate productivity growth over 2002-2016. More specifically, they are consistent with models of firm dynamics, which predict that conditional on initial size, high-productivity firms are more likely to expand and low-productivity firms are more likely to contract (or exit). But the extent to which this is true has diminished over time. For example, the implied difference in employment growth between a high and low productivity firm – one standard deviation above and below the mean, respectively – declined by over 2 percentage points between 2003 and 2016,

with much of the decline occurring after 2009. We also find evidence that low productivity incumbent firms are increasingly likely to survive over the sample period. Given that they remain after controlling for a range of possible cyclical influences, these changing patterns of market dynamism may be structural in nature.

A declining likelihood that high-productivity firms expand and low-productivity firms contract (or exit) carries material consequences for aggregate productivity growth. Counterfactual simulations show that the weakening responsiveness of employment growth to firm productivity since 2012 entailed a drag on aggregate labour productivity growth by around 0.15 per cent per year by 2016. This can account for roughly one-quarter of the slowdown in aggregate labour productivity growth for the industries included in our sample. Furthermore, this drag is material given future headwinds to growth, such as an aging population, which imply that an additional 1 percentage point of labour productivity growth is required over the next decade just to maintain income growth at its 30 year historical average (Gaetjens, 2018).

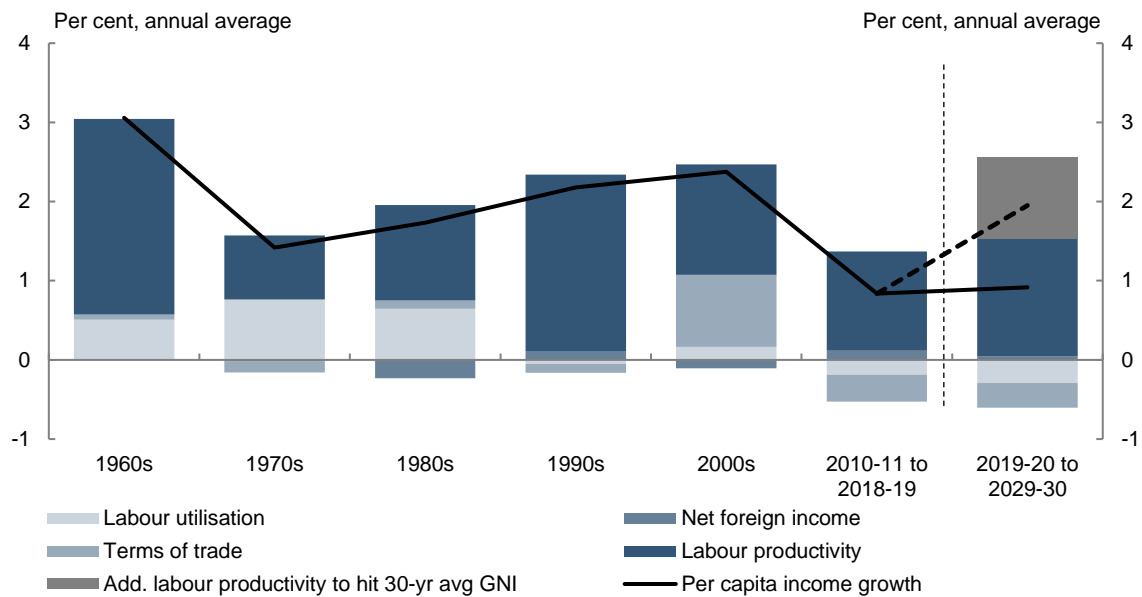
While we leave an analysis of the drivers of the decline in efficient reallocation to future research, our findings are relevant from a policy perspective for a number of reasons. First, they motivate a closer inspection of structural policy settings that affect competition and labour mobility, which – according to cross-country evidence (Andrews and Cingano, 2014) – loom large for allocative efficiency. Second, since higher productivity firms pay higher wages, the decline in the rate at which labour is reallocated to high productivity firms implies fewer high paying jobs are being created than otherwise. This provides a new insight into why aggregate wage growth over recent years has been weaker than would have been expected based on historical relationships with its main macroeconomic determinants (Cassidy 2019; Quinn 2019). It also complements our ongoing research agenda into the extent to which declining labour market dynamism – particularly job switching rates – has constrained aggregate wage growth (Deutscher 2019; Andrews, Deutscher, Hambur and Hansell, 2019).

The next section discusses international evidence on productivity-enhancing resource reallocation, while Section 3 describes the underlying firm-level data. Section 4 presents new evidence on the nature of static allocative efficiency in the Australian business sector, while Section 5 explores how the process of dynamic allocative efficiency has evolved over time. The final section discusses the broader implications of the results and identifies avenues for future research.

## **2. PRODUCTIVITY AND REALLOCATION**

Research on productivity requires little motivation from a policy perspective. Indeed, Paul Krugman's maxim that 'Productivity isn't everything but in the long run is almost everything' can perhaps be best understood from the perspective that the large and persistent differences in income per capita observed across countries mostly reflect differences in labour productivity (as opposed to labour resource utilisation). This is also true in the case of Australia, whose GDP per capita gap with the United States entirely reflects a shortfall in labour productivity, and in turn multifactor productivity (MFP) (OECD, 2018). Raising productivity growth will be essential if Australia is to sustain future gains in living standards, particularly given demographic headwinds and terms of trade normalisation (Gaetjens, 2018). Indeed, these headwinds imply that an additional 1 percentage point of labour productivity growth is required over the next decade just to maintain income growth at its 30 year historical average (Figure 1).

**Figure 1: Decomposition of growth in Real GNI per capita**



Source: ABS (2019), Treasury.

From this perspective, the stakes are high and the search for the sources of productivity growth is on in earnest. A key starting point is that labour productivity can be decomposed into the contributions of capital deepening and MFP, which reflects the efficiency with which inputs are used. While considerable attention has been paid to the prospects for capital deepening (Heads of Treasuries, 2017; DeBelle, 2017), less is known about the drivers of MFP growth in Australia. This is perhaps not surprising given the fact that while economists are typically confident in their ability to understand capital deepening in macroeconomic terms (Furman, 2015), getting a handle on MFP is fundamentally more complex and requires a firm-level perspective (Syverson, 2011). Moreover, this knowledge imbalance with respect to the drivers of productivity growth is particularly stark in Australia, largely due to historical constraints on access to firm-level data sources, which are now beginning to ease.

This is a welcome development given the growing recognition of the importance of the widespread heterogeneity in firm productivity outcomes for aggregate productivity (Bartelsman et al., 2013). For example, even within narrowly defined industries (that is, ready-mix concrete) in the United States, firms at the 90th percentile of the MFP distribution are twice as productive as firms at the 10th percentile (Syverson, 2004). Similarly, Campbell et al (2018) document the widespread dispersion in firm-level labour productivity within Australian industries. The literature initially focused on how such large differences in productivity could be sustained in equilibrium, emphasising imperfect product substitutability that prevent customers from easily shifting purchases between producers, and supply-side factors related to technology shocks, management skill and R&D (Bartelsman and Doms, 2000). More recent studies, however, have emphasised that a small number of star performers disproportionately drive aggregate growth (Haltiwanger, 2013), while recognising that many existing technologies remain unexploited by a large share of firms (Andrews, Criscuolo and Gal, 2016).

While the source of these within-firm differences in productivity is complex, a more straightforward implication is that it creates scope for the reallocation of scarce resources from low to high productivity firms to raise aggregate productivity. This is particularly the case for reallocation within industries, as opposed to between industries, reflecting the idea that factors are inherently more substitutable within industries, as well as the tendency for within-sector differences to dwarf between-sector differences in firm behaviour (Mora Sanguinetti and Fuentes, 2012; Foster, Haltiwanger and Krizan, 2001).

Well-functioning economies take advantage of this scope, with relatively more productive firms tending to be larger (for example, static allocative efficiency; see Olley and Pakes, 1996). For example, manufacturing sector labour productivity in the United States is around 50 per cent higher than it would be were labour randomly allocated across firms (Bartelsman et al., 2013). While a similar pattern holds for Scandinavian countries, static allocative efficiency is considerably lower in other OECD economies, especially in Southern Europe (Andrews and Cingano, 2014). Similarly, manufacturing MFP could rise by an estimated 30-50 per cent in China and 40-60 per cent in India if these economies aligned their static allocative efficiency with the US level (Hsieh and Klenow, 2009; Rotemberg and White, 2017).

While these patterns reflect many factors, including differences in the structural policy environment,<sup>3</sup> static allocative efficiency can only be achieved when resources move towards more productive firms at the expense of less productive firms over time (Haltiwanger 2011). Indeed, a range of empirical studies show that the contribution of (within-industry) reallocation to aggregate productivity growth is significant. For example, Bailey, Hulten and Campbell (1992) found that over a five-year period about half of a typical US industry's MFP growth was due to the reallocation of factors between plants, rather than within-plant productivity growth. In the United Kingdom, this reallocation process accounts for over 80 per cent of MFP growth in the manufacturing sector (Disney et al, 2003), while decompositions for the Canadian economy as a whole and the United States retail sector yield similar conclusions.<sup>4</sup> More recent studies highlight the reallocation of resources towards firms that patent – a proxy for innovation – at the expense of non-patenting firms (Balasubramanian and Sivadasan, 2011), which tends to be stronger in the United States than in continental Europe (Andrews, Criscuolo and Menon, 2014).

While the contribution of reallocation to aggregate productivity growth is significant, it may have declined over time. In the United States, this is reflected in a declining responsiveness of firm growth (employment and investment) and firm exit to productivity over recent decades. This implies that the propensity of high-productivity firms to expand and low-productivity firms to downsize or exit has fallen (Decker et al., 2018), with important implications for aggregate productivity.<sup>5</sup> Meanwhile, the responsiveness of firm capital growth to productivity has declined in Southern Europe since the early 2000s. This capital misallocation has been linked to the rising prevalence of 'zombie' firms – that is, unviable firms that would typically exit in a competitive market – which crowd-out growth opportunities for more productive firms (Adalet McGowan, Andrews and Millot, 2018). The rise in zombie firms can account for one-quarter of the decline in business investment in Italy between 2008 and 2013, underscoring the material aggregate consequences of weakening market selection.

The tendency for highly productive firms to coexist with low-productivity firms within narrowly-defined sectors has triggered a significant research inquiry into the nature of productivity-enhancing resource reallocation in OECD countries over the past decade. However, little is known about how effective the Australian economy is at reallocating resources to high productivity firms, let alone how the process of dynamic allocative efficiency has evolved over time. Accordingly, this paper exploits recently released firm-level data to shed light on these questions, with a view to lend a stronger micro foundation to the Australian growth narrative.

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3 Using estimates of static allocative efficiency at the industry level for 22 OECD countries, Andrews and Cingano (2014) show a causal link between more stringent product and labour market regulations, and bankruptcy laws that excessively penalise business failure, and less efficient resource allocation.

4 Baldwin and Gu (2006) for Canada find that this reallocation accounts for about 70 per cent of aggregate labour productivity growth. Foster et al. (2006) find that entry and exit explain almost all labour productivity growth of the US retail sector.

5 Simulations show that aggregate labour productivity would have been 2.5 per cent higher in 2013 if their metric of reallocation – the responsiveness of firm growth to productivity – had returned to the more efficient levels of the late 1990s levels.

### 3. BUSINESS LONGITUDINAL ANALYSIS DATA ENVIRONMENT - BLADE

The analysis in this paper exploits firm-level data from the Business Longitudinal Analysis Data Environment (BLADE), compiled by the Australian Bureau of Statistics. BLADE consists of administrative data from the Australian Taxation Office (ATO) – making it akin to a business census – matched with ABS-produced survey microdata, such as the Business Characteristics Survey.

Our productivity analysis draws on two key administrative data sources. First, measures of output and intermediate use are sourced from Business Activity Statements (BAS).<sup>6</sup> While each annualised BAS dataset contains more than two million records, only around 800,000 or more units report formal employment via annual payment summaries.<sup>7</sup> We also draw on this payment summary information in combination with the industry of origin of the employing business to estimate full-time equivalent employees – our measure of labour input.<sup>8</sup>

The main demographic information in BLADE consists of industry and institutional sector codes, which permit us to focus on industries and businesses that are privately-owned. The ABS adds an additional year of administrative and survey data to BLADE each year. As of writing, the latest available year was 2016 and so our sample – unless specified otherwise – encompasses the period 2002 to 2016.<sup>9</sup>

Following the literature, we restrict our analysis to the market sector (that is, we exclude utilities; education, public administration and safety and health) and exclude finance and insurance where productivity measurement is notoriously difficult.<sup>10</sup> Our final firm-level dataset for analysis covers around 75 per cent of gross value added and 84 per cent of compensation of employees in the market sector over 2002-2016. Our dynamic reallocation analysis in Section 5 also abstracts from highly volatile commodity producing sectors such as agriculture and mining, which have been affected by large relative price shifts over recent times. Summary statistics for key variables are provided in Table B1 of Appendix B.

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6 The third administrative dataset in BLADE is the Business Income Tax (BIT), which contains detailed balance sheet information on income and expenditure, assets, liabilities and the like.

7 It is important to note that the ABS does not permit access to person-level data. All information from the payment summaries has been aggregated to the business unit.

8 For more information see Hansell, Nguyen and Soriano (2015).

9 The Australian fiscal year ends in June. For simplicity, we refer to the last year of the fiscal year, and so the 2001-02 fiscal year becomes 2002.

10 Note that firms with less than one FTE are also excluded as conventional in the international literature.



## 4. STATIC ALLOCATIVE EFFICIENCY

### 4.1 Empirical framework

Allocative efficiency measures the extent to which more productive firms in an industry employ more resources. Using a formula developed by Olley and Pakes (1996), we decompose aggregate productivity ( $P_t$ ) as,

$$P_t = \sum s_{it} p_{it} \\ = 1/n \sum p_{it} + \sum (s_{it} - \bar{s}_t)(p_{it} - \bar{p}_t) \quad (1)$$

Where  $s$  is the employment share of firm  $i$  at time  $t$ , lower case  $p$  is a firm's log labour productivity, and a bar above  $s$  or  $p$  refer to the mean. The second term in (2) is the measure of allocative efficiency, sometimes referred to as the OP gap or covariance term. It reflects the extent to which firms with higher (lower) than average productivity have larger (smaller) labour shares. Moreover, the allocative efficiency term can be interpreted as the percentage increase in the economy wide or industry level of productivity due to the actual allocation of labour. This is because if the allocation of labour were random, the share weighted level of productivity ( $\sum s_{it} p_{it}$ ) equals the unweighted mean of productivity ( $1/n \sum p_{it}$ ) and hence the OP gap ( $\sum (s_{it} - \bar{s}_t)(p_{it} - \bar{p}_t)$ ) is zero. Finally, this measure abstracts from the difference in prices since the percentage difference is expressed relative to the groups under study, which facilitates comparisons within an economy and among countries.

Note that this decomposition is equivalent to how aggregate (labour) productivity for an industry or economy is measured: the sum of output divided by the sum of inputs is directly related to the sum of each firm's labour share multiplied by its productivity level.

$$\sum s_{it} p_{it} = \frac{\sum output_{it}}{\sum labour_{it}} = \frac{\sum labour_{it} (output_{it}/labour_{it})}{\sum labour_{it}} \quad (2)$$

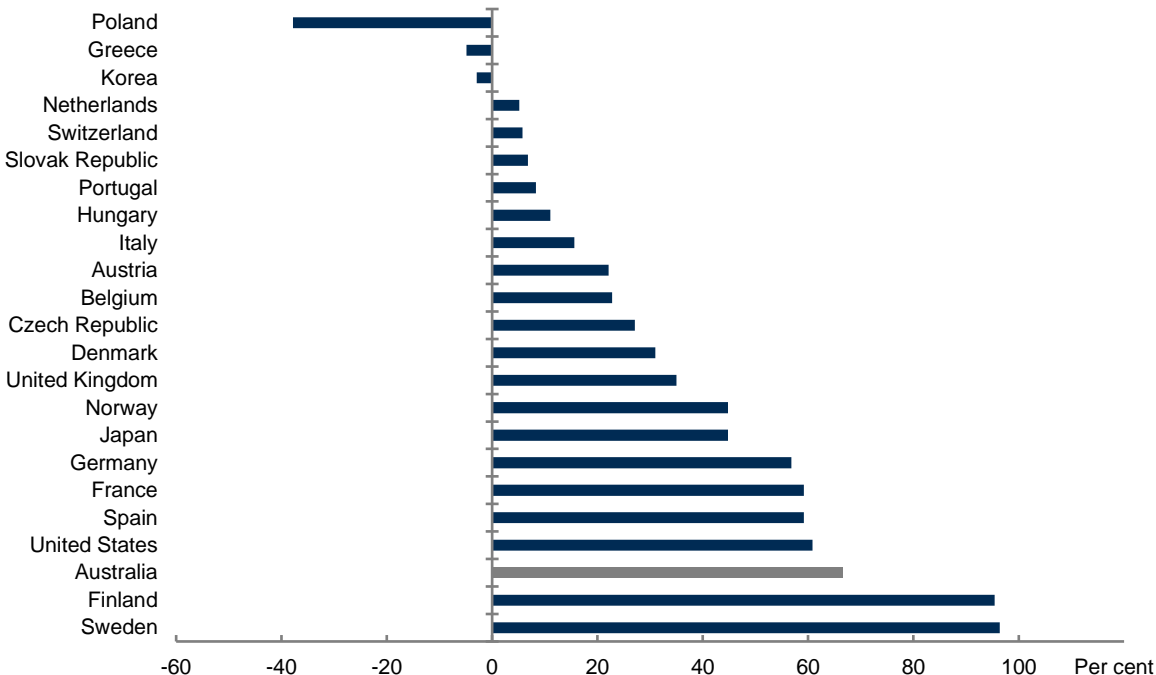
### 4.2 Empirical results

Figure 2 shows static allocative efficiency for the manufacturing sector of selected OECD countries in 2005. With the exception of Poland, Greece and Korea more productive firms have larger labour shares in OECD countries. In Australia, static allocative efficiency is particularly high, with aggregate manufacturing labour productivity around 66 per cent higher than it would be if labour were randomly allocated. Australia's high ranking on this index can be seen as validation of the microeconomic reforms of the 1980s and 1990s, which aimed to enhance the capacity of the Australian economy to reallocate scarce resources to more productive firms (although data limitations prevent us from presenting direct evidence on this issue).

Important differences also emerge across sectors with the efficiency of resource allocation significantly lower in services than in manufacturing (Figure 3). This is consistent with the idea that market services tend to be more sheltered from competition due to less trade exposure and more stringent market regulations. Labour productivity in the service sector is only 20 per cent higher compared to a random draw in Australia, whereas it is around 40 per cent higher in the United States (Australia ranks sixth on this metric; see Figure B1). Back-of-the-envelope calculations imply that if Australia could lift allocative

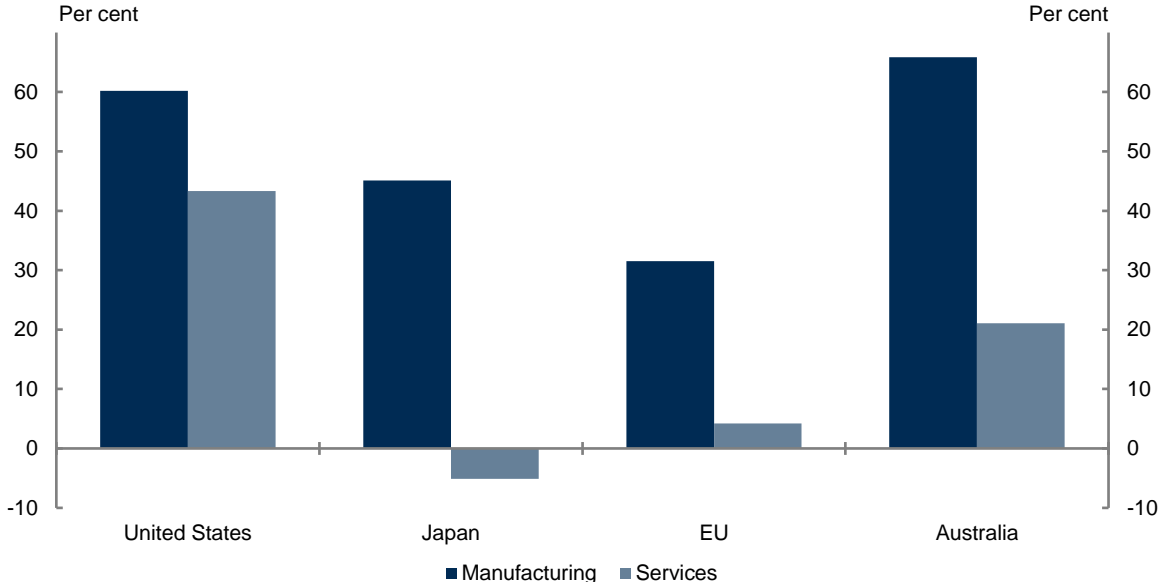
efficiency in market services to the US level, then it could close one-half of its aggregate labour productivity gap with the United States.<sup>11</sup>

**Figure 2: Allocative Efficiency in Manufacturing – Selected OECD Countries, 2005**



Notes: International estimates sourced from Andrews and Cingano (2014).

**Figure 3: Allocative Efficiency in Manufacturing and Services – International Comparison**

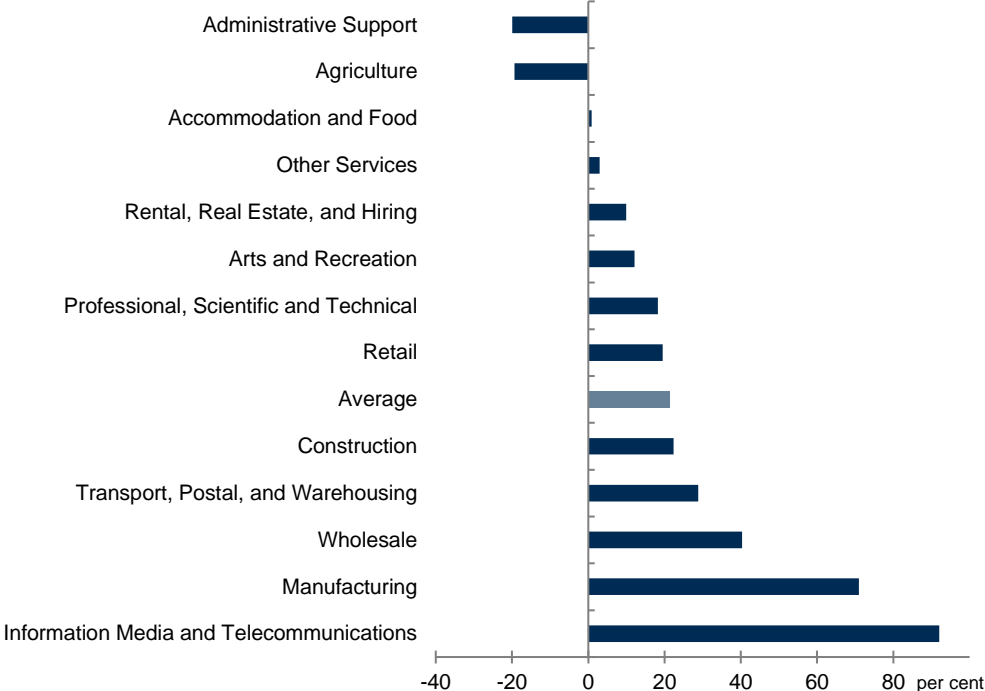


Source: International estimates sourced from Andrews and Cingano (2014).

<sup>11</sup> Aggregate labour productivity in Australia is around 80 per cent of the US level. Given that market services account for around 50 per cent of total employment in Australia, lifting services sector allocative efficiency in Australia by around 20 percentage points would imply a 10 per cent rise in aggregate labour productivity, which would close one-half of Australia’s (20 per cent) labour productivity gap with the US.

In support of the posited link between allocative efficiency and competitive pressure, Figure 4 charts the static allocative efficiency index across selected market sector industries, alongside the average across industries.<sup>12</sup> Most industries for which allocative efficiency is below average are domestically-focused services sector activities, including: administration support services, accommodation and food, real estate, and arts and recreation. The exception is agriculture where the less productive firms have larger employment shares, which reduces the level of labour productivity in agricultural sector by 20 per cent compared to a random draw. This may be symptomatic of high exit barriers with around 35 per cent of businesses in beef and sheep farming remaining in the market despite recording persistent losses (that is, total expenses greater than total income) for three consecutive years or more.

**Figure 4: Allocative Efficiency – Selected Australian Industries, Average 2002-2016.**



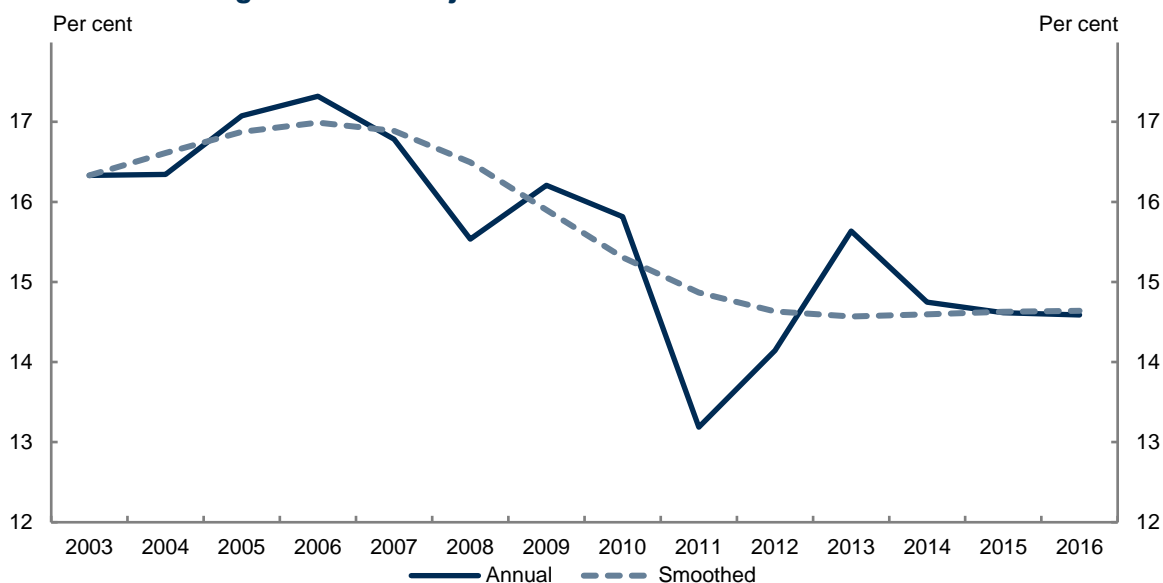
Notes: Industry-level estimates are based on the decomposition in equation 1. Average allocative efficiency reflects an unweighted average of division-level estimates.

## 5. DYNAMIC ALLOCATIVE EFFICIENCY

While the previous section suggests that the Australian economy is relatively efficient at allocating resources to the most productive firms at any point in time, it is also important to analyse how the nature of productivity-enhancing labour reallocation is evolving over time. By way of introduction, Figure 5 plots the evolution of excess job reallocation rates, which presents that part of job reallocation (that is, job creation plus job destruction) over and above the amount required to accommodate the net employment change (see Davis and Haltiwanger, 2002). According to this leading metric of labour market churn, job reallocation has fallen by around 2 percentage points since the early-to-mid 2000s. This raises the prospect that dynamic allocative efficiency – which measures the extent to which resources flow to more productive firms over time – may have slowed, given that labour market churn is necessary to accommodate the growth of productive firms.

12 Figure 4 shows estimates for 13 of the 16 market sector industries. We exclude Mining and Utilities because they are highly concentrated while we exclude Finance and Insurance due to the well-known problems in measuring productivity in this sector.

**Figure 5: Excess job reallocation rates have declined**



Notes: Excess job reallocation is calculated as  $|(JC+JD)/(JC-JD)|$  where JC refers to job creation rates and JD refers to job destruction rates. The smoothed series utilises STATA's robust nonlinear smoothing command, *smooth* (option = 4235eh).

## 5.1 Empirical framework

To investigate more formally, we apply a model outlined by Decker, Haltiwanger, Jarmin and Miranda (2018) for estimating the responsiveness of employment growth and firm exit to productivity. Their approach is motivated by canonical models of firm dynamics, which predict that conditional on initial size, more productive firms should grow more quickly than less productive firms and that less productive firms should have a greater likelihood of market exit.

For our employment growth model, the dependent variable is defined as the change in employment divided by the average employment across both periods following Davis, Haltiwanger and Schuh (1996):

$$g_{i,t+1}^E = \frac{E_{i,t+1} - E_{i,t}}{0.5(E_{i,t+1} + E_{i,t})}$$

where  $E$  is employment of firm  $i$  in period  $t$ . This measure is bounded between -2 and 2 and it is a second order approximation of the log difference for growth rates around zero. Further it can accommodate growth of entering and exiting firms, in which case the function takes a value of 2 (entry) or -2 (exit).<sup>13</sup>

For ease of exposition, we begin with the simplest version of the full model; that is,

$$g_{i,t+1}^E = \beta_0 + \beta_1 LP_{it} + X'_{it}\theta + \varepsilon_{it+1} \quad (3)$$

Where: future growth ( $g_{i,t+1}^E$ ) is a function of current (labour) productivity (LP) of firm  $i$  at time  $t$ , expressed in relative terms as a deviation from the industry average (see below). Our baseline model defines LP as the natural logarithm of real revenue per FTE in order to avoid indirectly censoring units

13 Given the model we estimate covers two periods, including exiting firms in the sample tends to overstate growth. This is because the final growth rate of -2 is not matched by the initial growth rate of entrants (that is, 2) since this growth rate has no corresponding lag.

with negative value-added.<sup>14</sup> That said, results based on a real value-added per FTE measure of LP are very similar. While future analysis will look to exploit new estimates of multi-factor productivity (MFP),<sup>15</sup> US evidence shows that measures of within-industry relative labour productivity are highly correlated with within-industry relative MFP, suggesting that capital shares are similar across firms within industries (Foster, Haltiwanger and Krizan, 2001, 2006).<sup>16</sup> Finally, the vector  $X'$  includes controls for firm size, time fixed effects, and the change in state unemployment rates alone and interacted with labour productivity.

Since our aim is to identify how productivity-enhancing reallocation is evolving in a structural sense, the model controls for cyclical influences in three key ways. First, the firm-level labour productivity is expressed as a deviation from the industry average at the four digit ANZSIC06 level (the finest possible level of industrial classification), which is akin to controlling for time-varying industry-specific shocks. Second, the impact of common time-varying shocks (that is, the national business cycle) is absorbed by the inclusion of time fixed effects. Finally, the inclusion of the state unemployment rate directly controls for state-level business cycles alone and through its interaction with the labour productivity term, sweeps out the impact of state-level shocks on the responsiveness of employment growth to firm productivity.<sup>17</sup>

Across all versions of the broader model, we are interested in the sign and significance of the coefficient on productivity. If positive, we can infer that labour flows to more productive firms at the expense of less productive firms within industries, indicating that the process of labour reallocation is productivity-enhancing, even after controlling for a range of cyclical influences.

To estimate how labour reallocation has changed over time, we interact productivity with a linear time trend and its square, to account for non-linearity in the trend. That is, we estimate:

$$g_{i,t+1}^E = \beta_0 + \beta_1 LP_{it} + \beta_2 LP_{it} Trend_t + \beta_3 LP_{it} Trend_t^2 + X'_{it} \theta + \varepsilon_{it+1} \quad (4)$$

Finally, we focus on the changing nature of labour reallocation within broad firm age groups, in order to allow for differential growth dynamics and to mitigate the identification challenges posed by declining firm entry rates observed in many OECD countries. We follow Decker et al (2018) and distinguish between young (0 to 5 years) and mature (6 plus years) firms and then incrementally add the interactions with the time trend variables. More formally, the full model is specified as follows:

$$g_{i,t+1}^E = \beta_0 + \beta_1 LP_{it} Young_{it} + \beta_2 LP_{it} Young_{it} Trend_t + \beta_3 LP_{it} Young_{it} Trend_t^2 + \beta_4 LP_{it} Mature_{it} + \beta_5 LP_{it} Mature_{it} Trend_t + \beta_6 LP_{it} Mature_{it} Trend_t^2 + X'_{it} \theta + \varepsilon_{it+1} \quad (5)$$

To explore market selection dynamics, we also estimate a corresponding version – via probit model – where the probability of firm exit is the dependent variable. Standard empirical models of exit (for example, Syverson, 2011) demonstrate that less productive firms have a higher likelihood of exiting the market, implying that the estimated coefficient on labour productivity is expected to be negative.

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14 Alternatively we could use the inverse hyperbolic sign function (Bellamare and Wichman 2018) to deal with negative value added observations. Moreover, in margin industries such as wholesale and retail trade, real revenue is a valid specification of each firm's contribution to output

15 These estimates are currently under construction. See Fox (2019).

16 Given this, it is unsurprising then that the estimated responsiveness of firm employment growth to (lagged) productivity in Decker et al (2018) is insensitive to the choice of LP or MFP.

17 Note that replacing changes in the state unemployment rates with state by year fixed effects – which controls for the impact of all state-specific time-varying shocks – yields very similar results (these results are available upon request). This suggests that the state unemployment rate is a sufficient proxy for state-level business cycle effects, such as the varying cross-state impacts of the mining construction boom.

## 5.2 Baseline empirical results

Table 1 presents baseline estimates of the responsiveness of firm employment growth (Panel A) and firm exit (Panel B) to productivity for selected market sector industries and the manufacturing sector.

In column 1, the coefficient on productivity is positive and significant at the 1 per cent level, suggesting that on average over the sample period, more productive firms are more likely to expand and less productive firms are more likely to contract. Similarly, in our firm exit regression (see Column 5 of Table 1) the coefficient on productivity is negative and significant at the 1 per cent level, suggesting that on average over the sample period, less productive firms are more likely to exit the market in the following year. Indeed, additional analysis in Figure B2 of Appendix B shows that the typical exiting firm is less productive relative to survivors up to 10 years prior to exit, with this gap tending to grow up until the point at which the firm ceases operation – a pattern labelled the 'shadow of death' by Griliches and Regev (1995).<sup>18</sup>

**Table 1: The Effect of Lagged Productivity on Firm-Level Employment Growth and Survival**

	A: Employment Growth - OLS				B: Exit Margin - Probit			
	Selected Industries		Manufacturing		Selected Industries		Manufacturing	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prod	0.0523***	0.0532***	0.0650***	0.0653***	-0.176***	-0.194***	-0.227***	-0.255***
Prod*Trend		0.00184***		0.00292***		0.000553		0.00286
Prod*Trend <sup>2</sup>		-0.000217***		-0.000333***		0.000236***		0.000171
Size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
D.State Unemp Rate (D*SU)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
D.SU*Prod	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,347,042	4,347,042	434,732	434,732	5,062,496	5,062,496	489,649	489,649
R2/Pseudo R2	0.029	0.029	0.038	0.039	0.0538	0.0539	0.0721	0.0722

Robust standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Note: Sample encompasses 2002-2016 with one period sacrificed because the model uses two periods of data. Size dummies refer to the following number of full-time equivalent employees: 0-4, 5-19, 20-199, 200-499, and 500 plus.

Overall, the significant firm-level relationship of productivity with employment growth and exit implies that – on average – resources are flowing in the right direction over time and thus there is a positive contribution of reallocation to aggregate productivity growth. Columns 3 and 7 show that this is especially the case in more trade exposed parts of the economy such as manufacturing (see also Figure B3 of Appendix B), consistent with estimates of static allocative efficiency in Section 4.

## 5.3 The changing nature of reallocation

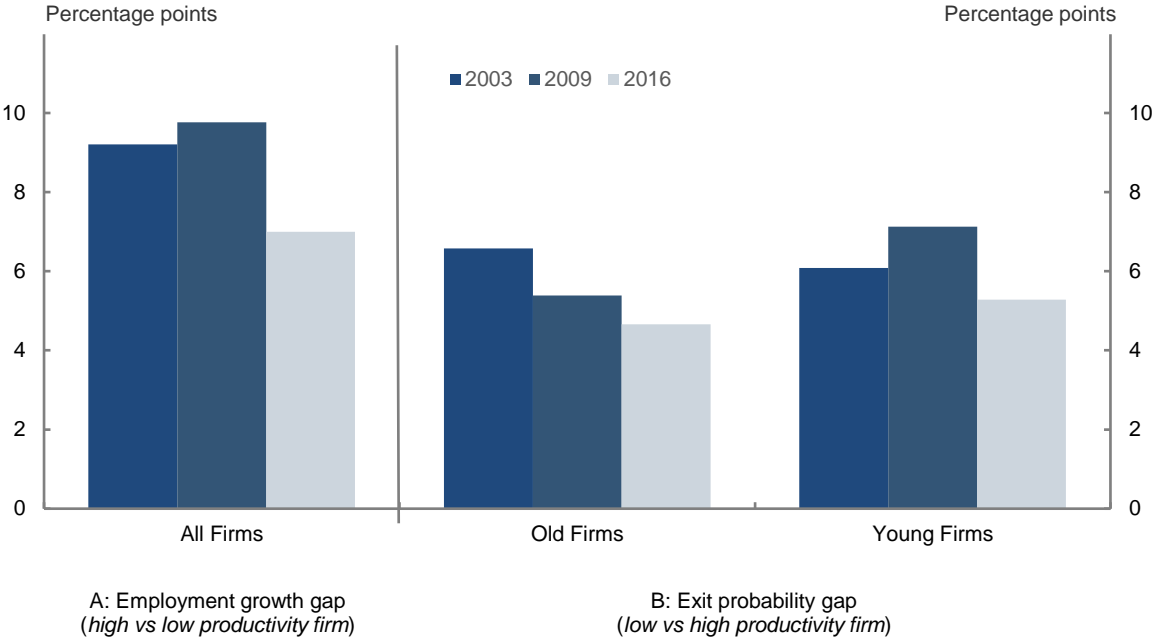
The even numbered columns of Table 1 explore how this relationship has changed over time. For example, the positive coefficient on Prod\*Trend coupled with a negative coefficient on Prod\*Trend<sup>2</sup> in Column 2 suggests that the efficiency of labour reallocation initially rises before declining later in the sample period. This time-varying non-linear pattern is also generally evident within firm age categories (see Table B2 of Appendix B).

We use the estimated coefficients in Columns 2 and 6 to illustrate how the nature of productivity-enhancing labour reallocation has changed over time. Since LP is expressed as a deviation

18 See Nguyen and Hansell (2014) for additional evidence for Australia.

from the industry-year mean, we calculate the difference in employment growth (and exit probability) between a high-productivity firm – that is, a firm one standard deviation above the industry mean – and a low-productivity firm – that is, a firm one standard deviation below the mean. As is typical in the literature and for simplicity, we fix the standard deviation at its value over the entire sample (of 0.86) and then multiply the total regression coefficient for each year by two standard deviations. Figure 6 (Panel A) shows that the implied difference in employment growth between a high and low-productivity firm declined by over 2 percentage points between 2003 and 2016. Digging deeper, over the first few years of the sample, the employment growth differential between a high and low productivity firm rises slightly but then declines from around 2010 to reach around 7 percentage points by 2016.

**Figure 6: Reallocation and market selection has weakened**



Note: Panel A shows the implied difference in employment growth between a high productivity firm (that is, one with labour productivity one standard deviation above the industry labour productivity mean) and a low productivity firm (that is, one with labour productivity one standard deviation below the industry labour productivity mean) based on the estimated coefficients in Table 1. Panel B shows the implied difference in exit probability between a low productivity firm and a high productivity firm, based on the estimated coefficients in Table B3.

Similar patterns emerge on the exit margin, with the strength of market selection – as proxied by the responsiveness of firm exit to productivity – weakening over time (see Column 6 Table 1), although the time profile varies somewhat with firm age (see Table B3). The results suggest that low-productivity incumbent firms are increasingly likely to survive, with the difference in exit probability between low and high productivity incumbent (that is, old) firms falling by around 2 percentage points over the sample period (Figure 6, Panel B). For young firms, exit selection initially intensifies before weakening in the second half of the sample, but the overall change in the exit probability gap between 2003 and 2016 is more modest at around 1 per cent.

Overall, it became less likely that more productive firms expand and less productive firms contract (or exit) after 2009, suggesting that (within-industry) labour reallocation continued to contribute to aggregate productivity growth but to a lesser extent than in the early-to-mid 2000s. Importantly, the coefficient estimates are virtually identical if we exclude Western Australia and Queensland – two states that were particularly affected by the mining boom – reinforcing the idea that cyclical factors are not driving the results.

The reduced responsiveness of employment growth to firm productivity after 2009 is also robust to alternative functional forms besides the quadratic time trend, such as including an interaction term between firm productivity and a dummy variable that takes the value of one in the post-2009 period (see Table B4 of Appendix B). This interaction term is negative and statistically significant, which suggests that the efficiency of labour reallocation was significantly lower in the latter part of the sample – a pattern that is broad-based across industries (Table B4). This decline employment growth responsiveness is also evident when we shift the break point to latter years such as 2012 (see: Andrews, Deutscher, Hambur and Hansell, 2019). Finally, these estimated patterns in dynamic allocative efficiency are also consistent with a decline in other measures of labour market dynamism, such as excess job reallocation rates (Figure 5) and job switching rates (Deutscher, 2019).

#### 5.4 Aggregate implications

How important are these changes in labour reallocation for aggregate productivity? To address this question, we follow Decker et al (2018) and create indexes of aggregate labour productivity that combine actual realisations of firm-level labour productivity with the implied predicted employment shares from an estimated model: *i*) where the responsiveness of employment growth to (lagged) productivity is allowed to vary over time via the inclusion of time trend interactions; and *ii*) reflecting responsiveness at the beginning of the sample period (i.e. where the LP\*time interactions are set equal to zero). The employment share prediction for a firm in  $t+1$  applies the model's prediction of employment growth in  $t+1$  to the (initial) level of employment for the firm in  $t$ .

Specifically, we calculate a base year productivity (6) and two other indexes using the shares from the model with a trend (7) and without (8), where the latter leaves the productivity-growth relationship at the level present at the beginning of the sample:

$$P_t = \sum s_{it} p_{it} \quad (6)$$

$$P_{t+1}^{Trend} = \sum s_{i,t+1}^{Trend} p_{it} \quad (7)$$

$$P_{t+1}^{No Trend} = \sum s_{i,t+1}^{No Trend} p_{it} \quad (8)$$

Then we estimate the counterfactual aggregate productivity as:

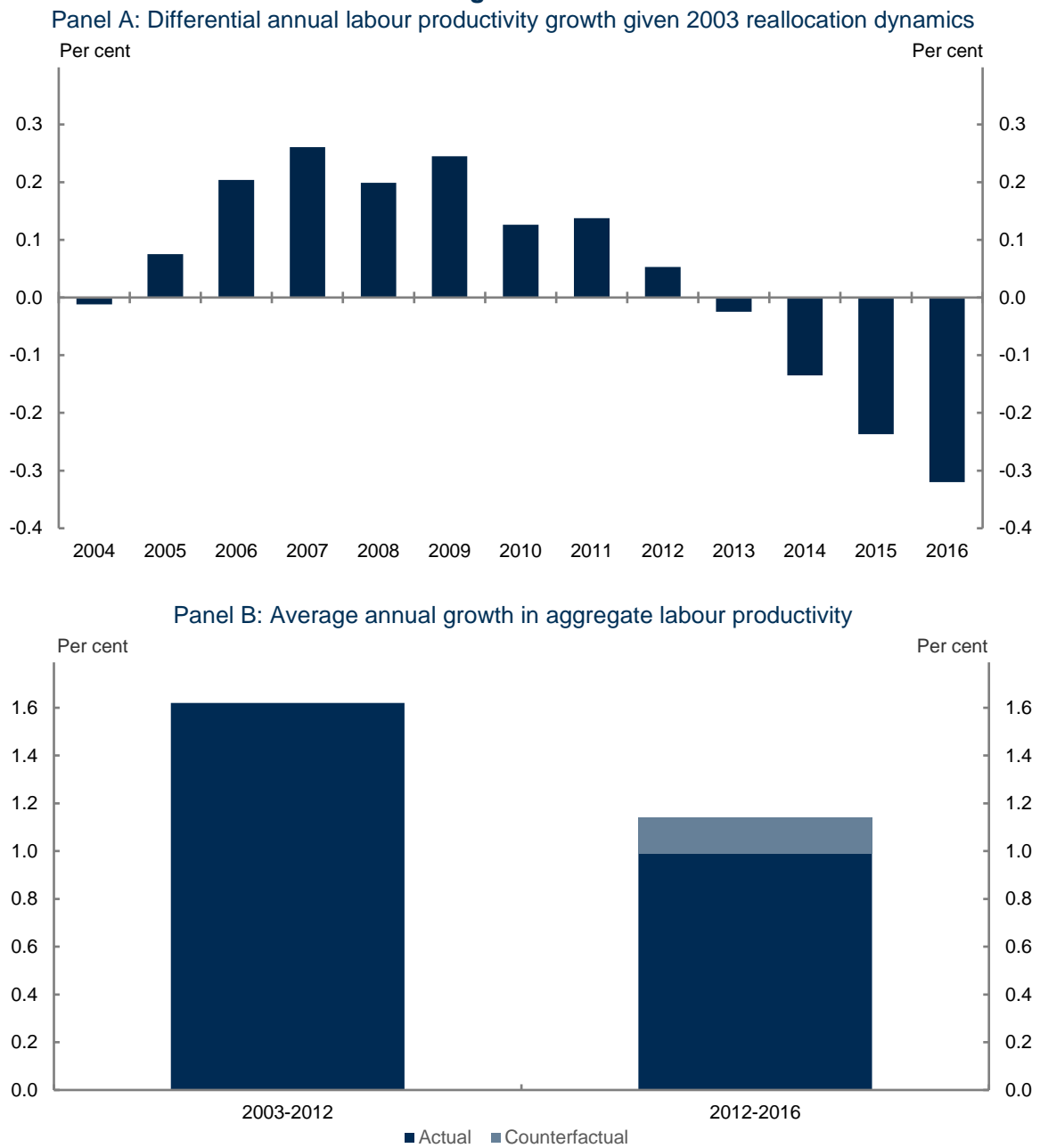
$$\begin{aligned} & (P_{t+1}^{Trend} - P_t) - (P_{t+1}^{No Trend} - P_t) \\ &= \sum_i (s_{i,t+1}^{Trend} - s_{i,t+1}^{No Trend}) p_{it} \quad (9) \end{aligned}$$

Figure 7 (Panel A) illustrates the results of this exercise for value-added labour productivity. The 2007 observation shows that, given the firm productivity and size distribution in 2006, aggregate (value-added) labour productivity growth was 0.3 per cent per annum higher due to the (estimated) actual responsiveness from 2006 to 2007, compared to if responsiveness remained at its estimated 2003 level. The decline in responsiveness in the second half of the sample implies a drag on aggregate market sector labour productivity growth of around 0.15 per cent per year by 2016, compared to if reallocation dynamics had remained at their 2003 levels.<sup>19</sup>

19 We calculate this as the geometric mean of the annual movements (as depicted in Figure 7) from 2011-12 to 2015-16. These results are robust to measuring labour productivity in terms of real revenue per FTE.



**Figure 7: The changing contribution of reallocation to aggregate labour productivity growth**



Notes: Panel A depicts annual movements in the counterfactual index in equation (9). The counterfactual in Panel B shows how much higher aggregate labour productivity growth would have been over 2012-2016 had the efficiency of labour reallocation not declined, based on the estimates in Panel A. The actual data in Panel B are based on ABS industry level labour productivity data and refer to the market sector excluding agriculture, mining, utilities and finance and insurance.

A simple back-of-the-envelope calculation suggests that the drag from slowing reallocation can account for roughly one-quarter of the slowdown in aggregate labour productivity growth for the industries included in our sample, which declined by around 0.6 percentage points from 2003-2012 to 2012-2016 (Figure 7, Panel B). Some caution should be applied to precisely interpreting these magnitudes at the end

points, given the use of a quadratic trend. Instead, the point is that the decline in the efficiency of labour reallocation is likely to carry material consequences for aggregate labour productivity performance.<sup>20</sup>

Finally, our results may also provide insights into why aggregate wage growth over recent years has been weaker than would have been expected based on historical relationships with its main macroeconomic determinants (Cassidy 2019; Quinn 2019).<sup>21</sup> Figure 8 shows that nominal wage growth – as measured by the wage price index (WPI) – has declined from an average of 4 per cent in the five years leading up to the Global Financial Crisis, to an average of 2.1 per cent in the past five years. Interestingly, sluggish wage growth over this period has coincided with an increase in the share of firms reporting it more difficult to find suitable workers – which historically has implied higher wage growth – raising the prospect that structural factors may be at play (Lowe 2018).

**Figure 8: Constraints on Output and Wages Growth**



Notes: The wage growth measure is year-ended growth in WPI. NAB survey measure shows share of firms reporting availability of suitable labour as a minor or significant constraint on output.  
Source: ABS; NAB.

One possible contribution to reducing this puzzle is that the decline in the rate at which labour is being reallocated to high productivity firms implies that fewer high-paying jobs are being created than in the past. We cite three ideas to support this conjecture. First, higher productivity firms pay higher wages, with the average wage paid by a high productivity firm about 15 per cent higher than that paid by a low productivity firm in the same industry, after controlling for a range of cyclical and firm-level factors (see Appendix C).<sup>22</sup> Second, the timing appears to match with the responsiveness of employment growth to productivity weakening particularly from around 2012 (Figure 7, Panel A) when wages growth significantly weakens. Finally, if high productivity firms have a greater reliance on skilled labour, then a rise in adjustment frictions which reduce the ability of the economy to reallocate labour to high productivity firms could partly account for why more firms are reporting it more difficult to find suitable workers.

20 Higher order polynomial trends were used, but made no substantial difference to the counterfactual exercises.  
21 These include lower inflation and inflation expectations, slower productivity growth, high rates of participation and spare capacity in the labour market, and the unwinding of the once in a century commodity price boom.  
22 As in Figure 5, a high (low) productivity firm is defined as one with labour productivity one standard deviation above (below) the industry labour productivity mean.

## 6. CONCLUSION

This paper exploits firm-level data to explore the link between productivity, labour reallocation and market selection in Australia over the period 2002-2016. We first show that the level of aggregate labour productivity is significantly higher owing to the fact that more productive firms on average account for a higher share of industry employment, particularly in sectors that are more exposed to competitive pressure. Moreover, the level of static allocative efficiency in Australia is higher than in most other OECD countries, perhaps reflecting the cumulated gains of past structural reforms, which may have enhanced the capacity of the Australian economy to reallocate scarce resources to high productivity firms.

We then show that high-productivity firms are more likely to expand and low productivity firms are more likely to contract (or exit), implying a positive contribution from dynamic reallocation to aggregate productivity growth. But the extent to which this is true has diminished over time. Counterfactual analysis shows that the weakening responsiveness of employment growth to firm productivity entails a significant drag on aggregate productivity, potentially accounting for up to one-quarter of the slowdown in aggregate labour productivity growth for the industries covered in our analysis. This raises important questions as to why the forces of reallocation and market selection have seemingly weakened.

One possibility is that productive firms are increasingly expanding on margins other than labour, such as capital. An important next step will be to utilize firm-level capital stock and MFP estimates (Fox, 2019 forthcoming) to examine the responsiveness of capital growth to firm MFP. The experience from international studies, however is that such definitional changes rarely alter the results. Another possibility is that productive firms are increasingly expanding offshore, but this seems unlikely to be driving results given that the decline in reallocation in manufacturing – a sector where this phenomenon should be most relevant – is broadly similar to the rest of the market economy.

The fact that declining reallocation has not occurred in isolation, but has instead been accompanied by a systematic decline in firm entry and job switching rates, suggests an explanation other than mismeasurement. If declining market dynamism is real, then what are the implications for policy?

There are plausible reasons why declining dynamism may be innocuous and not necessarily a concern for policymakers. If firm-specific human capital has become more important due to the rise of intangible capital and the ideas-based economy, then the cost of job separation from the perspective of both employers and workers may have risen (Cairo and Cajner, 2018). It then follows that the level of job reallocation and market dynamism required to accommodate a given level of aggregate growth may have fallen. The same is true for demographic-based explanations – such as population ageing or a rising share of dual income households – which both imply less job switching and labour mobility more generally. Indeed, that market dynamism has also declined in other OECD countries over the past 15 years lends some support to this view that a common global driver could account for these patterns.

But the results are also consistent with a rise in adjustment frictions – including barriers to labour mobility and competition – that slow down firm responsiveness. High priority should be placed on investigating these potential frictions as the decline in reallocation from less productive to more productive firms is holding down overall productivity growth and implies fewer high paying jobs are being created than otherwise, given that high-productivity firms pay higher wages. Indeed, the latter provides a new insight into why wage growth has been unexpectedly low since 2012 (Lowe 2018). It also complements our ongoing research agenda into the extent to which declining labour market dynamism – particularly job switching rates – has constrained aggregate wage growth (Deutscher 2019; Andrews et al., 2019).

## REFERENCES

- Adalet McGowan, M., D. Andrews and V. Millot (2018), 'The walking dead? Zombie firms and productivity performance in OECD countries', *Economic Policy*, 33(96), pp. 685–736.
- Andrews, D., C. Criscuolo and P. Gal (2016), 'The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy', *OECD Productivity Working Papers*, No. 5, OECD Publishing, Paris.
- Andrews, D., C. Criscuolo and C. Menon (2014), 'Do Resources Flow to Patenting Firms?: Cross-Country Evidence from Firm Level Data', *OECD Economics Department Working Papers*, No. 1127, OECD Publishing, Paris.
- Andrews, D and F. Cingano (2014), 'Public Policy and Resource Allocation: Evidence from Firms in OECD Countries', *Economic Policy* 29(78), pp. 253–296.
- Andrews, D., N. Deutscher, J. Hambur and D. Hansell (2019), 'Wages Growth in Australia: Lessons from Longitudinal Microdata', *Treasury Working Paper* 2019-04.
- Andrews, D and A. Saia (2016) 'Coping with Creative Destruction: Reducing the Costs of Firm Exit', *OECD Economics Department Working Papers* No. 1353.
- Australian Bureau of Statistics (2019), 'Australian National Accounts: National Income, Expenditure and Product', cat. no. 5206.
- Bailey, M., C. Hulten and D. Campbell (1992), Productivity Dynamics in Manufacturing Plants, *Brookings Papers on Economic Activity*, vol 23, issue 1992, Microeconomics: 187-267.
- Balasubramanian, N and J Sivadasan, (2011), 'What Happens When Firms Patent? New Evidence from U.S. Economic Census Data', *The Review of Economics and Statistics*, 93, issue 1, p. 126-146,
- Baldwin, J and W. Gu (2006), 'Competition, Firm Turnover and Productivity Growth', *Research Paper Economic Analysis*, Research Paper Series, Statistics Canada.
- Bartelsman, E., J. Haltiwanger and S. Scarpetta (2013), 'Cross-Country Differences in Productivity: The Role of Allocation and Selection', *American Economic Review*, 103(1): 305-34.
- Bellemare, M.F. and C. Wichman (2018), 'Elasticities and the inverse hyperbolic sine transformation'. Mimeo., Department of Applied Economics, University of Minnesota.
- Cairo, I and T. Cajner (2018), 'Human capital and unemployment dynamics: Why more educated workers enjoy greater stability', *Economic Journal*, vol 128 March (609): 652-682.
- Cassidy, N (2019), 'Low Wages Growth: An Introduction' in *Low Wage Growth*, Reserve Bank of Australia Annual Conference.
- Criscuolo, C, P. Gal, C. Menon (2014), 'The Dynamics of Employment Growth: New Evidence from 17 Countries', *OECD STI Policy Papers* No. 14.
- Campbell, S, T Nguyen, A Sibelle and F Soriano (2019), 'Measuring Productivity Dispersion in Selected Australian Industries', *Treasury-ABS Working Paper*.
- Davis, S, J. Haltiwanger and S. Schuh (1996), 'Job Creation and Destruction' Cambridge, MA: MIT Press.

- Debelle, G (2017), 'Business Investment in Australia,' speech to UBS Australasia Conference 2017, Sydney – 13 November 2017
- Decker, R, J Haltiwanger, R Jarmin and J Miranda (2018), 'Changing Business Dynamism and Productivity: Shocks vs. Responsiveness' *NBER Working Paper* No. 24236.
- Deutscher, N (2019), 'Job-to-job transitions and the earnings of Australian workers', *Treasury Working Paper 2019-07*.
- Disney, R, J. Haskel and Y. Heden (2003), 'Restructuring and Productivity Growth in UK Manufacturing', *Economic Journal* 113, 666-694.
- Eisfeldt, A.L. and A.A. Rampini (2006), 'Capital Reallocation and Liquidity', *Journal of Monetary Economics*, No. 53, pp. 369-399.
- Foster, L, J Haltiwanger and CJ Krizan (2001), 'Aggregate Productivity Growth: Lessons from Microeconomic Evidence,' Chapter in NBER book *New Developments in Productivity Analysis* (2001), Charles R. Hulten, Edwin R. Dean and Michael J. Harper, editors (p. 303 - 372), University of Chicago Press.
- Foster, L, J Haltiwanger and CJ Krizan (2006), Market Selection, Reallocation, and Restructuring in the U. S Retail Trade Sector in the 1990s, *Review of Economics and Statistics* 88, 748-758.
- Fox, K (2019), 'Estimates of Multifactor Productivity using BLADE', forthcoming.
- Furman, J (2015), Remarks at the launch of the OECD Study on the Future of Productivity, Peterson Institute for International Economics 9 July 2015.
- Gaetjens, P (2018), Bateman Lecture, UWA Public Policy Institute 04 September 2018.
- Griliches, Zvi and Haim Regev (1992), 'Productivity and Firm Turnover in Israeli Industry: 1979-1988', *NBER Working Paper Series* No. 4059.
- Haltiwanger, J. (2011), 'Firm Dynamics and Economic Performance', mimeo.
- Haltiwanger, J, R. Jarmin and J. Miranda (2013), 'Who Creates Jobs: Small vs Large vs Young' *Review of Economics and Statistics* 95(2), pp. 347-61.
- Hansell, D, T Nguyen and F Soriano (2015), 'Can we improve on a headcount? Estimating unobserved labour input with individual wage data', *Paper presented to the Australian Labour Market Research Workshop*, Adelaide 3 December.
- Hansell, D and B. Rafi (2018), 'Firm-level Analysis Using the ABS' Business Longitudinal Analysis Data Environment (BLADE)', *Australian Economic Review*, Vol. 51(1): 132-138.
- Heads of Treasuries (2017), *Intergovernmental Review of Business Investment* September 2017.
- Hendrickson, L, A Balaguer, S Bucifal and D Hansell (2015), 'The Employment Dynamics of Australian Entrepreneurship', Office of the Chief Economist, Department of Industry and Science, *Research Paper 4/2015*
- Hsieh, C-T. and P. Klenow (2009), 'Misallocation and Manufacturing Productivity in China and India,' *Quarterly Journal of Economics*, 124(4), pp. 1403-1448.

- Jovanovic, B. and P.L. Rousseau (2002), 'The Q-Theory of Mergers', *American Economic Review Papers and Proceedings* 91, pp. 336–341.
- Lowe, P (2018), 'Productivity, Wages and Prosperity' Address to Australian Industry Group, Melbourne – 13 June 2018.
- Meltitz, M and Saso Polanec (2015), 'Dynamic Olley-Pakes Productivity Decomposition with entry and exit', *RAND Journal of Economics*, Rand Corporation, June, vol. 46(2): 362-375.
- Mora Sanguinetti, J. and A. Fuentes (2012), 'An Analysis of Productivity Performance in Spain Before and During the Crisis: Exploring the Role of Institutions', *OECD Economics Department Working Papers*, No. 973, OECD Publishing, Paris.
- Nguyen, T and D Hansell (2014), 'Firm Dynamics and Productivity Growth in Australian Manufacturing and Business Services', *ABS Research Paper (Cat No. 1351.0.55.052)*
- OECD (2018), 'Economic Policy Reforms 2018: Going for Growth Report', *OECD Publishing*, Paris
- Olley, G.S and A. Pakes (1996), 'The Dynamics of Productivity in the Telecommunications Equipment Industry', *Econometrica*, 64(6), pp. 1263-97.
- Petrin, A, J. Reiter and K White (2011), 'The Impact of Plant-level Resource Reallocations and Technical Progress on U.S. Macroeconomic Growth,' *Review of Economic Dynamics*, vol. 14(1), pp.3-26.
- Quinn, M (2019), 'What's driving low wages growth in Australia?' Speech to Australian Conference of Economists 16 July 2019.
- Rotemberg, M and K White (2017), 'Measuring Cross-Country Differences in Misallocation' Mimeo.
- Syverson, C. (2004), 'Substitutability and Product Dispersion,' *Review of Economics and Statistics*, 86 (2), pp. 534-550.
- Syverson, C (2011), 'What Determines Productivity?' *Journal of Economic Literature*, 49 (2): 326-65.

## APPENDIX A: DERIVING IMPLICIT PRICE DEFLATORS FOR ANZSIC06 DIVISIONS

This appendix describes the method used to derive implicit price deflators from the Australian System of National Accounts – ASNA (ABS cat no 5204) and Estimates of Industry Multifactor Productivity (ABS cat no 5260.0.55.002), also known as the productivity data cube.<sup>23</sup>

The first stage involves backing out gross output and intermediate use in current prices at the one-digit ANZSIC06 level. To do this we require the published estimates of value-added in current prices ( $VA_{it}$ ) from cat no 5204, and the income shares for capital ( $SK_{it}$ ), labour ( $SL_{it}$ ) and intermediate use ( $SI_{it}$ ) from table 19 of the productivity data cube. Then we calculate intermediate use and gross output in current prices as:

$$\text{Intuse}_{it} = VA_{it} * (SI_{it} / (SL_{it} + SK_{it})) \text{ and so}$$

$$GO_{it} = VA_{it} + \text{Intuse}_{it}$$

Noting that the chain volume measure in the period prior to the most recent period is equal to the current price value, we can create dollar values of real gross output ( $RGO_{it}$ ) and real intermediate use ( $RIU_{it}$ ) using the real gross output ( $RGO\_Index_{it}$ ) and real intermediate use indexes ( $RIU\_Index_{it}$ ) published in Table 8 of the productivity data cube. That is:

$$RGO_{it-2} = RGO_{it-1} * (RGO\_Index_{it-2} / RGO\_Index_{it-1})$$

Hence if  $GO_{it-1} = RGO_{it-1} = \$1,500$  and the  $RGO\_Index_{it-2} = 98.3$  and  $RGO\_Index_{it-1} = 100$ , then

$$RGO_{it-2} = \$1,500 * (98.3 / 100) = \$1,474.5$$

Finally, the implicit price deflator is obtained by dividing the current price estimate by the real since the quantity for each period is the same and so we obtain the implicit change in prices. Note we use the term implicit because unlike a price index, an implicit price deflator changes when revisions are made to the national accounts due to improved information or methodological changes. Note also that the implicit price deflator for value-added is readily obtained by dividing the published estimates of industry value-added at current prices by the chain volumes found in Table 5 of the ASNA.

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23 Thanks to Derek Burnell of the Australian Bureau of Statistics for pointing out this method.

## APPENDIX B: ADDITIONAL EMPIRICAL RESULTS

**Table B1: Summary Statistics**

	Full time equivalent employment	Real revenue	Log real revenue per worker	Employment Growth
Mean	15.011	5,447,531	12.096	0.017
Median	3.780	702,436	12.020	0.005
25th Percentile	1.995	320,646	11.593	-0.107
75th percentile	8.345	1,790,186	12.551	0.142
Interquartile range	6.350	1,469,540	0.959	0.249
Standard deviation	229.477	111,000,000	0.865	0.325
Observations	4,347,042	4,347,042	4,347,042	4,347,042

**Table B2: The Effect of Lagged Productivity on Firm-Level Employment Growth: Within Firm Age Groups**

	Selected Industries		Manufacturing	
	(1)	(2)	(3)	(4)
Prod*Young	0.0416***	0.0379***	0.0356***	0.0449***
Prod*Young*Trend		0.00338***		-0.000812
Prod*Young*Trend <sup>2</sup>		-0.000311***		-0.000107
Prod*Mature	0.0577***	0.0648***	0.0781***	0.0818***
Prod*Mature*Trend		5.10E-05		0.00254**
Prod*Mature*Trend <sup>2</sup>		-0.000119***		-0.000346***
Size	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
D.State Unemp Rate (D.SU)	Yes	Yes	Yes	Yes
D.SU*Prod	Yes	Yes	Yes	Yes
Observations	4,347,042	4,347,042	434,732	434,732
R-squared	0.029	0.03	0.038	0.041

Note: Sample encompasses 2002-2016 with one period sacrificed due to the lag. Size dummies refer to the following number of full-time equivalent employees: 0-4, 5-19, 20-199, 200-499, and 500 plus.



**Table B3: The Effect of Lagged Productivity on Firm Exit: Within Firm Age Groups**

Exit Margin Probit - Selected Industries				
	(1)	(2)	(3)	(4)
Prod	-0.176***	-0.194***		
Prod*Trend		0.000553		
Prod*Trend2		0.000236***		
Prod*Young			-0.198***	-0.185***
Prod*Young*Trend				-0.0114***
Prod*Young*Trend2				0.00102***
Prod*Mature			-0.164***	-0.200***
Prod*Mature*Trend				0.00734***
Prod*Mature*Trend2				-0.000220***
Size	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Change in State Unemployment (d. SU)	Yes	Yes	Yes	Yes
d.SU*Prod	Yes	Yes	Yes	Yes
Observations	5,062,496	5,062,496	5,062,496	5,062,496
Pseudo R-squared	0.0538	0.0539	0.0539	0.0540

Robust standard errors in parentheses; \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

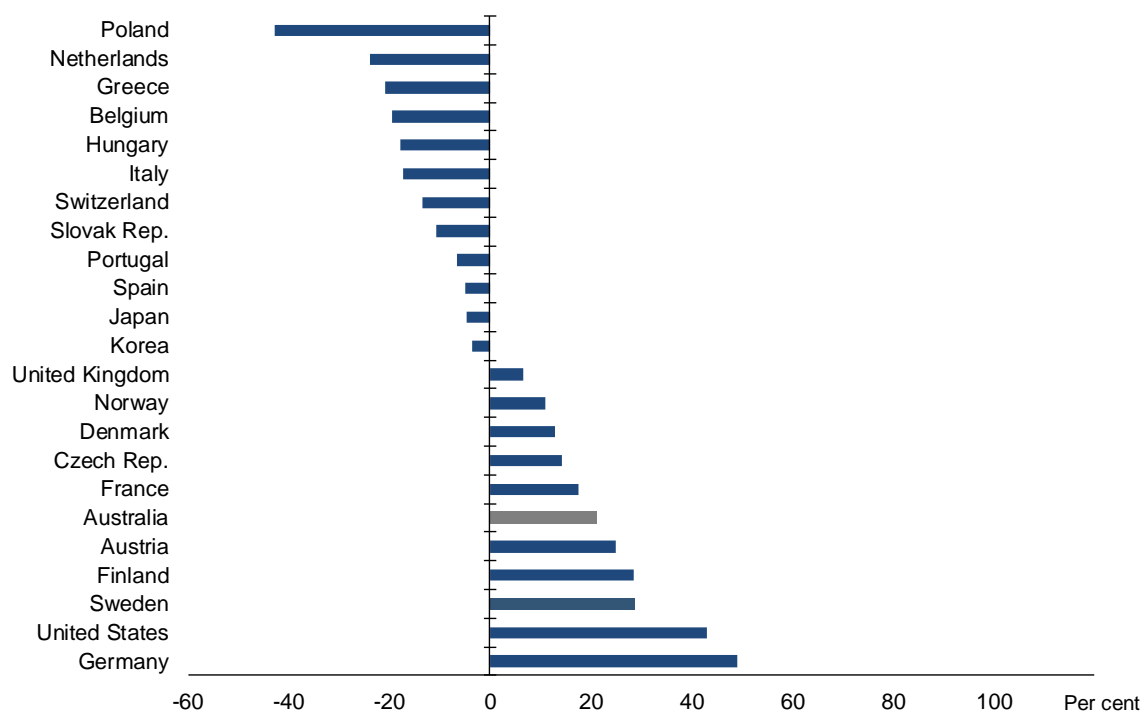
Note: Sample encompasses 2002-2016 with one period sacrificed due to the lag. Size dummies refer to the following number of employees: 0-4, 5-19, 20-199, 200-499, and 500 plus. Dependent variable is a binary indicator which takes a value of 1 if the firm exits, and zero otherwise. Exit models have higher sample sizes because exit is defined in the year after the units ceases reporting. Contemporaneous definitions of exit yield very similar results.

**Table B4: The Effect of Lagged Productivity on Firm-Level Employment Growth: Robustness to Alternate Functional Forms**

	All Selected	Manufacturing	Construction	Wholesale Trade	Retail Trade	Accommodation and Food	Transport, Postal and Warehousing	Information Media and Telecommunications	Rental, Hiring and Real Estate	Professional, Scientific and Technical	Administration and Support	Arts and Recreation	Other Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Prod	0.0572***	0.0708***	0.0622***	0.0502***	0.0648***	0.0775***	0.0603***	0.0568***	0.0405***	0.0574***	0.0386***	0.0563***	0.0499***
Prod*Post 2009	-0.00938***	-0.0118***	-0.00373**	-0.00654***	-0.0120***	-0.0263***	-0.0104***	-0.00548	-0.00584***	-0.0139***	-0.00519**	-0.00593	-0.00863***
Size	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Change in State Unemployment (d. SU)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
d.SU*Prod	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4,347,042	434,732	731,903	325,964	562,044	350,526	225,978	48,334	253,438	709,315	217,955	64,397	422,456
R-squared	0.0293	0.0386	0.0337	0.0351	0.0321	0.0341	0.0284	0.0331	0.0278	0.0228	0.023	0.0266	0.0263

Note: Sample encompasses 2002-2016 with one period sacrificed due to the lag. Size dummies refer to the following number of full-time equivalent employees: 0-4, 5-19, 20-199, 200-499, and 500 plus. Post 2009 is a binary indicator which takes a value of one for all periods post 2009 and zero otherwise.

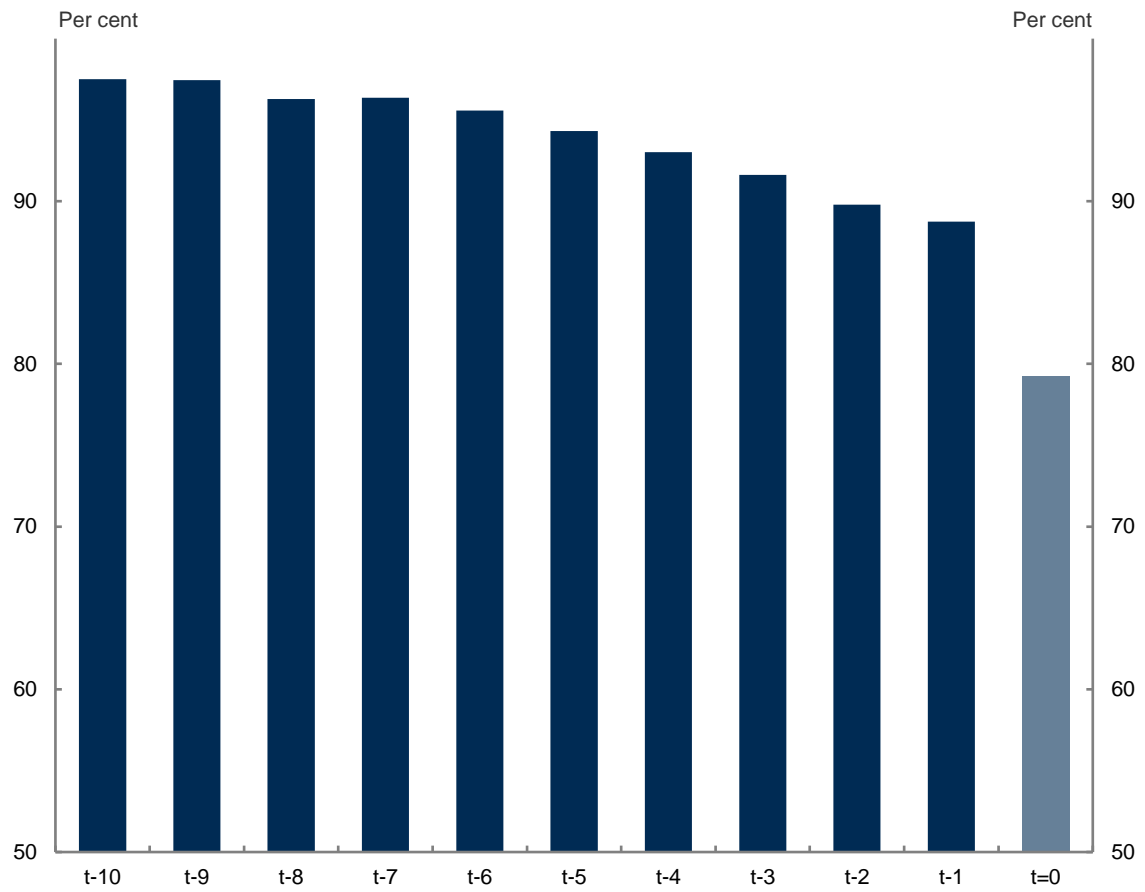
**Figure B1: Allocative Efficiency in Services – Selected OECD Countries, 2005**



Notes: International estimates sourced from Andrews and Cingano (2014).

### Figure B2: The Shadow of Death

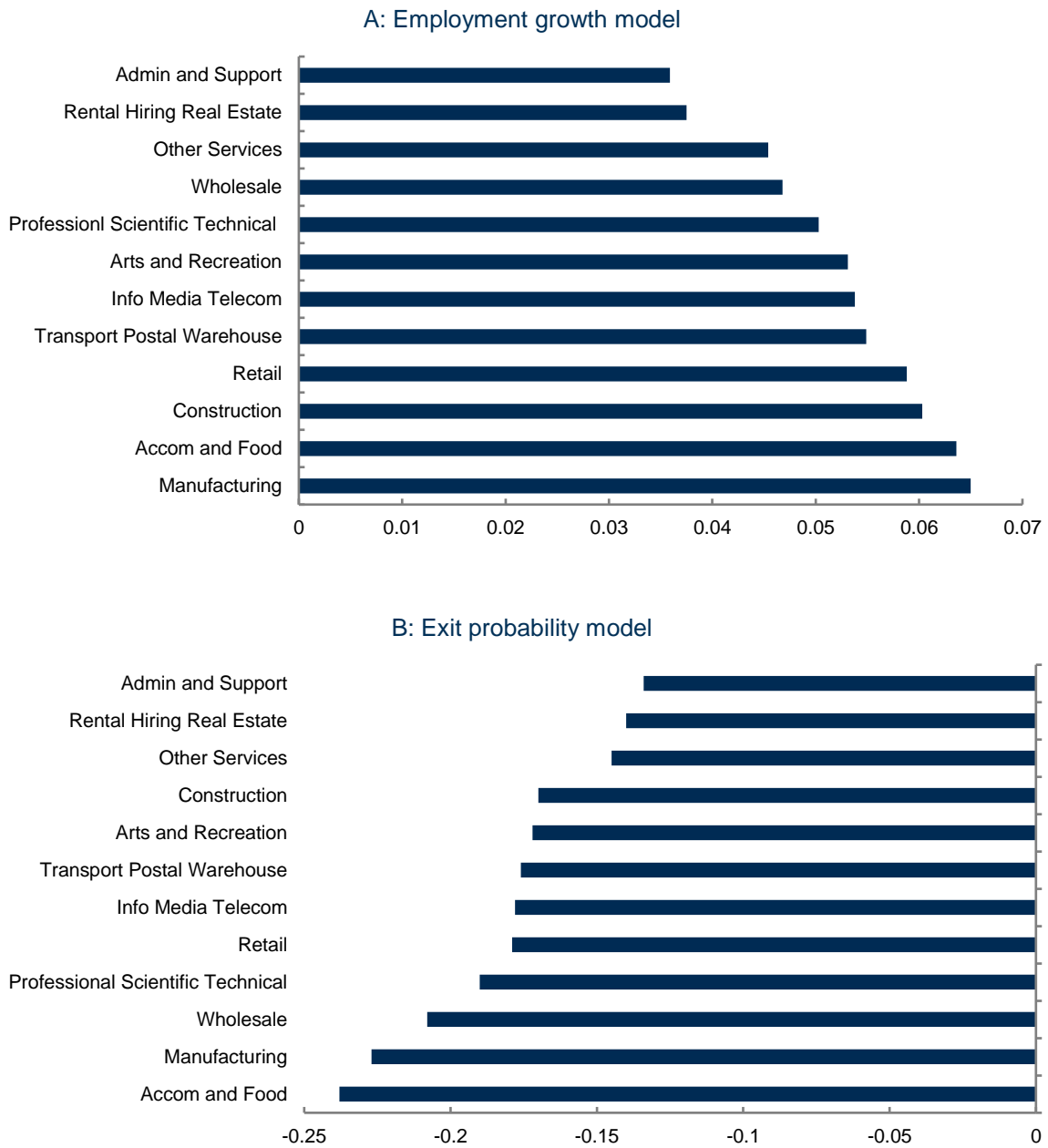
Labour productivity of exiting firms at t=0 as per cent of continuing firms productivity



Notes: The above chart plots the unweighted mean of the median productivity of each exiting cohort. Productivity is defined as real value-added per employee. Time is measured in years prior to exit. Exit = 1 if a unit reports no further information to the ATO. Consequently, there is a minimum of four cohorts at t-10.

**Figure B3: Dynamic Allocative Efficiency in Selected Australian Industries**

Estimated coefficient on lagged labour productivity



Note: Employment growth chart reports coefficients on productivity term (see equation 4) for industry-level regressions without the trend and trend-squared terms. Sample encompasses 2002-2016 with one period sacrificed due to the lag. Size dummies refer to the following number of full-time equivalent employees: 0-4, 5-19, 20-199, 200-499, and 500 plus. Exit margin chart reports coefficient on productivity term where dependent variable is a binary indicator for exit, otherwise all independent variables as the same as the employment growth chart. Both models include the change in state unemployment levels alone and interacted with the productivity term to control for state-level business cycle effects

## APPENDIX C: PRODUCTIVITY AND WAGES: FIRM LEVEL EVIDENCE

**Table C1: The link between wages and labour productivity at the firm level**

	Wage Bill	Average Wage	Wage Bill	Average Wage
Prod	0.139***	0.0963***		
Prod*Young			0.102***	0.0856***
Prod*Mature			0.157***	0.101***
Year Dummies	YES	YES	YES	YES
Size Controls	YES	YES	YES	YES
State Controls	YES	YES	YES	YES
Size by Year Dummies	YES	YES	YES	YES
Year by State Dummies	YES	YES	YES	YES
Observations	4,342,368	4,342,368	4,342,368	4,342,368
R-squared	0.416	0.046	0.416	0.046

Notes: Dependent variables are  $\log(\text{wages})$  and  $\log(\text{wage} / \text{full-time equivalent employment})$ . Sample encompasses 2002-2016 with one period sacrificed due to the lag. Size dummies refer to the following number of full-time equivalent employees: 0-4, 5-19, 20-199, 200-499, and 500 plus.