



# REACHING FOR THE STARS: AUSTRALIAN FIRMS AND THE GLOBAL PRODUCTIVITY FRONTIER

Dan Andrews, Jonathan Hambur, David Hansell and Angus Wheeler<sup>1</sup>

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- <sup>1</sup> Jonathan Hambur is Macroeconomic Group. Dan Andrews, David Hansell and Angus Wheeler were all formerly in Macroeconomic Group, The Treasury, Langton Crescent, Parkes ACT 2600, Australia. Correspondence: [Jonathan.Hambur@treasury.gov.au](mailto:Jonathan.Hambur@treasury.gov.au). We thank Peter Gal and Natia Mosiashvili for their comments and assistance with global frontier data. We also thank seminar participants at the RBA, OECD Global Forum on Productivity, as well as Rebecca Cassells, Nathan Deutscher and Mark Cully.
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Reaching for the stars: Australian firms and the global productivity frontier  
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## ABSTRACT

A feature of the recent global slowdown in productivity growth is that progress at the technological frontier has remained strong, while the gap between firms at the global frontier and other ‘laggards’ within an industry has grown. This growing gap reflects the fact that laggard firms now seem to be slower to adopt cutting-edge technologies and processes, and catch-up to the global frontier than they were previously. However, little is known about whether these patterns hold true for Australia. We exploit a novel dataset merging international microdata from OECD-Orbis with Australian microdata from BLADE. Consistent with overseas evidence, we find that the gap between global frontier firms and Australian firms has grown over time in the non-resource, non-financial market sector. Moreover, Australian firms catch up to the global frontier more slowly than previously, suggesting slower adoption of cutting-edge technologies and processes. The slowdown has been more notable in industries with declining measures of dynamism and competitive pressures, suggesting the slowdown may reflect weaker incentives and imperatives for firms to improve. This suggests that policies to address barriers to business dynamism and competitive pressures can improve Australia’s productivity performance, by increasing incentives for firms to adopt, innovate and improve.

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Keywords: productivity, dispersion, firm-level, BLADE, frontier

Jonathan Hambur  
Macroeconomic Group  
The Treasury  
Langton Crescent  
Parkes ACT 2600

# 1. INTRODUCTION

Over the medium term, growth in Australia's living standards will be driven by growth in productivity. However, like other advanced economies, productivity growth in Australia has slowed since the mid-2000s. Understanding the causes of this slowdown, and therefore which policies could address it, represents one of the most crucial roles for academics and policymakers. As such, over the past decade there has been a large amount of research and debate around the causes of the global productivity slowdown.

One key question is whether the productivity slowdown reflects slower technological progress. For example, some argue that the productivity slowdown reflects a 'return to normal' following a period of transformative technological innovation (for example, electrification and information technology; Gordon 2012). Others argue that current innovations can be just as transformative (see Brynjolfsson and McAfee 2011; Mokyr 2013).

Supporting this latter view, international evidence suggests progress for firms at the global frontier has remained strong. However, cutting-edge technologies and processes appear to be diffusing to other firms more slowly. In particular, Andrews et al (2019) find that the gap between global frontier firms and other 'laggard' firms within the same industries has grown, and laggard firms now seem to be slower to catch up to the global frontier. This suggests that the issue is slower diffusion of knowledge, not slower technological progress

While these patterns have been documented internationally, little is known about whether they hold true for Australia. This paper exploits firm-level data from in Australia's BLADE dataset and the OECD's international Orbis dataset to provide new evidence on the labour productivity of Australian firms and how this compares to productivity for industry peers at the global frontier. We focus our analysis on the subset of non-financial non-resource market sector industries that are well-suited for benchmarking, consistent with the overseas literature. This covers manufacturing, goods distribution and retailing, and business and household services. However, we do exclude some sectors where Australian firms may be at the frontier, such as mining.

First, we show that the productivity gap between the global frontier and Australian firms has grown over time. This pattern is consistent with evidence overseas, where firms across many countries have fallen further behind global leaders. In Australia, the divergence is particularly striking in the services sector, which is more protected from global competitive pressures.

More importantly though, we find that Australian firms are catching up to the frontier more slowly than they did in the early 2000s. This suggests that Australian firms have been slower to adopt cutting-edge technology and processes, and to improve their productivity performances more generally. In turn, slower within-firm productivity growth has weighed on aggregate productivity growth.

We then attempt to identify factors that could explain the slower catch-up, focusing on business dynamism and competition. We focus on dynamism because the entry and exit of firms intensifies competitive pressure on incumbents, forcing them to improve or exit. Entry also brings young firms into the market, who may be more likely to innovate and adopt new technologies or processes.

Consistent with this expectation, firms in industries with higher entry, exit and turnover rates catch up to the global frontier more quickly, as do firms in industries with lower mark-ups (and therefore higher competitive pressures). Simple calculations suggest that the previously documented declines in business dynamism and competitive pressures therefore appear to account for half to three-quarters of the slowdown in the rate at which Australian firms catch up to the global frontier.

Overall, our findings suggest that part of the slowdown in aggregate productivity growth in Australia reflects slower diffusion of cutting edge-technologies and processes, and firm-level improvements, as in other advanced economies. They also suggest that, while global factors could be contributing to slower diffusion, policies that remove barriers to business dynamism and competitive pressure can encourage firms to catch up to the global frontier, thereby improving aggregate labour productivity performance. This motivates a greater focus on the potential obstacles to dynamism. Policies that facilitate more widespread adoption of emerging digital technologies can also play a role in improving productivity performance.

The next section of this working paper discusses international evidence on the global productivity slowdown, models of firm catch-up, and market dynamism. Section 3 focuses on the datasets and the steps taken to clean the data, before presenting some preliminary findings. Section 4 sets up the econometric framework used to test for productivity convergence. Section 5 presents our key results before Section 6 concludes.

## 2. INTERNATIONAL LITERATURE

Productivity growth has slowed significantly in advanced economies over the past two decades. While the exact timings and magnitudes differ across countries, productivity measures, and even studies, there is consistent evidence that productivity growth today is slower than it was previously. For example, comparing the periods 1996-2005 to 2006-2017, Goldin et al (2021) document declines in labour productivity growth of between 0.8 and 1.75 percentage points across five advanced economies.

Given the centrality of productivity growth to long-run growth in GDP and living standards, a large literature has evolved trying to document the slowdown and understand its causes.

### 2.1. Techno-optimists and techno-pessimists

A key strand of this literature relates to the pace and economic potential of current innovations. Techno-pessimists argue that the productivity slowdown reflects diminishing returns to new innovations. All the ‘low-hanging fruit’ innovations of the 19th and early 20th centuries, like electrification, were far more significant and transformative than anything seen since, and these innovations can only occur once (Gordon 2012). On the other hand, techno-optimists argue that current advancements, such as Artificial Intelligence, are just as transformative (Brynjolfsson and McAfee 2011; Mokyr 2013).

How can this view latter view be squared with slowing productivity growth? One explanation put forward in the literature is that the process of technological diffusion has slowed. Technological diffusion is a key step in economic growth. Frontier firms innovate, and then over time other firms can adopt the new technologies, improving their performance and helping to further lift the productive capacity of the economy. This process of adoption means that firms further away from the frontier can improve productivity quickly and converge towards the frontier. Several empirical papers have found evidence supporting this notion of firm-level productivity convergence (for example, Andrews et al 2019; Griffith, Redding and Simpson 2009; Berlingieri et al 2020; Bartelsman et al 2008; Iacovone and Crespi 2010).

But why would technological diffusion have slowed? One more benign explanation is that some recent innovations are ‘general purpose technologies’. These are technologies with broad use and application, which often take time to diffuse fully through the economy as they require substantial investments before they can be integrated fully into the economy. A past example is electricity; the process of electrification took decades even in more advanced economies (Bojanovic and Rosseau 2005). Another, less benign explanation is that structural factors that either prevent adoption – like financing frictions or anticompetitive use of intellectual property (Akcigit and Ates 2019) – or declining incentives to do so due

due to declining dynamism and less competitive pressure, have slowed the diffusion process (Andrews et al 2019).

As can be gathered from the above discussion, a key aspect of the debate between techno-pessimists and techno-optimists is whether current technologies are inherently less transformative, or whether they are just diffusing more slowly through the economy. In the former case, the productivity frontier should be pushing out more slowly; in the latter case the frontier could still be growing quickly, but other firms will be slower to catch-up. Differentiating between these two explanations inherently requires firm-level data.

## 2.2. Growth of the frontier and productivity convergence

A key recent piece of evidence in this debate was provided by Andrews et al (2019). They use cross-country firm-level OECD-Orbis dataset to examine productivity growth for firms at the frontier, and for laggard firms in the same industries. They find that progress for firms at the frontier has remained during the global productivity slowdown. This suggests that the techno-pessimist view is likely to be overstated.

They also find that the gap between the global frontier firms and laggards in the same industry has grown, and that the rate at which firms converge to the productivity frontier has slowed. They argue that this suggests slower adoption and diffusion of cutting-edge technologies and processes throughout the global economy, and that this has weighed aggregate productivity growth.

To understand the underlying driver of these patterns, Andrews et al (2019) explore the role of product market regulation. They find that in industries with less competition friendly regulatory regimes, the gap between the frontier and laggards tends to be larger. While the relationships between competition, and innovation and technology adoption is theoretically ambiguous (Aghion et al 2005), this provides some empirical evidence on the importance of competition in technology diffusion and adoption.

Berlingieri et al (2020) similarly find evidence of slowing convergence across a number of advanced economies, though they focus on the national rather than the global frontier. Moreover, they find evidence that convergence tends to be slower where there are skill shortages/mismatches, such as in more digitally intensive sectors, and where financing constraints are more binding.

Meanwhile, Akcigit and Ates (2019) examine the potential implications of slowing technology diffusion in a theoretical model with endogenous firm dynamics. Their results suggest that slower knowledge diffusion could explain the well-documented decline in business dynamism.

Our paper adds to this existing literature by examining productivity convergence in Australia. We also contribute to the international literature by more formally examining the relationship between productivity convergence, and business dynamism and competition.

## 3. DATA AND GRAPHICAL RESULTS

### 3.1. 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 (ABS). BLADE captures administrative data from the Australian Taxation Office (ATO) for almost the entire population of

Australian firms, matched with ABS-produced survey microdata, such as the Business Characteristics Survey.

We use data from firms' Business Income Tax (BIT) forms, as well as their Pay-As-You-Go (PAYG) employment forms. BIT data are used to construct measures of gross value-added, defined as total compensation to labour plus gross operating surplus. Productivity is then measured as labour productivity, the ratio of gross value-added to full-time equivalent employees. We also use demographic information on firms contained in BLADE, such as age and industry.

The focus of this analysis is on labour productivity, rather than multifactor productivity (MFP). This allows us to cover a larger sample of firms, both companies and unincorporated businesses, whereas we could only examine companies if we used MFP due to a lack of balance sheet and capital stock information for unincorporated business.<sup>3</sup> Focusing on labour productivity may also be preferable given some technologies might be capital-embodied, and so abstracted from in using MFP. Still, future work could examine the results using MFP, which may be a cleaner measure of technological progress.

As is common in the literature, we do not have access to firm-level input and output prices. As such we deflate value-added using industry deflators (1-digit ANZSIC). This is not ideal, as it means that our productivity measure will be affected by firm price differences, which could in turn reflect differences in market power, or product differentiation more generally. Nevertheless, numerous papers have shown that price- and quantity-based measures of productivity tend to move similarly, and failing to account for firm-level prices, while not ideal, does not have substantial impacts in firm-level studies of this type (Andrews et al 2019; Foster, Haltiwanger and Syverson 2008)

### 3.2. Data on the global productivity frontier

Labour productivity data for the global productivity frontier come from the OECD-Orbis database. The database contains measures of labour productivity (similarly defined as gross value-added divided by full-time equivalent employees) at the firm-level and covers 24 OECD countries for the non-farm, non-financial business sector (Gal 2013; Andrews et al 2019). These data are sourced from annual balance sheet and income statements using a variety of underlying sources such as credit rating agencies, national banks and financial information providers.<sup>4</sup>

Labour productivity at the global frontier in each industry is taken to be the (unweighted) average labour productivity of the most productive 5 per cent of firms in that industry for a given year. Consistent with Andrews et al (2019), we identify the top 5 per of firms using a fixed number of firms across years. However, while the number of frontier firms is fixed over time, the set of frontier firms changes. This allows for churning at the frontier. The Australian frontier is defined in the same way using BLADE data.

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3 See Hambur (2021) for a discussion.

4 For more information on the OECD-Orbis database, see Gal (2013) and the appendix of Andrews et al (2019).

### 3.3. Data cleaning and sample

We take three main steps to clean the data and ensure comparability between the Australian and international datasets.

First, we ensure comparability of nominal variables across countries and over time by adjusting for country-industry level differences in the purchasing power of currencies and applying industry-level deflators.<sup>5</sup> Second, we convert Australian industry codes (ANZSIC 2006) to the NACE Rev 2 European classification system (which is equivalent to the international classification system ISIC Rev 4) using ABS concordances. Third, we clean the Australian data using the same methodology that Andrews et al (2019) use to clean the international data. This involves excluding outliers (defined as firms in the top and bottom 0.5 per cent of the labour productivity growth distribution), firms with less than three full-time equivalent employees, and any observations missing key information such as industry code, value-added and labour input.

To be consistent with Andrews et al (2019), we confine our analysis to the market sector (that is exclude utilities, education, public administration and safety, arts and recreation, and health), exclude finance and insurance where productivity is notoriously hard to measure, and exclude highly volatile commodities sectors such as agriculture and mining. Quality data on the frontier are not available for many of these industries. We also remove construction due to difficulty measuring labour inputs given the use of contractors. This means retaining 2-digit NACE Rev 2 industry codes 10-33 and 45-82 (excluding 64-66), for which we have international comparator data. This covers just under half of gross value added in the Australian economy, and captures manufacturing, goods distribution and retailing, and business and household services. We confine our analysis to the 2002-2016 period, when we have both Australian and global frontier data.

It is worth highlighting that Australian firms' productivity performance may have been stronger in some of the excluded sectors. For example, many of Australia's mining businesses are global leaders and may have had strong productivity growth over the period.

After cleaning the data, the sample is an unbalanced panel of 1,372,576 observations, with an average of around 90,000-100,000 individual firms in each year.

### 3.4. Descriptive statistics

As a first step, we plot unweighted-average productivity of firms in the global frontier, the Australian frontier, and Australian laggards, to understand of how Australian firms fair relative to the technological frontier. Figure 1 shows a growing gap between the productivity of the average global frontier firm and the average Australian firm. While productivity of those firms in the global frontier 60 per cent higher in 2016 compared to 2002, Australian frontier firms' productivity is only 25 per cent higher, and other

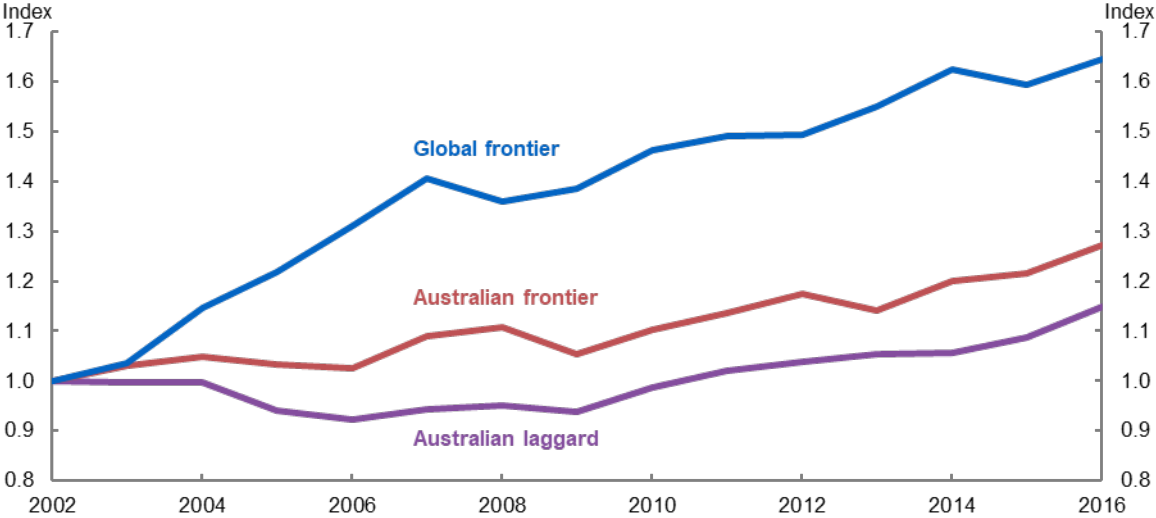
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5 To ensure monetary variables are comparable across countries, we adjust for differences in purchasing power of currencies. However, relative purchasing power across countries may differ by industry, for example as more developed countries often have higher services-goods price ratios. If this is the case, aggregate PPP conversions will not be sufficient to ensure comparability of labour productivity measures across countries. For this reason, we use industry-level PPP estimates compiled by Inklaar and Timmer (2014). To ensure comparability of monetary variables over time, we deflate the Australian data using ABS deflators at the 2-digit industry-level, and deflate the international data using 2-digit industry-level deflators from the OECD STAN database.



'laggard' firms 15 per cent higher.<sup>6</sup> It is worth reiterating here that the firms that make up the Australian and global frontier are allowed to change, so we are showing the average productivity of firms in each of these groups over time, rather than tracking the productivity growth of any given firms.

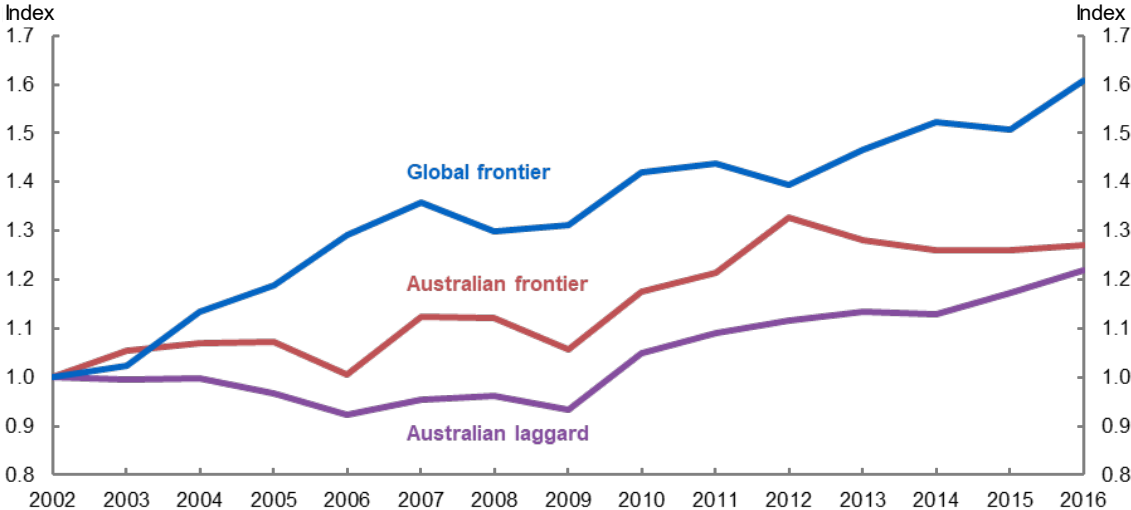
**Figure 1: Labour productivity dispersion – business sector**



Notes: Figure 1 plots average productivity for the global frontier, Australian frontier, and Australian laggards (defined as all Australian firms not classified as a frontier firm) for the business sector. The business sector is defined here as the manufacturing sector plus the services sector (NACE industry codes 10-33, 45-82, excluding 64-66). See 3.2 for details on frontier definition. Indexed to 2002=1, so that the vertical axis shows cumulative productivity growth. For example, if the global frontier series reaches 1.5 by 2013, this means that average global frontier firm productivity has grown by 50 per cent relative to its 2002 level.

As seen in Figures 2-3, the growing divergence is particularly striking in the services sector, but not as pronounced in the manufacturing sector, where growth rates are far more similar between Australian firms and the global frontier from around 2009 onwards. This could be consistent with the greater competitive pressures faced by manufacturing firms, given the high degree of import and export competition.

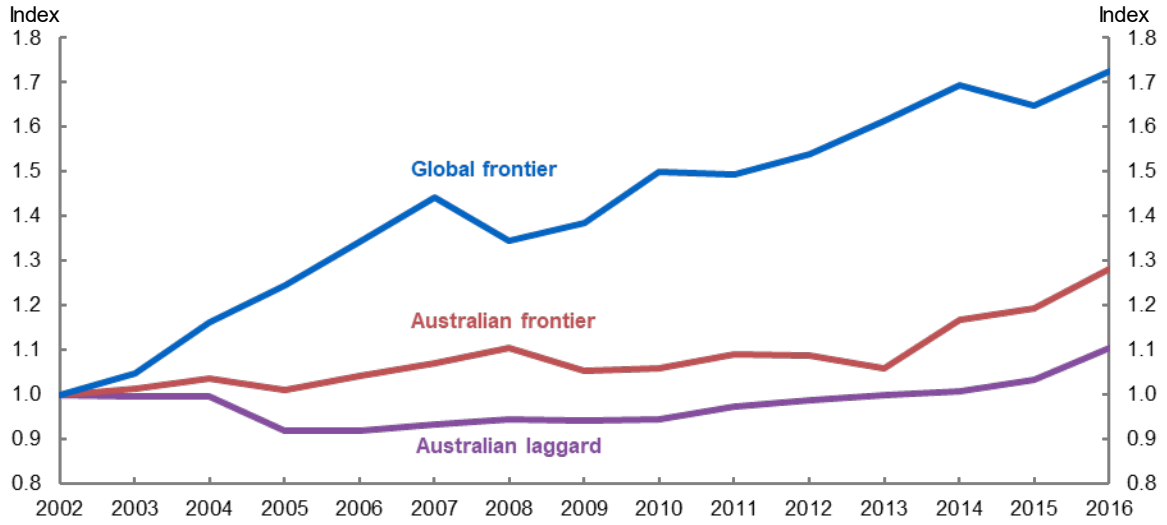
**Figure 2: Labour productivity dispersion – manufacturing sector**



Notes: See Figure 1. Manufacturing sector defined as NACE industry codes 10-33.

6 Year-to-year declines in these indices do not indicate technological regression. They can also be affected by demand induced decreases in capacity utilisation and churn in the constituent firms in each group. As such, it is best to focus on the trends.

**Figure 3: Labour productivity dispersion – services sector**



Notes: See Figure 1. Services sector defined as NACE industry codes 45-82, excluding 64-66.

While instructive, these results don't show us whether something has changed, or whether it is normal for productivity at the frontier to diverge from that of Australian firms. Assuming there is some change, the results also don't indicate whether this reflects faster growth at the frontier, a benign explanation, or slower convergence for Australian firms, a more pernicious explanation. And finally, the results don't provide any evidence on what may be driving the change. To answer these more important questions directly, we now turn to an econometric model.

## 4. ECONOMETRIC SPECIFICATION

Economic models tend to predict that, in a competitive economy, firms further from the frontier should have faster labour productivity growth, allowing them to converge towards the frontier. This generally reflects two factors:

1. Firms further behind the frontier have a larger stock of unexploited technology and knowledge to utilise;
2. Over time competitive pressures should force firms to either adopt technologies and become more productive or exit the market.

To test for this convergence, we adopt an econometric specification based on Aghion and Howitt's (1998) neo-Schumpeterian growth framework, which has been used in several empirical papers (Griffith et al, 2009; Andrews et al, 2019; Conway et al, 2016). We model firm productivity growth as a function of firm-level characteristics such as firm age, size and industry, productivity growth at the global industry frontier, and most importantly a firm's distance from the global industry frontier:

$$\Delta \ln LP_{ijt} = \beta_0 + \beta_1 \Delta \ln LP_{jt}^F + \beta_2 \ln \frac{LP_j^F}{LP_{ij,t-1}} + \gamma_{i,t} + \delta_j + \omega_t + \varepsilon_{ijt}$$

Here,  $\Delta \ln LP_{ijt}$  denotes labour productivity growth of firm  $i$  in industry  $j$  at time  $t$ ,  $\Delta \ln LP_{jt}^F$  denotes productivity growth at the global industry frontier, and  $\ln \frac{LP_j^F}{LP_{ij,t-1}}$  denotes the firm's distance from the global industry frontier in time  $t-1$ .  $\gamma_{i,t}$  represents a vector of controls for firm age and size.  $\delta_j$  are industry fixed effects that control for time-invariant factors affecting productivity growth of firms in a particular

industry.  $\omega_t$  are year fixed effects that control for shocks in a period affecting all firms, such as the business cycle.  $\varepsilon_{ijt}$  is the idiosyncratic error term.

We then add to the model by introducing industry-year fixed effects  $\varphi_{jt}$  to control for industry-specific shocks affecting all firms in that industry in a particular period. The introduction of industry-year fixed effects sweeps out the global frontier growth term  $\Delta \ln LP_{jt}^F$ , so that we estimate the model:

$$\Delta \ln LP_{ijt} = \beta_0 + \beta_1 \ln \frac{LP_j^F}{LP_{ij,t-1}} + \gamma_{i,t} + \varphi_{jt} + \varepsilon_{ijt}$$

The coefficient of interest is the coefficient on the distance to frontier term,  $\beta_1$  – the speed of convergence. A positive coefficient means that firms further from the frontier grow faster than firms close to the frontier.

We can then extend the baseline model by interacting various firm-level and industry-level characteristics with the distance to frontier term, to identify possible factors influencing this speed of convergence.

$$\Delta \ln LP_{ijt} = \beta_0 + \beta_1 \ln \frac{LP_j^F}{LP_{ij,t-1}} + \beta_2 W_{ijt} \ln \frac{LP_j^F}{LP_{ij,t-1}} + \beta_3 W_{ijt} + \gamma_{i,t} + \varphi_{jt} + \varepsilon_{ijt}$$

In this case  $\beta_2$  becomes the coefficient of interest. A positive  $\beta_2$  will indicate convergence is faster for firms, industries, or periods with a higher  $W_{ijt}$ , and a negative coefficient indicates it is slower.

## 5. RESULTS

This section provides the result from the regression analysis. The key findings are that, while firms further from the global frontier do grow more quickly and display a degree of convergence, the rate of convergence has slowed. This has been more notable amongst incumbent firms, and in sectors with declining competition and dynamism.

### 5.1. Baseline model

Column 1 of Table 1 shows the results for the baseline specification. The coefficient on the distance from frontier term in the baseline specification is positive and significant, meaning that firms further behind the global frontier experience stronger productivity growth. This result is consistent with similar studies in the United Kingdom (Griffith et al. 2009), New Zealand (Conway et al. 2016) and using cross-country data (Andrews et al. 2019).

**Table 1 – Baseline model**

	<i>Business Sector</i>		<i>Manufacturing</i>		<i>Services</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Distance from frontier</b>	0.423***	0.443***	0.468***	0.489***	0.409***	0.429***
	(0.002)	(0.003)	(0.003)	(0.006)	(0.002)	(0.004)
<b>Distance from frontier x 2005-07</b>		-0.009**		-0.019**		-0.006
		(0.004)		(0.008)		(0.005)
<b>Distance from frontier x 2008-10</b>		-0.005		-0.015*		-0.001
		(0.004)		(0.008)		(0.005)
<b>Distance from frontier x 2011-16</b>		-0.039***		-0.031***		-0.041***
		(0.004)		(0.007)		(0.004)
<b>Industry-year fixed effects</b>	Yes	Yes	Yes	Yes	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes	Yes	Yes	Yes	Yes
<b>R-squared</b>	0.209	0.209	0.230	0.230	0.203	0.203
<b>Observations</b>	1,372,576	1,372,576	331,415	331,415	1,041,161	1,041,161

Notes: Column 1 displays the results for the baseline specification, where the log of firm productivity growth is modelled as a function of the log of distance from the global frontier, with controls for firm age, size and industry-year. Column 2 displays the results for the baseline model with additional dummy variables for the 2005-07, 2008-10, and 2011-14 periods interacted with the distance from frontier term. Columns 3-4 and 5-6 estimate the same specification separately for the manufacturing sector (NACE codes 10-33) and the services sector (NACE codes 45-82, excluding 64-66), respectively. Standard errors are clustered at the firm-level and are shown in brackets underneath each estimate. \* significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

In Column 2 of Table 1, we measure how this convergence speed has changed over time, interacting the distance to frontier term with dummy variables for the 2005-07, 2008-10, and 2011-16 periods. The coefficient on the non-interacted distance to frontier term in Column 2 can now be interpreted as the convergence speed in the base period (2002-04). The coefficients on these dummy variables are negative and significant (except in the 2008-10 period), which implies that the speed of convergence has slowed over the sample. Specifically, the speed of convergence estimate at the start of the sample period is 0.443, but is around 9 per cent lower in the final period. This result is concerning, as it suggests that firms now adopt world-leading technologies and approaches, and converge to the global frontier, more slowly.

Columns 3-6 of Table 1 show that, as well as having a lower baseline convergence speed, the services sector has seen a more pronounced convergence slowdown than the manufacturing sector. This is consistent with the pattern that emerged in Figures 2-3 in our graphical results.

The next sections examine the role of declining economic dynamism and competition in contributing to the slowdown in convergence. We focus on these metrics for two broad reasons.

First, theory suggests that declining dynamism and competitive pressures could contribute to slower diffusion of technologies and productivity convergence:

- New firms may be more likely to adopt and invest in newer technologies, as they have no existing 'vintage' capital that they would need to replace. The entry of young firms can also provide an opportunity for existing firms to sell vintage capital and adopt new technologies (Ma, Murfin and Pratt 2021). Previous work has shown faster convergence amongst young firms (Berlingieri et al 2020).

- Entry of new firms and competitive pressures on incumbents can force firms to improve or exit, though increases in competition can also lower the returns to innovation (Aghion et al 2005).

Second, empirical evidence highlights the potential role of declining dynamism and competition in slower convergence and technology diffusion:

- Measures of economic dynamism and competitive pressures have declined over the same period that convergence has slowed (Andrews and Hansell 2021; Hambur 2021).
- Andrews et al (2019) found that convergence tended to be slower in markets with less competition-friendly market regulations, based on a cross-country study.

## 5.2. Business dynamism, competition and convergence

We construct measures of firm entry, exit and turnover by 2-digit industry using BLADE data. Each of measure has declined over recent years. For example, the average annual entry rate fell from 14.5 per cent to 11.5 per cent between 2004 and 2016.

Table 2 extends the baseline model by interacting industry-level firm turnover/churn, entry and exit rates with the distance to frontier variable. The results show that firms in industries with higher entry, exit and turnover rates converge more quickly to the global industry frontier. To give a sense of magnitudes, firms in a low entry industry (10th percentile of entry distribution – 8 per cent entry rate) would have a convergence speed that was speed 4.8 percentage points, or about 10 per cent, faster if their entry rate increased to be in line with a high entry industry (90th percentile of the entry distribution – 16 per cent entry rate).

**Table 2 – Turnover, entry and exit model**

	<i>Turnover</i>	<i>Entry</i>	<i>Exit</i>
	(1)	(2)	(3)
<b>Distance from frontier</b>	0.418***	0.415***	0.423***
	(0.011)	(0.012)	(0.012)
<b>Turnover rate x distance from frontier</b>	0.006***		
	(0.001)		
<b>Entry rate x distance from frontier</b>		0.009**	
		(0.003)	
<b>Exit rate x distance from frontier</b>			0.0146***
			(0.00346)
<b>Industry-year fixed effects</b>	Yes	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes	Yes
<b>R-squared</b>	0.210	0.210	0.210
<b>Observations</b>	1,372,576	1,372,576	1,372,576

Notes: Table 3 extends the baseline model by interacting industry-level firm turnover, entry, and exit rates with the distance from frontier term. The coefficients on the interaction terms estimate the additional convergence speed associated with a 1 percentage point increase in turnover, entry and exit rates. The interpretation of the coefficient on the distance to frontier term is slightly different in Table 2, as the distance to frontier variable and the turnover, entry and exit rates have been demeaned for ease of interpretation. For example, Column 2 implies that an industry with the average firm entry rate has an estimated convergence speed of 0.415. Standard errors are clustered at the industry-level and are shown in brackets underneath each estimate. \*significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

We previously posited that young firms are likely to converge more quickly to the global frontier than mature firms, given they can adopt new technologies from a blank slate. Table 3 confirms this assertion:

within size categories, young firms do converge more quickly to the global frontier than mature firms.<sup>7</sup> Moreover, while smaller firms converge more quickly than large firms, firm age has a larger impact on the rate of convergence. This is evident as the coefficient on the interaction between age and frontier are large, compared to the gap between the coefficients on un-interacted distance to the frontier variables across columns (particularly for small and medium firms).

**Table 3 – Convergence and firm age**

	<i>Small</i>	<i>Medium</i>	<i>Large</i>
	(1)	(2)	(3)
<b>Distance from frontier</b>	0.420***	0.394***	0.363***
	(0.002)	(0.004)	(0.031)
<b>Young</b>	0.012***	-0.00186	0.026
	(0.001)	(0.00283)	(0.029)
<b>Young x distance from frontier</b>	0.030***	0.037***	0.133**
	(0.002)	(0.005)	(0.058)
<b>Industry-year fixed effects</b>	Yes	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes	Yes
<b>R-squared</b>	0.213	0.199	0.319
<b>Observations</b>	1,135,386	234,114	3,076

Notes: Table 4 extends the baseline model by including a ‘young’ dummy variable as well as interacting this young dummy variable with the distance from frontier term. A firm is labelled as ‘young’ if it is less than 5 years old and labelled as ‘mature’ otherwise. Column 1 runs this model on a sub-sample of ‘small’ firms, column 2 runs the model on a sub-sample of ‘medium-sized’ firms, and column 3 runs the same model on a sub-sample of ‘large’ firms. The coefficient on the distance from frontier term can now be interpreted as the convergence speed for mature firms. \*significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

Given the importance of firm age, a natural question might be, could the slower rate of convergence simply reflect the declining share of young businesses in the Australian economy (as documented in OECD 2021)?

To consider this, we run the model from Column 2 of Table 1 separately for young and mature firms. Table 4 shows the results. Focusing only on mature firms there is still evidence of a slowdown in the speed of convergence. This indicates that the earlier results do not simply reflect compositional shift in the Australian economy away from faster converging young firms. In fact, the slowdown is only evident for older firms. Taken together with the earlier results, this could suggest that declining entry rates have lowered the competitive pressures faced by incumbents, thereby lowering their incentives to adopt and improve.

7 Size categories are defined as follows: firms with 1–19 full-time equivalent employees are labelled as small, firms with 20–200 full-time equivalent employees are labelled as medium-sized, and firms with more than 200 employees are labelled as large.

**Table 4 – Convergence slowdown on separate samples**

	<i>Full Sample</i>	<i>Mature Firms</i>	<i>Young Firms</i>
	(1)	(2)	(3)
<b>Distance from frontier</b>	0.443***	0.432***	0.463***
	(0.003)	(0.004)	(0.006)
<b>Distance from frontier x 2005-07</b>	-0.009**	-0.011**	0.000
	(0.004)	(0.005)	(0.007)
<b>Distance from frontier x 2008-10</b>	-0.005	-0.010**	-0.018**
	(0.004)	(0.005)	(0.007)
<b>Distance from frontier x 2011-16</b>	-0.039***	-0.047***	-0.001
	(0.004)	(0.005)	(0.007)
<b>Industry-year fixed effects</b>	Yes	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes	Yes
<b>R-squared</b>	0.209	0.197	0.243
<b>Observations</b>	1,372,576	996,829	375,747

Notes: Table 5 extends the baseline model by interacting the distance from frontier term with dummy variables for the 2005-07, 2008-10, and 2011-14 periods. Column 1 runs this model on the full sample. Column 2 runs the model on a sub-sample of mature firms. Column 3 runs the model on a sub-sample of young firms. The coefficient on the distance from frontier term can now be interpreted as the convergence speed in the base period (2002-04). Standard errors are clustered at the firm-level and are shown in brackets underneath each estimate. \*significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

This conclusion is also supported by re-running the earlier entry regression on a sub-sample of incumbent firms (Table 5). For these firms, convergence is slower when entry rates are lower, suggesting entry may affect convergence by intensifying competitive pressures on incumbents.

**Table 5 – Convergence and entry on separate samples**

	<i>Full Sample</i>	<i>Incumbent Firms</i>
	(1)	(2)
<b>Distance from frontier</b>	0.415***	0.401***
	(0.012)	(0.012)
<b>Entry rate x distance from frontier</b>	0.009***	0.008***
	(0.003)	(0.003)
<b>Industry-year fixed effects</b>	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes
<b>R-squared</b>	0.210	0.197
<b>Observations</b>	1,372,576	996,829

Notes: Table 6 extends the baseline model by interacting industry-level entry rates with the distance from frontier term. Column 1 runs this model for the full sample. Column 2 runs this model for the sample of incumbent firms. The distance from frontier and firm entry variables have been demeaned for ease of interpretation. The coefficient on the distance from frontier term can now be interpreted as the convergence speed for firms in an industry with the average firm entry rate. The interaction term can be interpreted as the additional convergence speed associated with a 1 percentage point increase in the firm entry rate. Standard errors are clustered at the industry-level and are shown in brackets underneath each estimate. \*significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

To test this more formally, we incorporate a direct measure of competitive pressure, mark-ups as estimated in Hambur (2021). These measure the ratio of a firm's sales price over their marginal cost of production and should capture the level of market power accruing to firms. They have increased over the past decade indicating decreasing competitive pressures in the Australian economy.

The firm-level mark-ups are aggregated to the industry level using either an unweighted average or a sales-weighted average. They are then interacted with the distance to the frontier, as was done with the measures of dynamism.<sup>8</sup>

Consistent with expectations, the rate of convergence declines as industries' mark-ups increase, as evidenced by the negative and significant coefficient on the interaction between mark-ups and distance to the frontier (Table 6). This provides more direct evidence that declining competitive pressures can explain some of the slowing in convergence observed in Australia.

**Table 6 – Convergence and industry mark-ups**

	<i>Unweighted mark-ups</i>	<i>Sales-weighted mark-ups</i>
	(1)	(2)
<b>Distance from frontier</b>	0.349***	0.390***
	(0.039)	(0.003)
<b>Industry level markup x distance from frontier</b>	-0.310***	-0.116***
	(0.057)	(0.019)
<b>Industry-year fixed effects</b>	Yes	Yes
<b>Firm age and size controls</b>	Yes	Yes
<b>R-squared</b>	0.212	0.212
<b>Observations</b>	1,270,768	1,270,768

Notes: Table 5 extends the baseline model by interacting industry-level mark-ups with the distance from frontier term. Column 1 runs this model for unweighted averages of the firm mark-ups. Column 2 runs this model for sales-weighted averages of the firm mark-ups. The mark-up variables are demeaned for ease of interpretation. The coefficient on the distance from frontier term can now be interpreted as the convergence speed for firms in an industry with the average markup. The interaction term can be interpreted as the additional convergence speed associated with a 1 percentage point increase in the firm entry rate. Standard errors are clustered at the industry-level and are shown in brackets underneath each estimate. \*significant at 10% level, \*\* significant at 5% level, \*\*\* significant at 1% level.

### 5.3. Quantifying the effect of declining dynamism and productivity

The previous section shows that in less dynamic or competitive industries firms appear to adopt new technologies and converge to the productivity frontier more slowly. Moreover, we know that measures of competitive pressures and dynamism have declined. So the natural question is, how much of the slowdown in productivity convergence can be explained by declining dynamism and competition?

To consider this, we do a simple counterfactual. For each firm we calculate the implied convergence rate based on the earlier models and the observed mark-ups, or dynamism rate, as well as the rates implied by the model had mark-ups or dynamism remained at 2004 levels. We can then compare these two estimates:

$$\text{Convergence rate}_{i,t}^{\Delta\mu} = \beta_1 + \beta_2 * \mu_{j,t}$$

$$\text{Convergence rate}_{i,t}^{\text{Cons}\mu} = \beta_1 + \beta_2 * \mu_{j,2004}$$

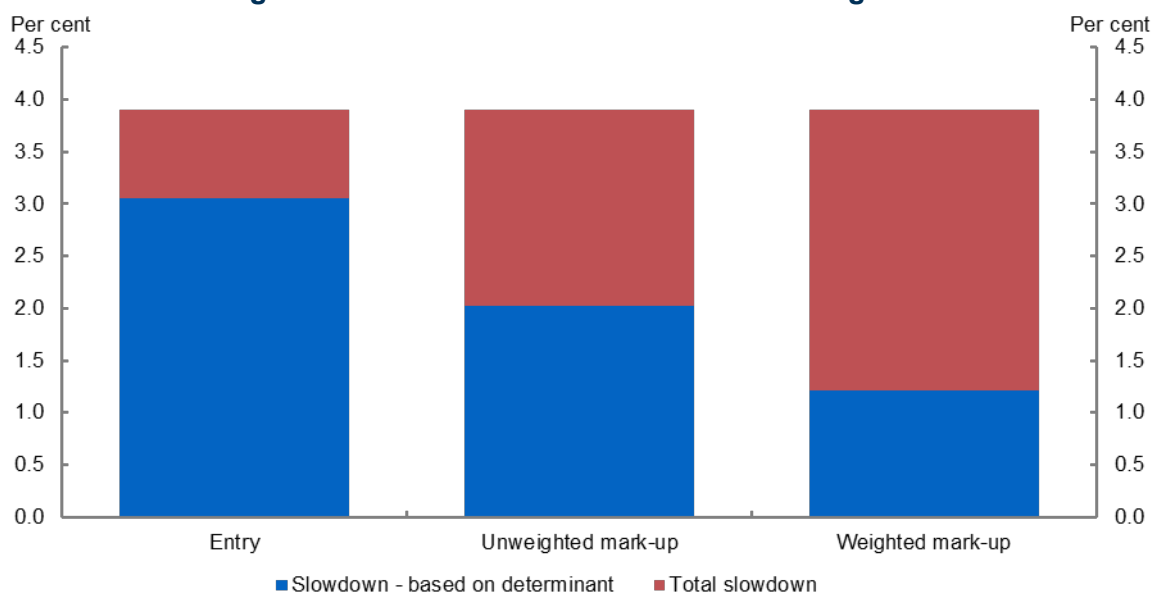
The results of this exercise are shown in Figure 4. The decline in entry rates can account for around a 3 percentage points of the slowdown in the convergence rates, or around ¼ of the slowdown, while the increase in mark-ups can account for between 1¼-2 percentage point slowdown in the rate of

8 The main difference is that we also include a term for industry interacted with distance to the frontier. This accounts for the fact the level of mark-ups may not be well identified, though changes will be (see Hambur 2021 for a discussion). Not including this additional term does not change the results substantially.



convergence, or around  $\frac{1}{2}$ - $\frac{2}{3}$  of the slowdown. While this is a simple exercise, it demonstrates that the decline in dynamism and competitive pressures have substantially lowered the rate of firm-level productivity convergence, and therefore productivity growth.

**Figure 4 – Drivers of the slowdown in convergence**



Notes: Figure shows total slowdown in convergence rate for 2011-2016 period based on Table 2 Column 2, as well as the portion of the slowdown explained by the entry rate, and mark-ups, using methodology discussed in section 5.3. Later component is shown for 2016, rather than for 2011-2016 average.

## 6. CONCLUSION

This paper exploits a novel dataset merging international microdata from OECD-Orbis with Australian microdata from BLADE to analyse the performance of Australian firms relative to the global frontier. We show that the gap between the global frontier and Australian firms has grown over time, and Australian are catching-up more slowly. This suggests that Australian firms have become slower to adopt, innovate and improve their productivity performance, which can explain part of the slowdown in aggregate productivity growth since the mid-2000s. Similar, dynamics have been observed overseas

Our results also show that slower catch-up and diffusion partly reflect declining business dynamism and competitive pressures. The motivates further research into the causes of the decline.

From a policy perspective the results also suggest that policies that remove barriers to business dynamism and competitive pressure can encourage firms to catch up to the global frontier, thereby improving aggregate labour productivity performance. Policies that facilitate more widespread adoption of emerging digital technologies can also play a role in improving productivity performance.

Understanding changes in productivity post-2016 and within the context of the COVID pandemic will be important research questions to pursue as data become available. Various data sources collected over this period have shown that Australian businesses have invested more in digitisation and innovative business practices, with the pandemic sparking an increase in technological adoption. This increased adoption of new technology will help Australian firms become more competitive in the global market and support future productivity growth. Worker mobility has also increased in recent times, leading to better matches between workers and employers. While much of this activity likely reflects delayed labour market movements due to the pandemic; continued labour market dynamism will also contribute to future productivity growth.

## REFERENCES

- Aghion P, N Bloom, R Blundell, R Griffith and P Howitt 2005, 'Competition and Innovation: An Inverted-U Relationship', *The Quarterly Journal of Economics*, 120(2), pp 701-728.
- Akcigit U and ST Ates (2019), 'What happened to US Business Dynamism?', *NBER Working Paper* No. 25756.
- Andrews D, C Cricuolo and PN Gal (2019), 'The Best versus the Rest: Divergence across Firms during the Global Productivity Slowdown', *CEP Discussion Paper* No. 1645, August 2019.
- Andrews D and D Hansell (2021), 'Productivity-enhancing Labour Reallocation in Australia', *The Economic Record*, 97(317), pp 157-169.
- Bartelsman E, J Haskel, and R Martin (2008), 'Distance to which Frontier?: Evidence on Productivity Convergence from International Firm-level Data', *Centre for Economic Policy Research Working Paper* No. 7032.
- Berlingieri G, S Calligaris, C Criscuolo and R Verhac (2020), 'Laggard firms, technology and its structural and policy determinants', *OECD Science, Technology and Industry Policy Papers* No. 86.
- Brynjolfsson E and McAfee A (2011), 'Race Against The Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy', Digital Frontier Press.
- Foster, L., Haltiwanger J and Syverson C (2008), 'Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?' *American Economic Review*, 98(1), pp 394-442.
- Gal PN (2013), 'Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS', *OECD Economics Department Working Papers* No. 1049, OECD, Paris.
- Goldin I, P Koutroumpis, F Lafond and J Winklet (2021), 'Why is Productivity slowing down?', *Oxford Martin School Working Paper Series on Economic and Technological Change* No. 2021-6, May 2019.
- Gordon, RJ (2012), 'Is US Economic Growth Over? Faltering Innovation Confronts Six Headwinds', *NBER Working Paper* No. 18315, August 2012.
- Griffith R, S Redding and H Simpson (2009), 'Technological Catch-Up and Geographic Proximity', *Journal of Regional Science*, 49(4), pp 689-720.
- Iacovone L and GA Crespi (2010), 'Catching up with the technological frontier: Micro-level evidence on growth and convergence', *Industrial and Corporate Change*, Vol. 19, No. 6, pp 2073-2096.
- Inklaar R and Timmer MP (2014). 'The Relative Price of Services', *Review of Income and Wealth*, 60(4), pp 727-746.
- Hambur J (2021), 'Product market power and its implications for the Australian economy', *Australian Treasury Working Paper* No. 2021-03.
- Jovanovic B and PL Rousseau (2005), 'General Purpose Technologies', *Handbook of Economic Growth*, Chapter 18, Vol. 1(B), pp 1181-1224.

Ma S, J Murfin, R Pratt (2021), 'Young firms, old capital', *Journal of Financial Economics*, Online Access 24 September 2021.

Mokyr J (2013), ['Is technological progress a thing of the past?'](#), VoxEU column, 8 September 2013.