PRODUCT MARKET POWER AND ITS IMPLICATIONS FOR THE AUSTRALIAN ECONOMY

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ABSTRACT

This paper documents the evolution of firm mark-ups in the Australian economy using a large and representative database derived from administrative tax data. I find that mark-ups have increased by around 5 per cent since the mid-2000s, which is less than previously documented for Australia, and slightly less than has been documented for the average advanced economy. While part of this appears to reflect technological change, there also appears to have been an increase in market power and decline in competition over the period. This increase in market power appears to explain part of the slowdown in productivity growth observed in Australia over the past decade, as it has been associated with slower efficient reallocation of resources from low-productivity to high-productivity firms.

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1. INTRODUCTION

Recent work has demonstrated that the slowdown in productivity growth in Australia has been underpinned by a decline in economic dynamism. For example, Andrews and Hansell (2019) find that the pace at which labour is reallocated from low- to high-productivity firms slowed since 2012, and that this can account for ¼ of the slowdown in productivity growth from 2012 to 2016. At the same time, other measures of dynamism, such as job switching rates and firm formation rates, have also declined (Quinn 2019). Given the important role competition plays in promoting dynamic and efficient markets it is natural to ask, has market power increased in Australia and could this account for declining dynamism, and slower productivity and wage growth?

Australia is not unique in this respect. Similar worrisome macroeconomic trends have been documented in a number of other countries. These include: soft investment growth despite declines in interest rates and funding costs (IMF 2019); slower adoption of world-leading technologies (Andrews et al 2019; Akcigit and Ates 2019); declining firm entry rates (Gutiérrez and Philippon 2019) and slower efficient reallocation of resources (Decker et al 2017).

This has led to an explosion of research globally into market power with numerous papers documenting increases in measures of market power such as mark-ups, industry concentration and entrenchment of industry leaders. However, the evidence for Australia is sparse. In particular, the only paper that documents mark-ups (my preferred measure of market power) for Australian firms is De Loecker and Eeckhout (2018). They find that mark-ups rose by a bit over 10 per cent between the early 2000s and 2016 (and by around 50 per cent between 1980 and 2016). However, this analysis — while seminal — uses a fairly limited set of listed firms in its analysis, so it is difficult to draw economy-wide conclusions.[3]

Accordingly, in this paper I provide new evidence on firms' market power in Australia, as captured by their mark-ups, and how this has changed over time. To do so, I use a comprehensive firm-level database from the Business Longitudinal Analysis Data Environment (BLADE). As these data cover almost all firms in Australia, the results are likely to be highly representative, and so provide important insights into the evolution of market power in Australia. To the best of my knowledge, this is the first such attempt for Australia using highly representative data.

First, I document that firms' mark-ups have increased by around 5 per cent on average since the mid-2000s, reflecting fairly broad-based increases across most firms. The magnitude of the increase is substantially smaller than that previously documented in De Loecker and Eeckhout (2018). It is also slightly smaller than the average increase documented in other advanced economies (IMF 2019). This latter finding could reflect differences in the policy environment, and is somewhat consistent with Australia's fairly high ranking in OECD measures of product market regulation.

I then evaluate competing explanations for the rise in mark-ups, with a view to better understanding the potential economic implications. Part of the increase appears to reflect technological factors, such as greater reliance on 'fixed' costs that firms need to recoup — such as investments in branding, processes and other intangibles — or other technological changes like outsourcing of certain functions. Consistent with this, mark-ups rose by more than twice as much in the most 'digitally intensive' quartile of industries, where investments in intangible investment and fixed costs are more important. However, even accounting for such costs, mark-ups have still increased, and increases have still been evident in sectors that are less digitally intensive.

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3   Hambur and La Cava (2018) document a rise in mark-ups using a more representative dataset, but they focus on the retail sector.

Higher mark-ups also appear to be symptomatic of less competitive pressures, as they are associated with weaker (within-industry) productivity-enhancing labour reallocation. This has significant implications for aggregate productivity growth, with a simple counterfactual exercise suggesting that higher mark-ups, and associated slower reallocation, can explain one fifth of the slowdown in non-financial market sector labour productivity growth. Declining competitive pressures are also likely to have weighed on productivity through decreased incentives to innovate, invest and adopt world-leading technologies, which can be explored in future work (Andrews et al forthcoming).

From a policy perspective, it is important to understand why market power has increased, and therefore whether any policies can and should be used to address the increase.[4] For example, competitive pressures could decline due to regulatory burdens on entry, or financing frictions that prevent new and innovative firms from entering, growing and challenging incumbents. Competition policy, and in particular how it relates to the growing use of data and digital platforms in business, could also be important. I leave to future research a more detailed analysis of the drivers of the rise in market power, and how these might differ between sectors. But this paper nevertheless brings into closer focus hurdles to competition, and highlights the importance of making policy with competition in mind.

This focus on competition is likely to become even more relevant as the economy recovers from the COVID-19 economic shock. Small young firms are known to be more exposed to shocks, suggesting that large incumbents may gain market share and market power as a result of COVID-19 (e.g. Fort et al 2017; OECD 2020). Moreover, having structural policy settings that help to facilitate productivity and growth will be crucial in supporting a quick and sustained recovery from such a shock (Dieppe et al 2020).

Besides the Australia-specific results, this paper also contributes to the broader literature on mark-ups and market power by using a highly representative dataset that allows me to test many of the assumptions used in the estimation of mark-ups elsewhere in the literature. These methodological contributions are outlined and discussed in more detail in Appendices A and C. But at a high level, the key takeaway is that combining labour and other intermediate inputs, as is common in the literature, can have substantial effects on mark-up estimates.

The remainder of the paper is structured as follows. Section 2 provides further motivation for examining market power, including a discussion of the overseas literature and the Australian evidence. Section 3 goes on to document mark-ups in the Australian economy, while Section 4 examines the implications of rising mark-ups for the Australian economy. Section 5 then concludes.

2. BACKGROUND AND MOTIVATION

2.1 International literature and evidence

In recent years there has been a growing focus amongst macroeconomists and policymakers on the role of market power in determining macroeconomic outcomes. In particular, numerous papers have documented increases in measures of market power, including mark-ups, industry concentration and industry leader entrenchment.

For example, De Loecker et al (2020) finds evidence of a substantial increase in mark-ups in the US since the 1980s, though Traina (2018) disputes the magnitude of the increase. Meanwhile, De Loecker and Eeckhout (2018) and Diez et al (2019) document substantial increases in mark-ups globally over the past three decades. Several papers have also documented increases in the degree of industry concentration,

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4   As discussed in Edmond et al (2019), many polices aimed at reducing mark-ups and market power could actually be harmful to the economy.

including Autor et al (2020) and Grullon et al (2019) for the US, and Bajgar et al (2019) for Europe and North America.

This heightened interest in market power has been prompted by a number of worrisome macroeconomic trends, which can potentially be explained by increasing market power amongst firms (IMF 2019). These trends include:

- Declines in the share of income being paid to labour and capital (Karabarbounis and Neiman 2014; Barkai 2019);

- Low rates of investment despite low capital costs (Gutiérrez and Philippon 2017);

- Slower diffusion of technologies (Andrews et al 2019);

- Less efficient reallocation of resources to efficient firms (Decker et al 2017), and declining labour market dynamism more generally; and

- Declining firm entry rates (Gutiérrez and Philippon 2019).

Increasing market power has the potential to explain all of these phenomena. As discussed in more detail below, market power allows firms to charge prices that are above their marginal costs of production. As prices are above the cost of production, the firm is able to earn 'excess economic' profits. That is, they make profits beyond what is required to pay labour, capital and other factors of production. Accordingly, these profits are often referred to as the 'profit share' of income, as they are additional income that is not paid to other factors. Mechanically, this lowers the share of income payable to other factors such as labour. Barkai (2019) demonstrates that the profit share in the US has increased, and links this to increasing market power and mark-ups.

The relationship between competition, and investment, innovation and technology adoption is more complicated. In many models, greater competition can lead to more or less innovation and investment, depending on the exact market structure (e.g. Aghion et al 2005). Weak competition can raise the potential profits from innovation and thus incentivise more innovative activity. But it can also blunt incentives to innovate and adopt, particularly if there is a large gap between the best and worst firms. Relatedly, Perla et al (2019) show the rate of technology adoption tends to increase when there is more competition from overseas.

While the theoretical predictions are somewhat ambiguous, numerous recent papers have found empirical links between competition, and investment, innovation and technology adoption. For example, Gutiérrez and Philippon (2017a, b) find that investment has been weaker than would be expected in less competitive industries, particularly for larger firms. Andrews et al (2019) finds that the rate at which laggard firms catch up to the global productivity frontier, an indicator the pace of technology adoption, is slower in industries that have had fewer pro-competitive reforms.

Increased market power can also potentially explain the fact that the pace at which resources are reallocated from less to more productive firms has slowed. For example, in many models higher market power and mark-ups are associated with less pass-through of changes in costs onto prices and quantities (e.g. De Loecker et al 2021). As such, the pass-through of productivity shocks to actual production, and therefore to the quantity of inputs, will be lower, meaning less efficient reallocation of resources in response to such shocks. From a more intuitive stand-point, if markets are less competitive, there will be less pressure for low productivity firms to shrink and exit the market, freeing up resources for more productive firms (Covarrubias et al 2019).

Finally, regarding firm entry rates, to the extent that increased market power relates to greater barriers to firm entry, the two will be necessarily linked. Gutiérrez and Philippon (2019) find some evidence that

such barriers have increased, as firm entry rates appear to have become less responsive to measures of industry profitability.

Nevertheless, it is important to note that numerous papers have argued that the documented increases in measures of market power could reflect other, more benign factors. For example, Autor et al (2020) argue that increases in measures of concentration and mark-ups reflect an *increase* in competition, which benefits the most productive firms as it drives out others. This leads to a reallocation of resources towards these productive firms who tend to have higher mark-ups, and so raises aggregate mark-ups.[5]

Others have argued that the documented increases reflect changes in technology, such as the increasing importance of intangible capital and other types of fixed costs, which lead to increasing returns to scale (e.g. Haskel and Westlake 2017). These greater returns to scale inevitably lead to larger firms, and so could account for greater industry concentration and potentially also higher mark-ups, particularly if firms need to charge mark-ups to cover their fixed outlays. This explanation for the documented increase in measures of market power is relatively benign, and could also account for many of the trends in dynamism that have been documented in the literature. However, to the extent that firms raise their mark-ups as they grow, which is the case in many models (e.g. Edmond et al 2019; De Loecker, Eeckhout and Mongey 2019), or can then use their scale to erect barriers to entry in the future, it is not entirely benign.

2.2 Australian evidence

As noted in the introduction, there is very little work documenting mark-ups amongst Australian firms. That said, there is some more indirect evidence that market power in Australia may have increased.

Some of this evidence relates to the potential macroeconomic effects of increased market power: investment has been weak, despite declines in funding costs (Van der Merwe et al 2018); the pace at which firms adopt world-leading technologies appears to have slowed (Quinn 2019; Andrews et al forthcoming); measures of labour market dynamism have declined (Figure 1 Panel A); reallocation of resources to more productive firms has slowed (Andrews and Hansell 2019; Figure 1 Panel B); and pass-through of firm-level profitability shocks to worker wages has declined (Andrews et al 2019). As discussed above, all of these trends could potentially reflect increased market power. Moreover, they all have substantive implications for productivity and wages.

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5   Baqaee and Fahri (2019) find evidence that allocative efficiency in the US has increased alongside increases in mark-ups, which would be consistent with this hypothesis.

Figure 1: Measures of Firm Dynamism

Early 2000s ■ Recent ■

2003 ■ 2016 ■

Employment growth gap
(*high vs low productivity firm*)

Exit probability gap
(*low vs high productivity firm*)
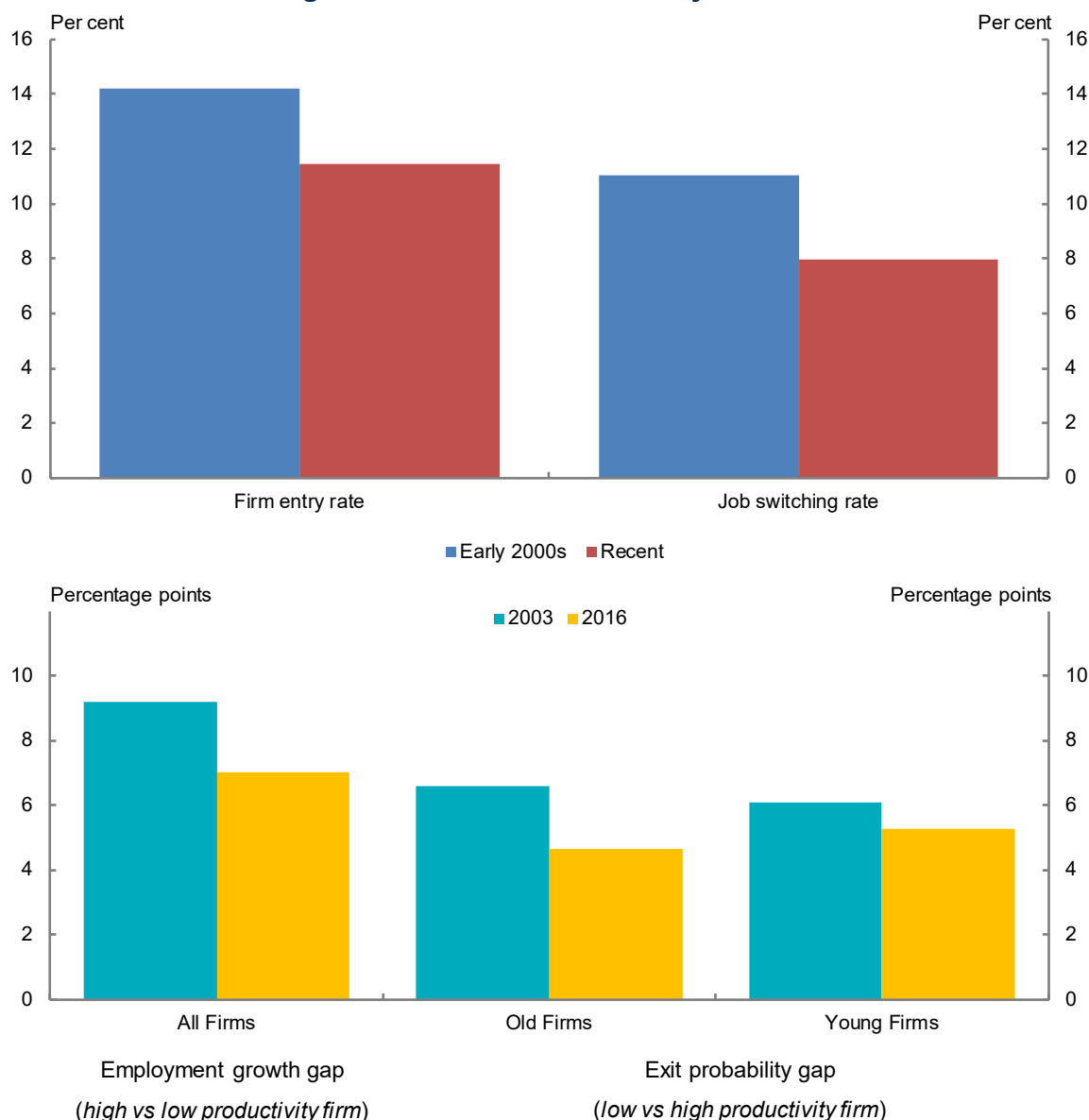
Note: In Panel A, early 2000s refers to 2002/03-2004/05. Recent refers to 2013/14-2015/17. Firm Entry rates are rates of entry for employing firms from ABS Cat. No. 8165.0 — Counts of Australian Businesses, including Entries and Exits. Job switching rate is from Deutscher (2019). Panel B shows the implied difference in growth and exit rates between high and low productivity firms across time. For more details, see Andrews and Hansell (2019).

Some papers have also found evidence that Australian industries have become more concentrated (Hambur and La Cava 2018; Bakhtiari 2019), which might be indicative of rising market power. This is confirmed in Figure 2, where I define concentration as the share of sales accruing to the largest 4 firms in an industry (4-digit ANSZIC industry). Doing so, I find that concentration has increased by around 2 percentage points since the mid-2000s (Panel A). This is smaller than the increases documented for Europe and North America over this period (Bajgar et al 2019). There is also some evidence that concentration is lower when measured using employment, and has potentially displayed a smaller increase, which is indicative of increasing mark-ups (Edmond et al 2019; see Appendix D).

Australian industries are also generally more concentrated than those in the US (Panel B). Though as I discuss below, this does not necessarily mean that firms have greater market power, given measures of concentration can have some drawbacks.

Figure 2: Share of Sales in Industries Made by Largest 4 Firms

Panel A: Average cumulative change in shares of largest 4 firms in an industry

Percentage points

Percentage points

Sales-weighted — Unweighted
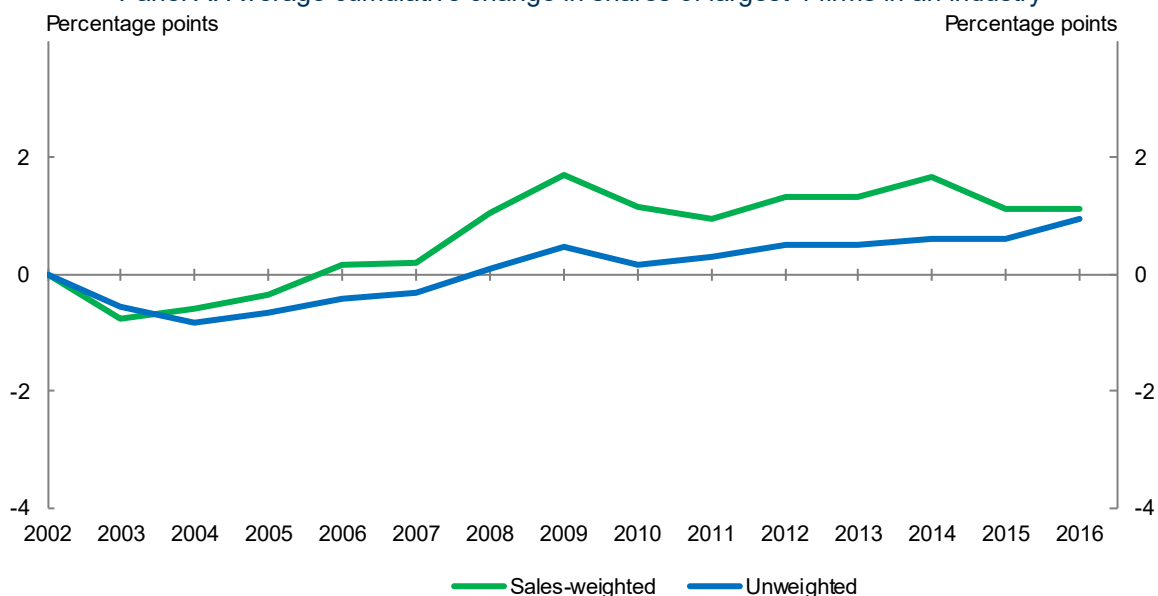
Panel B: Sales-weighted levels, by sector, 2012

Per cent

Per cent

■ United States ■ Australia
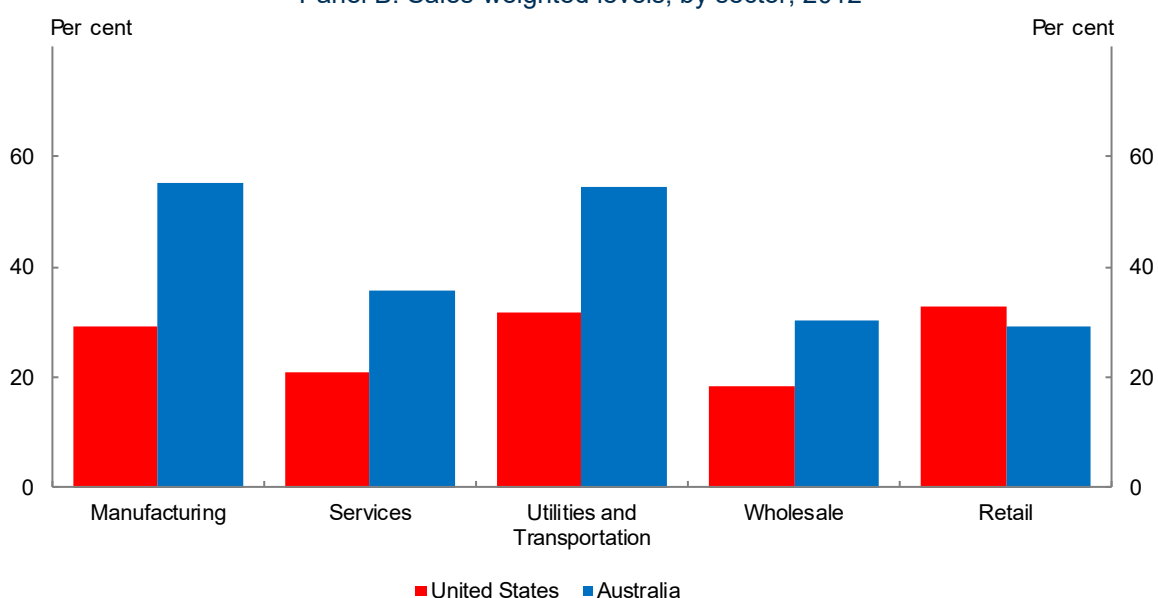
Note: Panel A takes the yearly changes in the share of sales accruing to the largest 4 firms in an industry and aggregates it using either an unweighted average, or the size of the industry in sales. These changes are cumulated over time. Panel B takes the share of sales accruing to the largest 4 firms in an industry, and creates a sales-weighted average of these metrics for each sector. Data for Australia come from ABS BLADE based on Treasury calculations. Services includes industries in the following ANZSIC divisions: Accommodation & Food Services; Information, Media & Technology; Rental Hiring and Real Estate; Professional, Scientific and Technical Services; Administrative Services, Art and Recreation Services; and Other Services. US data from US Census Bureau.

Moreover, not only do the largest firms account for an increasingly large share of industry sales, these firms have become more secure in their place at the top of the pile. To demonstrate this, I look at each industry in Australia and ask, of the top 4 largest firms in the industry, how many drop out in 3 or 5 years' time? This is relevant as a highly concentrated industry could still be quite competitive if there was a lot of churn amongst the leaders, with new firms growing and displacing the incumbents. However, it may be more concerning if the industry is concentrated and stagnant.

On average across industries, the probability of a top firm being displaced within 3 or 5 years has declined by around 5 percentage points, with this decline being statistically significant (Figure 3). So if I was a top

firm in 2003, there was about a 60 per cent chance I would still be at the top in 2008. But if I was a top firm in 2010, there was a 65 per cent chance I was still at the top in 2015. This increased entrenchment has been fairly broad-based across different sectors of the economy.

Figure 3: Share of Largest 4 Firms in an Industry not in the Top 4 X Years later
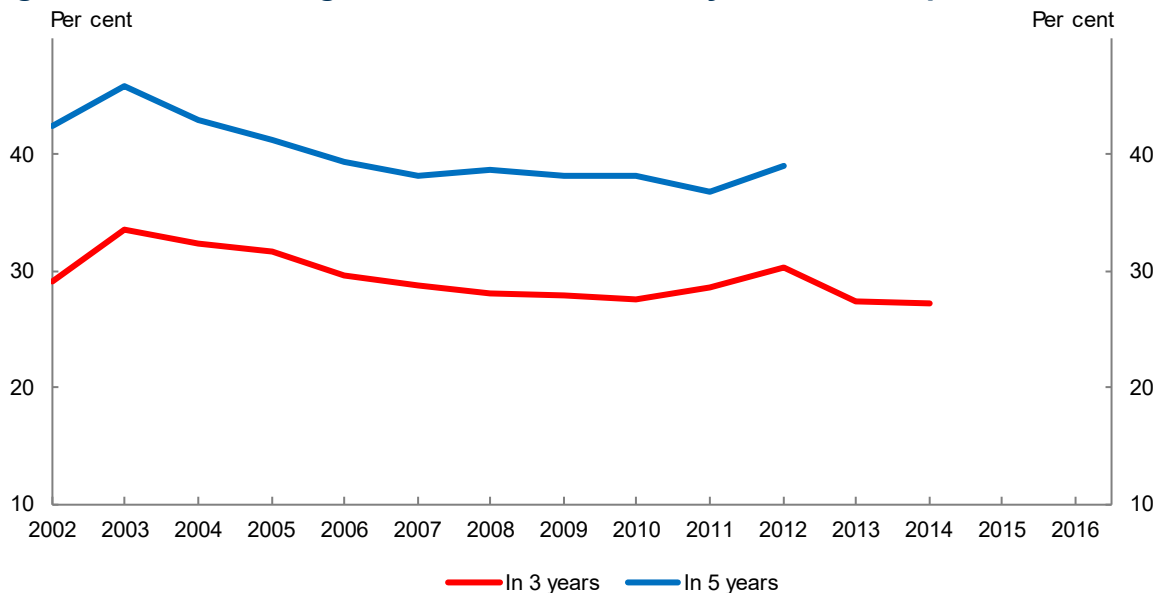
Note: For each industry, the largest 4 firms are identified. The proportion of these no longer amongst the largest 4 in 3 or 5 years' time is calculated. An unweighted average is then taken across the industry metrics. Treasury calculations based on ABS BLADE.

Nevertheless, as discussed in detail in Syverson (2019) and OECD (2018), industry concentration is an imperfect proxy for market power. For example, in thinking about market power the relevant concentration metric is concentration in the market for a particular product. Equating industries and markets abstract from the fact that firms can produce multiple different goods, and markets might have a geographic dimension, especially for less tradeable goods where people have to procure the good or service locally. In fact, some recent research has found that industry concentration in the US has been decreasing when geographic aspects are accounted for, at the same time that concentration has been increasing at a national level. The authors argue that this reflects the rise of large chain stores that raise concentration at the national level, but actually lower it at a local level by entering new markets and competing with local incumbent firms (Rossi-Hansberg et al 2019). Similar dynamics could potentially be at play in Australia. Moreover, even abstracting from the definition of a market, concentration is only a relevant measure of market power under certain competitive structures.[6]

Given these potential issues, I take the evidence on concentration as instructive, but focus on measures of mark-ups for the remainder of this paper. That said, similar analysis to that performed in Section 5 suggests that the concentration metrics are a reasonable proxy for competition, at least in certain industries (Appendix D).

3. MEASURING MARKET POWER

Product market power is defined as the ability of a firm to influence the price at which it sells its product (e.g. Pindyck and Rubinfeld 2012; Syverson 2019). It is therefore directly related to the elasticity of a firm's (residual) demand curve. If the demand curve is very elastic, the firm has little ability to influence

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6   Specifically, it will be appropriate if we assume the market is a Cournot oligopoly.

prices (without very large changes in quantities), and so has little market power. On the other hand, if the firm has a very inelastic demand curve, it has more power to change prices, and therefore more market power.

Unfortunately, the elasticity of a firm's demand curve is not observable. As such, economists use proxies to try to measure market power. One proxy that is increasingly popular in the literature is the firm's mark-up, or the ratio of its price to its marginal cost of production. I focus on this proxy for the remainder of this paper.

Mark-ups have a number of advantages over other proxies, such as measures of market or industry concentration:

- In measuring mark-ups we do not need to define a market. Rather, we can focus directly on the behaviour of the firm itself.

- Mark-ups are directly related to the elasticity of the demand function, and are therefore a more theoretically sound measure of market power.

- Unlike measures of economic or excess profits, in measuring mark-ups we do not have to estimate returns to capital, which can be difficult and subject to many assumptions.

Nevertheless, there are some downsides to using mark-ups. In particular, they are difficult to measure. It is rare, even in firm-level data sets, to observe firm-level prices. And it is even rarer to observe firm-level marginal costs of production. As such, mark-ups need to be estimated, rather than directly measured.

To estimate mark-ups, I follow the approach proposed by De Loecker and Warzynski (2012). This approach relies on the observation that, under fairly mild assumptions, firm i will optimally set its mark-up μ_i to be proportional to: its output elasticity with respect to a flexible input m ($\alpha_{i,m}$); and the expenditure on that input ($P_m M_i$), as a share of sales income ($P_i Y_i$). So:

$$\mu_i = \alpha_{i,m} \bigg/ \frac{P_m M_i}{P_y Y_i}$$

The intuition behind the result is as follows. In theory, a firm in a perfectly competitive market sets its price equal to the marginal cost of producing one more unit. This implies that the share of revenue that the firm spends on each input is equal to the elasticity of output with respect to that input (i.e. how much additional output is produced if the firm employs an extra unit of the input). In contrast, a firm with market power will tend to set its price at a higher level, which includes a mark-up over the marginal cost of producing another unit, to make a larger profit. As they set a higher price, the firm will tend to produce and sell fewer goods, and so will employ less of the input. The combination of a higher price and fewer inputs means that the amount spent on the input declines as a share of revenue. As such, as mark-ups rise, the amount spent on the good as a share of revenue will decline.

Firm sales can generally be observed in firm-level datasets, as can their expenditure on different inputs. However, their output elasticity cannot be observed. De Loecker and Warzynski (2012) suggest taking these elasticities from production functions, which can be estimated using various methods proposed in the literature.

In doing so, I need to make a number of decisions including the estimation technique and the functional form of the production function (see Box A for a brief overview, and Appendix A for a detailed discussion). In Appendix C I show that the key finding that mark-ups have increased is robust to such choices.

4. DATA

The data I use for this paper come from the ABS's Business Longitudinal Analysis Data Environment (BLADE). This is a longitudinal data set of administrative tax data matched to ABS surveys for (almost) the entire population of firms in Australia.

The particular data I use come from firms' Business Income Tax (BIT) forms and Pay-As-You-Go (PAYG) employment forms. The former contain data on firms' sales, income and expenses, as well as on their balance sheet. These are used to construct measures of firm output, intermediate inputs, labour and fixed costs, and capital (see Appendix B). The PAYG statements are used to derive a measure of full-time equivalent (FTE) employment (Hansell et al 2015), which I use as the labour input.

In place of firm-level input and output prices, I use division-level prices. A discussed in a number of papers, the use of industry deflators can lead to downward biases in the estimated output elasticities (e.g. Klette and Griliches 1996; De Loecker 2011; De Loecker et al 2016; Grieco 2016). This will potentially bias down the estimated level of the mark-ups by lowering the numerator in the mark-up equation. A more recent paper has argued more strongly that without observing firm-level prices we cannot infer anything about the level of mark-ups (Bond et al 2020). This is because we essentially replace the output elasticity with the revenue elasticity, which cancels out the information on the mark-up.

For these reasons, the estimates of the level of the mark-ups should be interpreted with a good deal of caution. That said, while the levels might be affected, the changes are unlikely to be overly affected. If the production function and its estimates remain broadly constant over time, the elasticity will be off by a constant factor, and so percentage changes in the mark-ups will be largely unaffected (De Loecker and Warzynski 2012; Appendix A). As such, the lack of firm-level prices is unlikely to substantially affect the results on changes in the mark-ups.

Regarding mark-ups, I take a relatively light-touch approach to trimming by removing only those in the top and bottom percentile of the mark-up distribution. The results are quite robust to more stringent rules, such as dropping firms with large changes, or removing for the full sample any firms that enter the top and bottom percentile at some point in the sample (see Appendix C).

While BLADE has data on the (near) universe of Australian firms, I have to make some exclusions. I focus on employing firms in the non-financial market sector. Even with these exclusions I capture a very large proportion of the non-mining, non-finance market sector, capturing on average about 60 per cent of the sales in each constituent industry division (Appendix B). This is substantially larger than is common in the literature, and so my results should be highly representative.

5. DOCUMENTING MARK-UPS IN AUSTRALIA

Figure 4 documents the average firm-level mark-up in the sample based on three aggregation methods: (i) an unweighted average; (ii) a sales-weighted average, as is common in the literature; and (iii) an input-weighted average, which is potentially more reflective of the effect of mark-ups than sales weights, as it does not inflate the importance of high-mark-up firms by incorporating their mark-ups into their weights (Edmond et al 2019). In all cases, mark-ups have increased by around 5 per cent since the mid-2000s, suggesting that market power might have increased over the period.

Figure 4: Average Firm-level Mark-ups
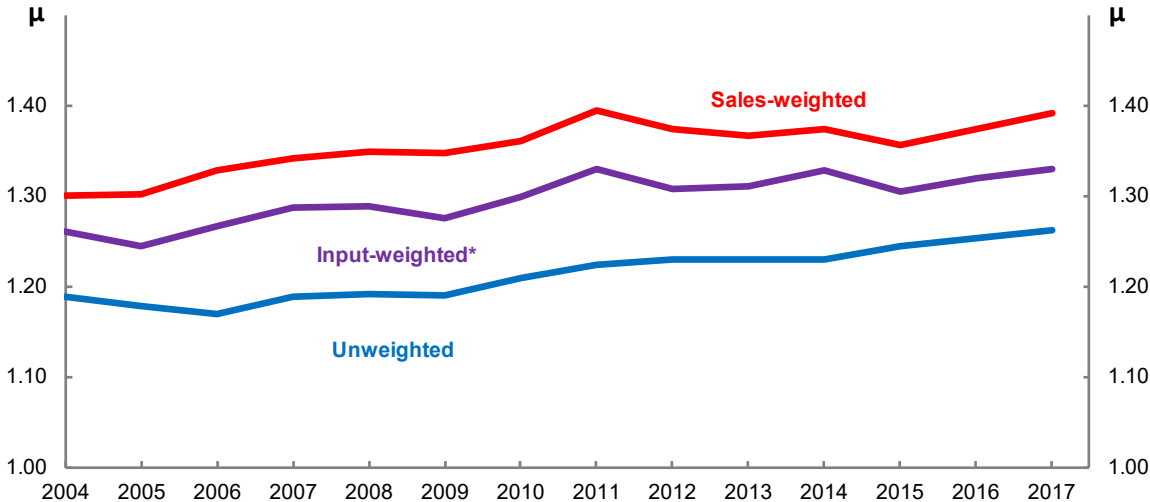
Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Treasury calculations based on ABS BLADE.

The sales- and input-weighted mark-ups are higher than the unweighted measure. This suggests that larger firms tend to have higher mark-ups, which is consistent with many models of competition, though, as noted above, care should be taken in interpreting the levels of mark-ups. I return to this below. It is also worth noting that the sales- and input-weighted averages have similar trends, in contrast to some other studies. Given this, and for ease of comparison with other studies, I focus on the sales-weighted measure for the rest of the paper, instead of the (more theoretically sound) input-weighted measure.

To better understand these changes I decompose the sales-weighted mark-up using the Bennet (1920) type decomposition suggested by Diewert and Fox (2010) (see Box B for more details). This allows me to understand whether the increase reflected: higher mark-ups for firms themselves ('Within changes'); firms with high mark-ups taking up an increasingly large share of the economy ('Reallocation'); or a combination of the two.

Box B: Decomposing the Sales-weighted Mark-up

To better understand what is behind the increase, I decompose the sales-weighted mark-up using the Bennet (1920) type decomposition suggested by Diewert and Fox (2010). This decomposition splits the change in the sales-weighted mark-up into the 'within-firm' changes, and the compositional shifts or 'reallocation effects':

$$\Delta \sum w_{i,t}\mu_{i,t} = \sum_{i\epsilon survivors} \Delta w_{i,t}\overline{\mu_{i,t}} + \sum_{i\epsilon survivors} \overline{w_{i,t}}\Delta\mu_{i,y} + Net\ Enxtry_t$$

Where $w_{i,t}$ and $\mu_{i,t}$ are firm i's sales weight and mark-up at time t, respectively, and the bar indicates the average over the current and previous period.

The first term is the reallocation component. It captures whether a firm has gained or lost market share, and how this affects the weighted-average given the level of the firm's mark-up (i.e. whether it is above or below the firm-level average). The second term is the within component. It captures increases in mark-ups for firms themselves, weighting them according to their share of aggregate sales.

This decomposition is different to the dynamic Olley-Pakes (DOP) decomposition proposed by Melitz and Polanec (2012). The DOP decomposes using the unweighted firm-level changes, and the change in the covariance of size and mark-ups. As such, in the DOP if mark-ups rise for large firms, the reallocation term will rise. This is not ideal in this case, and doesn't align with the decomposition used in De Loecker et al (2021).

The final term accounts for the fact that the entry and exit of firms will affect the weighted-average mark-up, if their mark-ups differ from those of other firms. I abstract from this component in the analysis as its effect on the mark-up is small.

Figure 5 shows the results of this decomposition. Over the sample, the increase in the sales-weighed mark-up reflected increases in firms' mark-ups, particularly over the mid-2000s. Moreover, if anything, there was some reallocation away from higher mark-up firms and towards lower mark-up firms. While part of this might reflect reallocation between sectors, it still suggests that reallocation has not played a large role in the increase. This finding is particularly relevant in the context of concerns about the interpretation of the levels of the mark-up estimates.

Figure 5: Decomposition of Sales-weighted Average of Firm-level Mark-ups
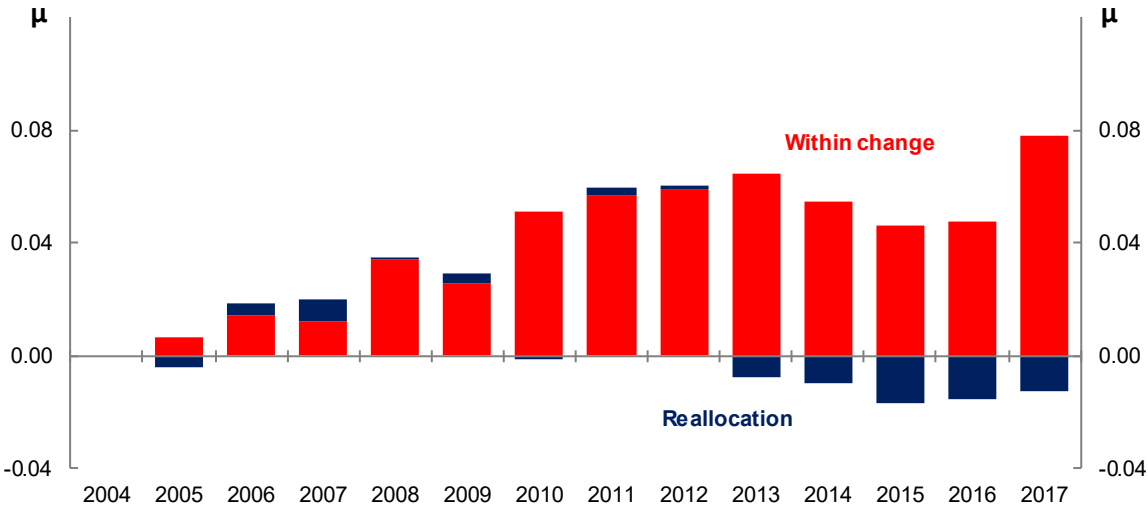
Note: Decomposition done using Bennet-style decomposition suggested by Diewert and Fox (2010). Contribution of net entry is not charted. Treasury calculations based on ABS BLADE.

Focusing on the cross-section, there is a large degree of heterogeneity across firms, consistent with findings in other papers, though some caution should be taken in interpreting the levels (Figure 6). Interestingly, the increase in mark-ups has been driven by firms in the upper part of the mark-up distribution, in particular those above the median. That said, a number of other papers have found the rise in mark-ups to be almost entirely attributable to firms at the very top of the distribution (e.g. IMF 2019), whereas the increase appears more widespread in this analysis.[7]

Figure 6: Unweighted Distribution of Firm-level Mark-ups

Panel A: Levels
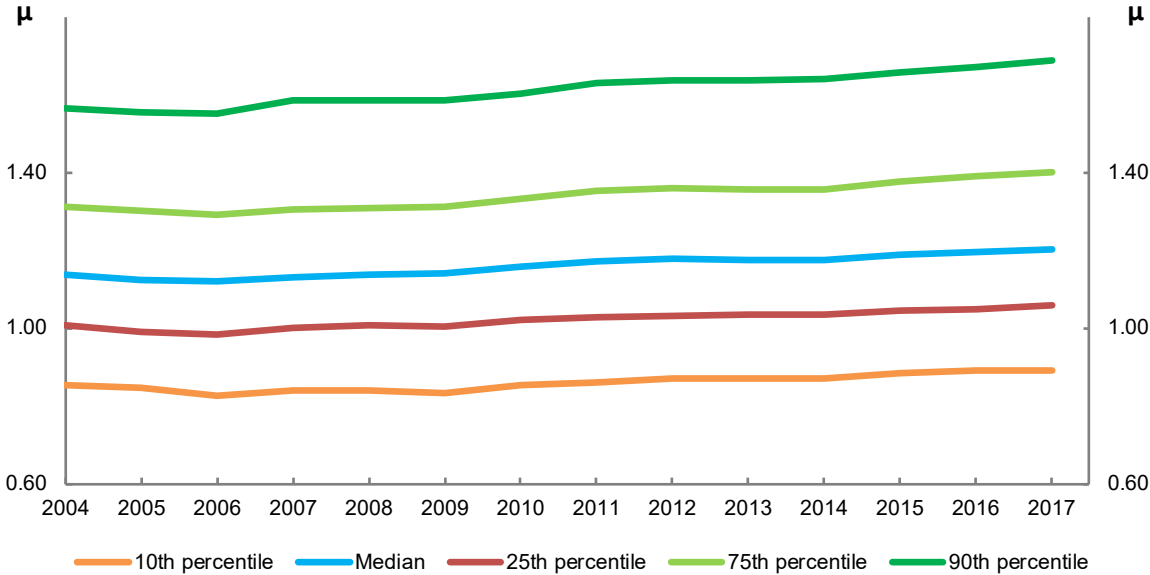
Panel B: Index 2004=100
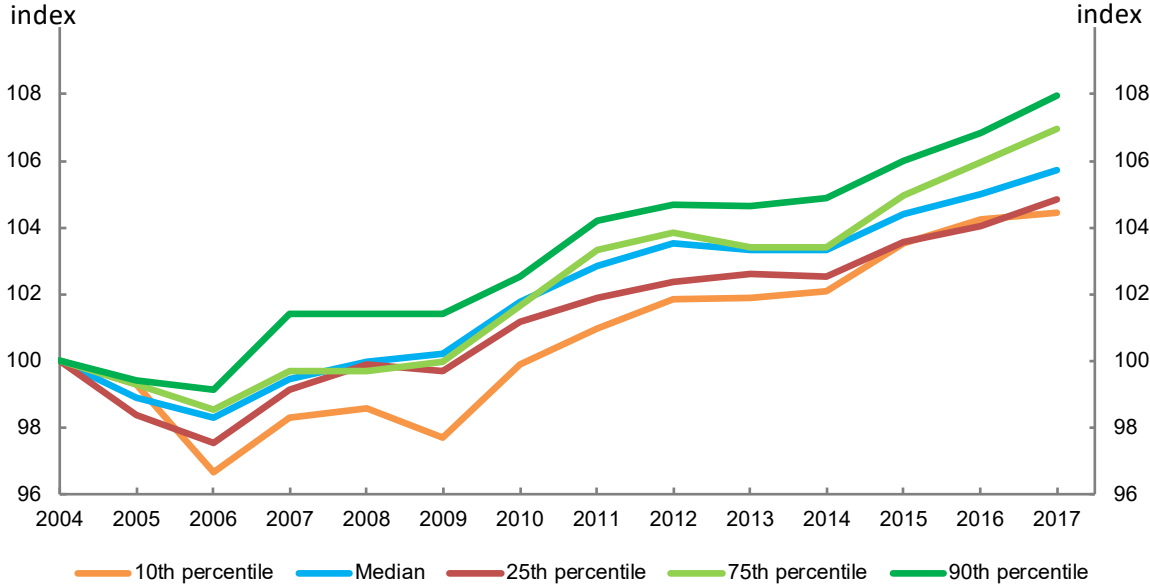
Note: Treasury calculations based on ABS BLADE.

At least part of the heterogeneity reflects differences across sectors, though again, care must be taken in comparing levels (Figure 7 Panel A). For example, mark-ups are estimated to be relatively high in the Information, Media & Technology division, and lower in the Retail Trade division. There is also a moderate

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7   The results are similar if we look at sales-weighted distribution, though in this case the upper part of the distribution does become relatively more important.

amount of variation in the evolution of mark-ups across divisions, though it does appear that mark-ups have increased for firms in most parts of the economy (Figure 7 Panel B).

Figure 7: Sales-weighted Average of Firm-level Mark-ups by Division

Panel A: Average 2003/04 to 2016/17 — Panel B: Change 2003/04 to 2016/17
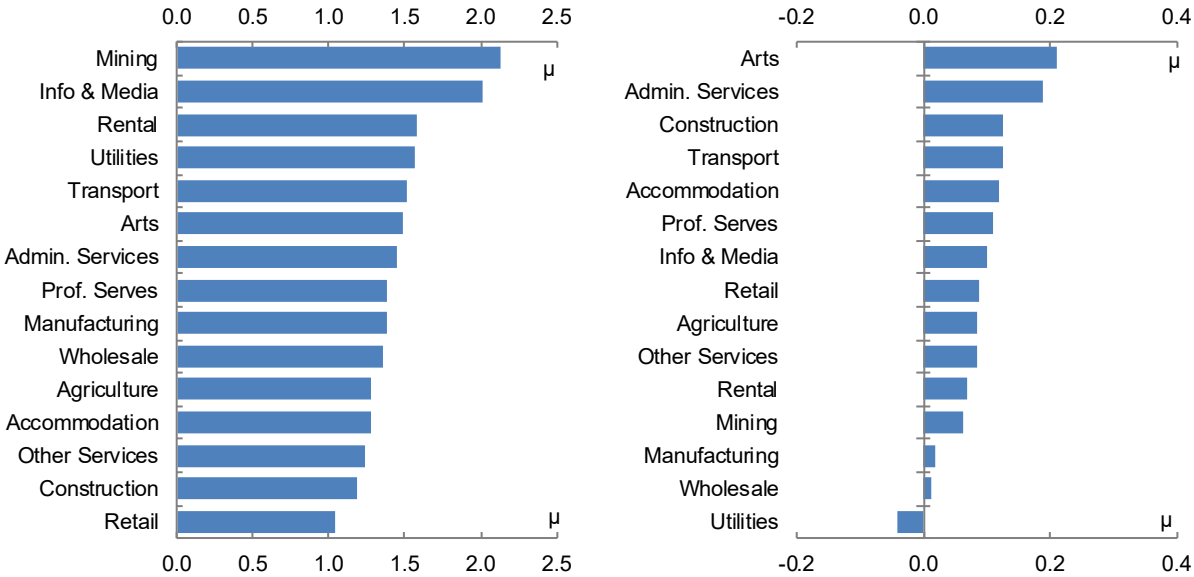
Note: Panel A shows the sales-weighted average of the firm-level mark-ups for firms in ANZSIC divisions. Level differences across divisions should be interpreted with caution. Panel B shows the sales-weighted sum of the firm-level changes, accumulated over the sample period. This is similar to the 'Within' Series in Figure 2. Treasury calculations based on ABS BLADE.

Heterogeneity in mark-ups may also be related to other observables, such as firm size, as evident in Figure 8. Firms with high mark-ups, relative to other firms in their industries, appear to account for a disproportionate share of output, suggesting that they are larger. This is consistent with models of Cournot oligopoly, where mark-ups are directly related to the share of the market held by the firm. Regression analysis confirms this finding, with higher, or increasing, market shares for firms tending to be associated with higher, or increasing mark-ups, and decreasing shares spent on intermediate inputs (see Appendix C). This is the case even when controlling for firm productivity, which should help to explain the relative size of each firm.

Figure 8: Market Share of Firms by Decile in Mark-up Distribution
Mark-ups deciles defined within industries
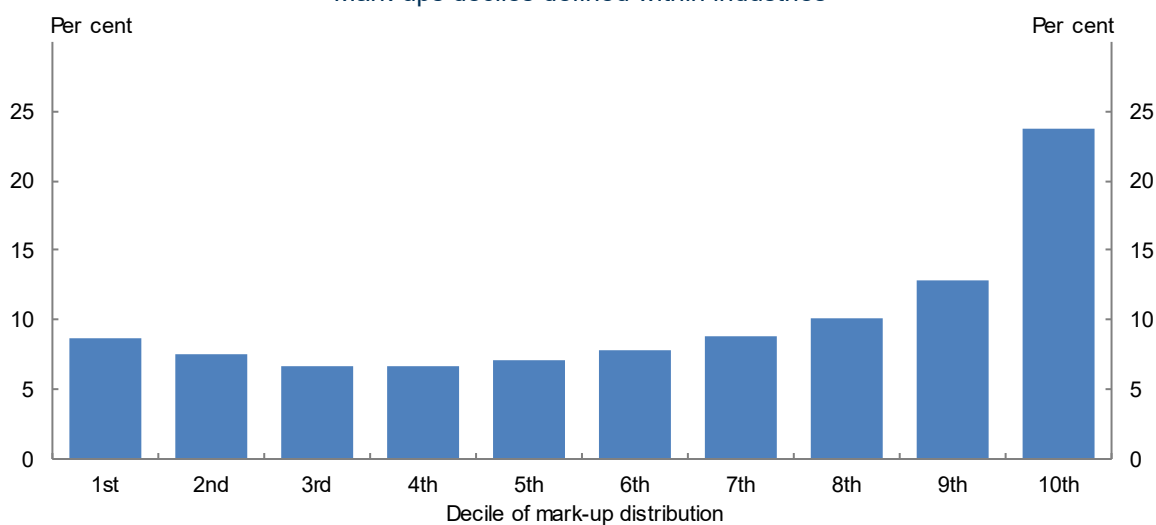
Note: Firms are allocated to a decile of the mark-up distribution within their own industry in each year. The sales of the firms are then summed, and expressed relative to total sales in that year to calculate yearly shares. Yearly shares are then averaged across 2003/04-2016/17. Treasury calculations based on ABS BLADE.

The regressions also show that higher fixed costs are associated with higher mark-ups. As noted above, fixed costs are excluded from mark-up calculations. All else equal, if firms spend a greater share on fixed inputs — such as rental and leasing costs, or advertising, processes and other intangibles — this would lead to an increase in the measured mark-up as the share spent on intermediate inputs will necessarily decline. This is confirmed in regression analyses, where I find that increases in mark-ups that are associated with increased fixed costs do not lead to an increase in profits — they just recoup the fixed cost (Appendix C).

This result suggests that the increase in mark-ups could potentially reflect changing technology rather than a rise in market power, with fixed costs becoming more important. More generally, this highlights that it is important to understand the drivers of mark-ups in trying to interpret them, as mark-ups could increase for more or less benign reasons. I turn to this in the next section.

6. UNDERSTANDING THE RISE OF MARK-UPS, AND ITS ECONOMIC IMPLICATIONS

Mark-ups appear to have increased in Australia over the past decade. But, as discussed above, this could reflect relatively benign factors, or it could reflect a less benign increase in market power. In broad terms, the overseas literature has put forward three potential explanations for increases in mark-ups.[8] These are:

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8   In reality, the delineation between the three explanations might not be as clean as described here and in the literature. Changing technologies amongst the most productive firms could allow them to grow and dominate and explain Superstar-type dynamics. As such, explanation 1 and 2 can be thought of more generally as the best firms pulling away, and broad-based changes in technologies, respectively. This does not substantially change the analysis though.

1. **Superstar hypothesis:** Increased competition has benefited the most productive firms at the expense of other firms. As a result, Superstar firms have become increasingly dominant leading to increases in measures of concentration and mark-ups (e.g. Autor et al 2020).

2. **Changing technology:** Firms are increasingly focusing on intangibles, software and other technologies that have returns to scale (or function like fixed costs). These increasing returns to scale mean that firms tend to be larger and may have to charge higher mark-ups to recoup the fixed costs (e.g. Traina 2018; Crouzet and Eberly 2019; Haskell and Westlake 2017).

3. **Less competition**: Competitive pressures have declined, for example due to increasing barriers to entry or growth for young small firms, or more permissive merger policies. As such, firms have become bigger and/or raised their mark-ups (e.g. Covarrubias et al 2019).

In order to differentiate between these potential explanations, I apply a theoretical framework that provides a number of testable hypotheses for each. Specifically, I adopt the model outlined in De Loecker et al (202).

This model has a number of appealing properties. In particular, it has endogenous mark-ups that are determined assuming Cournot oligopoly. As such, in the model, mark-ups are positively related to firm market share, consistent with the Australian data. The model also incorporates business dynamism via firm entry and exit decisions. It also has parameters that align reasonably closely with the proposed drivers of mark-ups discussed above. The comparative statics for each parameter provide testable hypotheses that can be used to identify the drivers of mark-ups.

These parameters are:

1. **The variance of productivity shocks:** As the variance of productivity shocks increases, the gap between the best and worst firms grows. As such, this parameter lines up reasonably well with the 'Superstar firm' explanation (though not perfectly).

2. **The share of fixed costs:** As fixed costs increase as a share of total costs, there will be greater returns to scale. As such, this parameter lines up well with the 'technological change' explanation.

3. **The number of potential competitors yet to enter the market**: When the number of potential competitors declines, the amount of competition facing the remaining firms declines. As such, this parameter lines up well with the 'less competition' explanation.

The comparative statics for each of the explanations are summarised in Table 1. They relate to the models predictions for: the distribution of mark-ups; whether sales-weighed mark-ups are driven by with firm changes or between firm reallocation (decomposition of sales-weighted mark-up); and whether low-productivity firms are more or less likely to be able to survive (selection effects).[9]

Table 1: Testable Predictions

	Superstar firm (1)	Changing technology (2)	Less competition (3)
Distribution of mark-ups	Increase at top of distribution	Broad-based increase	Broad-based increase

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9   It is worth noting that these predictions are not unique to this specific model. For example, the simpler model laid out in Covarrubias et al (2019) provides a similar set of predictions, though it is focused on measures on market concentration, not mark-ups *per se* (see Table 1 in that paper).

Decomposition of sales-weighted mark-up	Reallocation	Reallocation and within-firm increases (driven by fixed costs)	Within-firm increases
Selection effects	Stronger	Stronger	Weaker

Below I lay out the intuition for these results:

- **Distribution of mark-ups:** Under explanations 2 and 3, the increase in mark-ups should be relatively broad-based for most firms across the mark-up distribution. This is because most surviving firms become bigger and so can charge higher mark-ups. In contrast, under explanation 1 mark-ups should mainly increase for firms at the top of the distribution, as the large, high mark-up firms get even larger, and accordingly can raise their mark-ups further.

- **Decomposition of sales-weighted mark-up:** Under explanation 1, increases in the sales-weighted mark-up should be driven by a reallocation of resources to high mark-up firms, as these more productive firms grow at the expense of others. Under 3, the increase should be driven by increases in constituent firms' mark-ups, as most firms grow and raise their mark-ups. Under 2, we would expect to see both, with firms growing on average, but the most productive firms tending to grow more.

- **Selection effects:** Under 1 and 2, low productivity firms are more likely to exit.[10] In the former case, this reflects the fact that the profits available for small firms decline as large firms grow and dominate. In the latter case, this is due to the higher fixed outlay that firms need to make in order to produce, which smaller lower productivity firms struggle to recoup. In contrast, under explanation 3 there are fewer firms that can enter to compete away profits for low productivity firms, making it easier for them to survive.

As shown above in Figure 5, the increase in mark-ups is relatively broad-based across the distribution, and is driven by within-frim increases in mark-ups, rather than reallocation towards high mark-up firms. This would appear to rule out the Superstar Hypothesis, leaving technology changes and deceasing competition as the relevant hypotheses to explore.[11] The fact that there is little evidence of reallocation driving the increase also suggests that the technology change and increasing returns to scale are not the key driver, though we can't rule out that they accounted for some of the rise.

One explanation that I do not consider here is that the increase in mark-ups could reflect declining competition in input markets including labour markets, rather than in product markets. The approach assumes that firms are price takers in input markets, and any increase in monopsony power could raise measures of mark-ups. This will be explored in future work (Hambur forthcoming).

6.1 Understanding the role of fixed costs and technology change

To consider the role of fixed costs and technology change I take a few different approaches. Before this though, it is worth highlighting that the definition of fixed costs used in this paper is somewhat narrower than in other work owing to data constraints. In particular, some expenses that would often be

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10   Put another way, the level of productivity required to operate profitably, the productivity 'cut-off', increases. This type of result goes back to Hopenhayn (1992).

11   It is worth noting that we cannot rule out the possibility that actual mark-ups have been increasing due to reallocation, given concerns about identifying the *levels* of firm-mark-ups. But in this case, the increase would be on top of what we have observed in this data.

considered fixed, and might be relevant for the technology change story, are captured in my measure of variable cost. As such the headline numbers might already have abstracted from some of the technology change story. That said, using a narrower variable cost measure (that has some other drawbacks), leads to similar results to the headline numbers (Appendix B and C).

I first adopt the approach suggested in De Locker et al (2020) and calculate an excess mark-up. This is the difference between the observed mark-up, and the mark-up that would be required to recoup firms' fixed costs and ensure that they earn zero 'excess' profits (see Box 3 for details). The approach is quite similar to estimating excess economic profits, as in Barkai (2019). In this sense, it should be fairly robust to differences in the definition of fixed and variable costs between this and other work, and uncertainty about what expenses to include as fixed more generally. It also allows for the possibility that other technological changes could be driving the result, such as a general shift towards the use of capital (tangible or intangible).

Box 3: Excess Mark-ups

Excess mark-ups are defined as follows:

$$\mu_{i,t}^{excess} = \mu_{i,t}^{observed} - \mu_{i,t}^{required}$$

$$\mu_{i,t}^{required} = \frac{\alpha_{i,m}}{1 - \frac{r_{k,j,t} P_{k,t} K_{i,t}}{P_{y,t} Y_{i,t}} - \frac{W_{i,t} L_{i,t}}{P_{y,t} Y_{i,t}}}$$

The inputs into the calculation are the same as those used in estimating the mark-ups. The only additional term is $r_{k,j,t}$, the required rental return on capital in industry j.

The required rate of return on capital, $r_{k,j,t}$, is defined as:

$$r_{k,j,t} = (r_{d,s,t} - \pi_t + (1 + \pi_t) * \delta_{j,t})$$

The first term is the cost of debt. This is taken to be the small or large business indicator lending rate, as published in Table F5 of the RBA Statistics. Firms are considered large if their sales are above \$2 million. Inflation, π_t, is the trimmed-mean inflation rate, while $\delta_{j,t}$ is the real depreciation rate for industry j, taken from the ABS Annual National Accounts.

I exclude the Agriculture, Mining and Utilities divisions from this analysis. The excess mark-ups for these sectors are very volatile, potentially reflecting difficulty in measuring payments to capital associated with land.

While the excess mark-up approach has intuitive appeal, the results are very dependent on the required rate of return on capital used in the calculation. Constructing these rates of returns requires a large number of assumptions, for example regarding expected future capital price inflation and risk premia. Standard approaches also tend to impose a large degree of homogeneity on the rates of return, which may not be reasonable.

As such, as an alternative way to consider the role of fixed costs I (fully) re-estimate mark-ups, but include the fixed costs as an intermediate input. This approach is similar to that proposed in Traina (2018), and will be again be useful if we are uncertain about exactly which expenses should be treated as fixed. Finally, I also take the approach suggested by De Loecker et al (2020), and estimate the model treating the fixed costs as another fixed input in the production function.[12]

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12   Given the added complexity of the production function in this approach, these results should be treated with some caution.

Table C3 n Appendix C summarises the results from these robustness tests. Using most approaches, the increase in mark-ups is broadly around half of what was documented using the headline mark-ups measures. This suggests that fixed costs and changing technology have played some role in rising mark-ups (though as noted some of these might already be captured in the headline measure).

Still, none of these approaches is perfect. For example, firms might incur a large amount of fixed costs in R&D and advertising in previous years that are not capitalised, but which need to be recouped. This temporal shift might make it difficult to consider the role of fixed costs in influencing mark-ups.

As a final way of considering the role of fixed costs, I examine mark-ups for more and less digitally-intensive industries. As discussed in Calligaris et al (2018), digitally intensive industries may invest more heavily in intangibles assets, which can have network effects and tend to be more scalable. As such, if the increase in mark-ups reflects changing technology and increasing returns to scale, we might expect the increase to occur mainly in these industries.

Figure 9 shows the results. The key takeaway is that mark-ups have increased by more than twice as much for firms in the digitally intensive quartile, consistent with Calligaris et al (2018), suggesting some role for changing technologies. However, mark-ups have also increased for firms in the other quartiles, suggesting other dynamics, like an increase in market power, are also important.[13]

Figure 9: Mark-ups by Digital Intensity of Industry
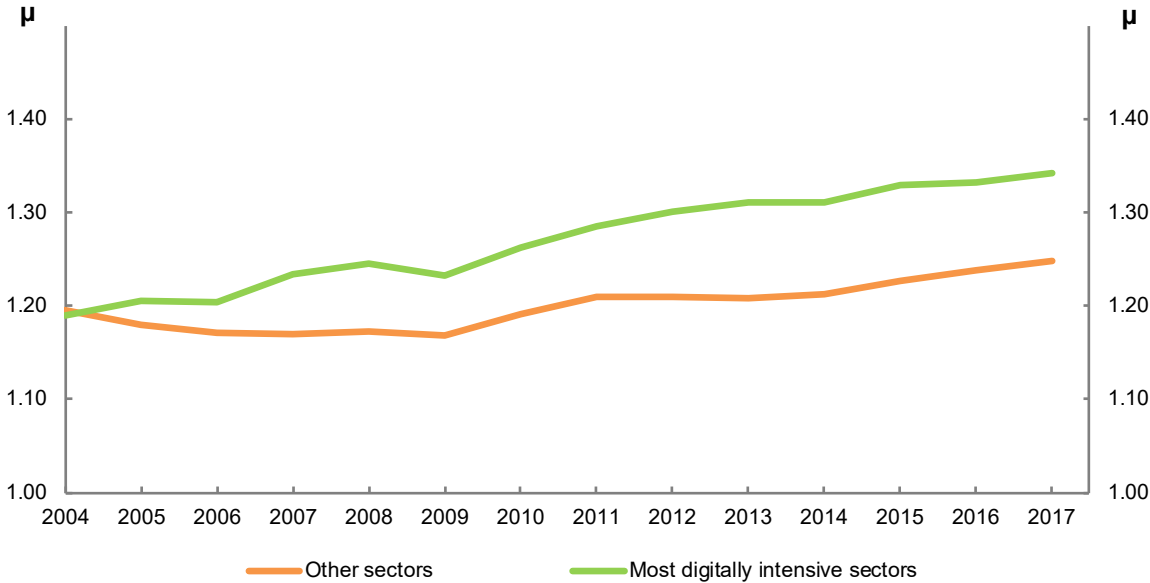
Notes: Industries assigned a digital intensity based on the taxonomy outlined in Table 3 of Calvino et al (2018). Requires mapping of ISIC classifications used in that paper, to the ANZSIC classifications used in BLADE. Firm-weighted averages then taken for each quartile of industries. Most digitally intensive sectors is top quartile. All other sectors is an unweighted average of the series for the other three quartiles. Treasury calculations based on ABS BLADE.

Overall, taken together these results suggest that fixed costs, increasing returns to scale, intangibles and changing technologies can account for some of the increase in mark-ups. While it is difficult to put a number on it, the results suggest that changing technologies could account for maybe half of the increase in mark-ups. However, this still leaves a substantial role for declining competition, which we explore next.

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13   Much of the volatility for the least digitally intensive industries reflects the mining sector. Mark-ups are lower and more stable if this sector is excluded.

6.2 Selection effects

As discussed above, selection effects can be used to differentiate between the two remaining explanations for rising mark-ups: technology change and decreasing competition. Previous work for Australia has shown that such selection effects have tended to weaken over time, alongside the increase in mark-ups (Andrews and Hansell 2019), which provides *a priori* evidence for decreasing competition. However, to look at this more directly, I examine whether this weakening has been more pronounced in industries with increasing mark-ups.

To do so I adopt the approach used in Decker et al (2017), and applied to Australian data in Andrews and Hansell (2019). The approach involves examining the relationship between firm exit and productivity. More specifically, it involves running a regression of the form:

$$Exit_{i,t+1} = \alpha_0 + \beta * Prod_{i,t} + X'_{i,t}\theta + \varepsilon_{i,t+1}$$

where the probability firm *i* exits next period is a function of its (log) productivity at time *t* — expressed relative to the industry average — and some controls. If less productive firms tend to exit, we would expect β to be negative.[14]

In this case, I am interested in whether the selection effects become weaker in industries with increasing mark-ups. To examine this, I extend the model to include an interaction between industry mark-ups, $\mu_{m,t}$, and productivity:

$$Exit_{i,t+1} = \alpha_0 + \beta * Prod_{i,t} + \gamma * Prod_{i,t} * \mu_{m,t} + X'_{i,t}\theta + \varepsilon_{i,t+1}$$

If the selection effects are weaker when mark-ups increase, we would expect the coefficient γ to be positive.

In running these regressions I include a number of controls. These include controls for firm size, as well as industry-by-year fixed effects, which capture time-varying industry specific shocks (and capture the direct effect of the industry level mark-up) as well as national shocks. I also include productivity interacted with an industry dummy. This controls for the possibility that there may be some third factor that affects both the industry mark-ups, and the strength of the selection effects. By including these controls, I am focusing on the effect of changes in mark-ups on selection, limiting concerns about issues in identifying the levels of mark-ups.[15]

I run the models using two different industry mark-up measures: unweighted mark-ups and sales-weighted mark-ups. I also consider two different measures of productivity. One is firm-level multi-factor productivity (MFP), taken from the production function estimation. This is the relevant productivity metric in most models, and allows me to abstract from the role of capital deepening/shallowing. The second is labour productivity (ratio of value-added to FTE). This metric is theoretically less appealing. However, it is available for all employing firms, not just firms for whom I can estimate mark-ups. As such, it allows me to estimate the model over a broader sample.[16]

As an extension, I also examine the relationship between mark-ups and the rate at which labour flows from less to more productive firms — dynamic reallocation. This allows me to consider whether increasing mark-ups could explain the slowing rate of dynamic reallocation in the Australian economy that is documented in Andrews and Hansell (2019). Theory states that this might be the case, as

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14   I use a linear probability model, instead of a probit, for ease of estimation and interpretation.
15   Excluding these interaction terms does not substantially affect the results.
16   Decker et al (2017) find that these models tend to be relatively robust to using MFP and LP.

production tends to be less responsive to productivity shocks when mark-ups and market power are higher.

To do this I replace $Exit_{i,t+1}$ with the growth in the firm's labour input, defined as:

$$g_{i,t+1}^L = \frac{L_{i,t+1} - L_{i,t}}{0.5 * (L_{i,t+1} + L_{i,t})}$$

Where $L_{i,t}$ is employment in period t. This approximates the log changes, can accommodate entry (2) and exit (-2).

Table 2 summarises the coefficients on the coefficients of interest, β and γ, across the different models. First focusing on exit, we can see that more productive firms are less likely to exit, as captured by the positive and significant coefficients on β. But, the coefficient γ is positive and significant, indicating that selection effects are weaker in industries with increasing mark-ups. This provides further evidence that increasing mark-ups have been associated with increasing market power.

Table 2: Results from Selection and Reallocation Regressions

Dependent variable: $Exit_{i,t+1}$

	MFP regressions		Labour productivity regressions	
	Unweighted mark-up	Sales-weighted mark-up	Unweighted mark-up	Sales-weighted mark-up
B	-0.283***	-0.156***	-0.031***	-0.013***
(s.e.)	(0.054)	(0.026)	(0.007)	(0.003)
γ	0.104**	0.0106	0.018***	0.005**
(s.e.)	(0.040)	(0.021)	(0.005)	(0.002)

Dependent Variable: $g_{i,t+1}^L$

	MFP regressions		Labour productivity regressions	
	Unweighted mark-up	Sales-weighted mark-up	Unweighted mark-up	Sales-weighted mark-up
β	1.059***	0.392***	0.176***	0.0119***
(s.e.)	(0.011)	(0.051)	(0.020)	(0.009)
γ	-0.666***	-0.187***	-0.069***	-0.029***
(s.e.)	(0.084)	(0.042)	(0.015)	(0.008)
Obs	~1.6 million	~1.6 million	~3.5 million	~3.5 million

Notes: *** p<0.01, ** p<0.05, *p<0.1. All specifications have industry*year fixed effects, controls for size and past sales growth, and industry*productivity. Top and bottom percentile of productivity distribution drop trimmed. Errors clustered at the industry level.

Focusing on reallocation, as in Andrews and Hansell (2019) the coefficient β is positive and significant, meaning less productive firms are more likely to shrink at the expense of more productive firms. However, as γ is negative the pace of reallocation is weaker in industries with increasing mark-ups. This

suggests that the results in Andrews and Hansell (2019) could reflect increasing mark-ups and market power.

Overall then, the results suggest that selection and dynamic reallocation are weaker in industries with increasing mark-ups. This provides further evidence that increasing mark-ups have reflected greater market power and decreasing competitive pressures.[17] Similar analysis using measures of industry concentration in Appendix D further supports this conclusion.

7. AGGREGATE IMPLICATIONS

The above results indicate that market power has increased in Australia, and that this has led to increased mark-ups. Numerous papers have documented that increasing market power can have negative implications for the economy, through less efficient allocation of resources, slower technology adoption, and decreased incentives to invest. All of these are likely to contribute to slower productivity growth, and, as such, the increase in mark-ups and market power may explain some of the slowdown in productivity growth evident in Australia over the past decade. The question is how much?

To answer this question, I look at one of the mechanisms by which increased market power could contribute to slower productivity growth: slower efficient reallocation of resources. To do so, I perform a simple exercise that builds off the results from Andrews and Hansell (2019), which finds that slowing dynamic reallocation has lowered productivity growth by around 0.15 percentage points each year, on average, since 2012, or around ¼ of the observed slowdown in market sector productivity. The exercises attempt to quantify what portion of this could reflect higher mark-ups, based on my reallocation regression results from section 6.2.

This is a relatively simple exercise that only looks at one channel through which mark-ups could affect aggregate productivity growth. Future work could look at other channels, such as firm-level productivity growth (see Andrews et al forthcoming), or could look to quantify the aggregate implications of mark-ups more formally using either a structural model or the non-parametric approach of Baqaee and Fahri (2019).

7.1 Dynamic reallocation

As in Andrews and Hansell (2019), I use the approach suggested by Decker et al (2017) to quantify the implications of decreased reallocation for aggregate productivity growth. This involves creating indexes of aggregate labour productivity that combine actual realisations of firm-level labour productivity with employment shares predicted from an estimated model.[18] The idea is that by varying the model, we can construct counterfactual productivity indices that allow us to understand how aggregate productivity would have evolved had mark-ups not increased, and therefore reallocation not slowed.

I consider two different models: *i*) where the responsiveness of employment growth to (lagged) productivity is allowed to vary alongside variation in mark-ups; and *ii*) where the mark-ups, and therefore the responsiveness, are held constant at the level evident at the start of the sample. These models give predictions for employment growth. I can then combine these predictions with the (initial) level of

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17   An alternative explanation could be increasing fixed costs in adjusting intermediate inputs. This could lead to lower measured mark-ups and less reallocation. This would also be a negative outcome. However, given similar results are evident using concentration in place of mark-ups as the measure of competition Appendix C, this seems unlikely to be driving the result.

18   Productivity is taken to be the log level for the purpose of this discussion.

employment for the firm in t to get predicted employment shares, which I can use to construct productivity indices.

With these predictions in hand, I can construct 3 different productivity indices: one using observed employment shares in the previous year (1); one using the using the shares from the model where mark-ups are allowed to vary (2); and one using the share from the model where mark-ups are held steady, leaving the productivity-employment-growth relationship at the level present at the beginning of the sample (3). More formally:

$$P_t = \sum s_{it} p_{it} \qquad (1)$$

$$P_{t+1}^{\Delta\mu} = \sum s_{i,t+1}^{\Delta\mu} p_{it} \qquad (2)$$

$$P_{t+1}^{Cons\,\mu} = \sum s_{i,t+1}^{Cons\,\mu} p_{it} \quad (3)$$

The difference between the base index and either of the other indices shows the predicted productivity growth due to reallocation. For example, the predicted gains in productivity based on the model with varying mark-ups is:

$$(P_{t+1}^{\Delta\mu} - P_t) = \sum_i (s_{i,t+1}^{\Delta\mu} - s_{it}) p_{it}$$

The difference in these differences then captures how much slower aggregate productivity growth will be due to slower reallocation:

$$(P_{t+1}^{\Delta\mu} - P_t) - (P_{t+1}^{Cons\,\mu} - P_t) = \sum (s_{i,t+1}^{\Delta\mu} - s_{i,t+1}^{Cons\,\mu}) p_{it}$$

Figure 10 (Panel A) illustrates the results for this exercise using the unweighted average mark-up. It indicates that the drag on productivity growth associated with increase mark-ups was around between 0.10 and 0.13 percentage points per annum, on average since 2011/12. This accounts for around ¾ of the slowdown documented in AH, and around ⅓ of the slowdown in overall aggregate productivity growth observed in recent years.

Figure 10: The Changing Contribution of Reallocation to Aggregate Labour Productivity Growth

Panel A: Differential annual labour productivity growth with unweighted average mark-up at 2004 level
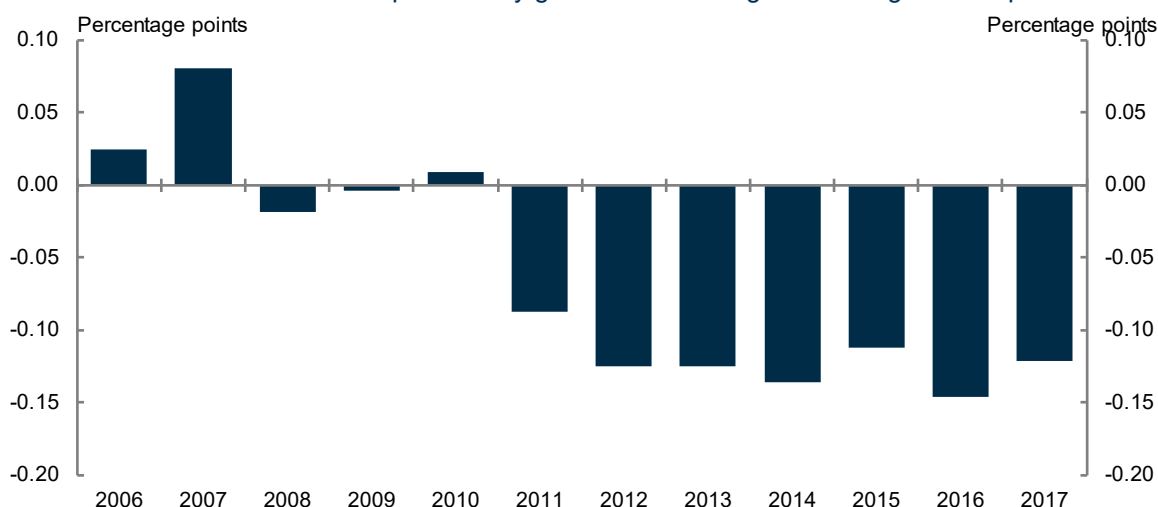
Panel B: Average annual growth in aggregate labour productivity

Note: Panel A depicts annual movements in the counterfactual index, which shows how much slower productivity growth was than predicted by this counterfactual exercise were mark-ups remained unchanged. Panel B shows how much higher aggregate labour productivity growth would have been over 2012-2016 had the efficiency of labour reallocation not declined (Counterfactual – AH), and the portion that can be accounted for by mark-ups rising (Counterfactual – Mark-up), based on the estimates in Panel A and Andrews and Hansell (2019). Treasury calculations based on ABS BLADE.
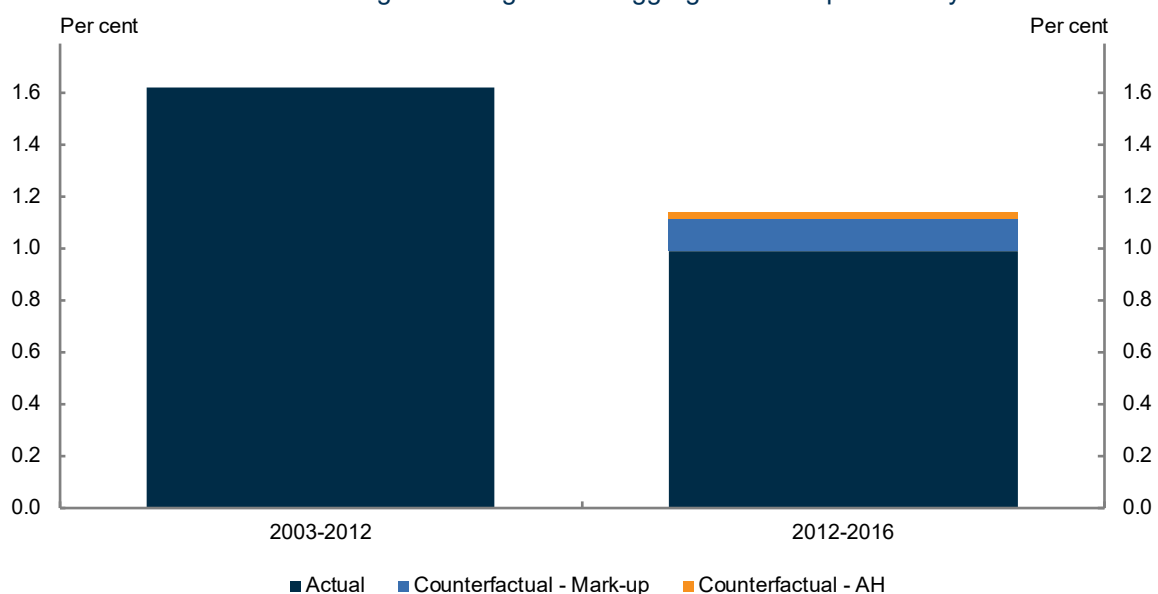
8. CONCLUSION

Like many other countries, Australia has experienced a slowdown in productivity growth underpinned by declining dynamism. This has very real implications for wages, government balances, and economic growth and welfare more generally, and so it is crucial to better understand the underlying causes.

This paper demonstrates that firms' mark-ups and market power have increased in Australia in the non-finance market sector since the mid-2000s, and that this has weighed on dynamism and labour productivity growth. In particular, rising market power has reduced the rate of (within-industry)

productivity-enhancing labour reallocation, which has in turn lowered annual labour productivity growth by 0.1 percentage points since (about one fifth of the observed slowdown since 2012). This helps to explain the findings of Andrews and Hansell (2019), who document slowing labour reallocation as a key micro-driver of Australia's productivity slowdown. Moreover, this estimate abstracts from other potential negative effects of increased market power, such as decreased incentives for innovation and within-firm productivity growth, suggesting that the true effects are larger.

Nevertheless, it is significant that the estimated increase in mark-ups is smaller than previously documented for Australia in De Loecker and Eeckhout (2019), and slightly smaller than the average increase observed for other advanced economies. In part, this might reflect the larger and more representative dataset used in this study. But there is also a real possibility that the increase in market power in Australia over this period has been smaller than in other advanced economies, which could reflect differences in the policy environment. Indeed, this finding is somewhat consistent with the fact that Australia performs well in the OECD product market regulation rankings, consistently ranking in the top one-third of countries during the sample period.

The paper also highlights the potentially important role for technology change, intangibles and fixed costs in explaining higher mark-ups. Indeed, mark-ups increased by more than twice as much in more digitally intensive sectors that may rely more heavily on intangible investments, such as R&D, or on platform or network effects. This highlights the important and complex competition-related issues associated with such technologies, which are beyond the scope of this paper.

Future research could look to quantify the impacts of increasing market power and mark-ups on the Australian economy using other approaches, such as structural models (e.g. Edmond et al 2109; De Loecker et al 2021) or the non-parametric approach of Baqaee and Fahri (2019). It could also explore whether market power has affected productivity growth through within-firm channels, such as by weighing on incentives to innovate or adopt world leading technologies (Andrews et al forthcoming).

Finally, future work could try to better understand the causes of declining competition to inform potential policy responses and thereby increase productivity growth. This may become even more vital in the post COVID-19 world given its likely implications for competition, and the need to have structural policy settings that accommodate the innovation, dynamism and productivity growth required to drive a quick and sustained recovery (Dieppe et al 2020).

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APPENDIX A: MARK-UP METHODOLOGY

To estimate mark-ups, I follow the approach proposed by De Loecker and Warzynski (2012).They show that, under fairly mild assumptions, firm i will optimally set its mark-up μ_i to be promotional to: its output elasticity with respect to a flexible input m ($\alpha_{i,m}$); and the expenditure on that input ($P_m M_i$), as a share of sales income ($P_i Y_i$). So:

$$\mu_i = \alpha_{i,m} \Big/ \frac{P_m M_i}{P_y Y_i}$$

This is a general result that holds for various different competitive structures and price-setting mechanisms (see Online Appendix to De Loecker and Warzynski (2012)).[19] However, the result only holds for an input that can be varied without any frictions or costs — such as hiring and firing costs, or costs in changing the capital stock — as these frictions might prevent the firm from using the 'optimal' amount of the input.

Firm sales can generally be observed in firm-level datasets, as can their expenditure on different inputs. However, their output elasticity cannot be observed. De Loecker and Warzynski (2012) suggest taking these elasticities from production functions, which can be estimated using various methods proposed in the literature.

Specifically, this involves estimating production functions of the form:

$$y_{i,t} = F_{i,t}\big(l_{i,t}, k_{i,t}, m_{i,t}\big) + \omega_{i,t} + \epsilon_{i,t}$$

Where $F_{i,t}$ is some functional form, and $y_{i,t}$, $l_{i,t}$, $k_{i,t}$ and $m_{i,t}$ are the firm's output, labour input, capital input and intermediate inputs, respectively, all expressed in terms of log quantities. $\omega_{i,t}$ is the firm's (log) productivity level, assumed to be Hicks neutral, and $\epsilon_{i,t}$ is some measurement error or noise.[20]

I follow most of the literature and estimate the production function using a proxy approach, in the vein of Olley and Pakes (1996). In particular, I take the two-step approach suggested by Ackerberg, Caves and Fraser (2012).

The first step involves regressing gross output on a (fifth order) polynomial in labour, capital and intermediate inputs — the fitted value of which is taken to be productivity. I also include my measure of wages in this polynomial. As discussed in De Loecker and Scott 2017, including an auto-correlated firm-specific input price in the estimation can help to get around issues in identifying the parameters in the gross output production function (Gandhi et al 2017). As is common in the literature, I also include year-fixed effects in the estimation. The results are generally robust to both of these inclusions, though in some specifications the exclusion of the wage term can have a substantial effect on the level of mark-ups, suggesting difficulty in identifying the output elasticities.

Consistent with other papers, the error-term from this first step is removed from the output in constructing factor shares. The idea is to abstract from unexpected demand shock or measurement errors

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19   This relatively general result contrasts with the demand-estimation approach to estimating mark-ups, where specific assumptions need to be make regarding the price setting mechanism (De Loecker 2011).

20   Recent papers have questioned the assumption of Hicks'-neutral productivity, instead suggesting the use of labour-augmenting productivity (e.g. Raval 2019). However, for consistency I assume the former.

that could have moved the actual factor share away from the intended level. Exclusion of this step does not appear to substantially affect the results.

The second step involves combining the fitted productivity measure, which is assumed to be a first-order Markov process, with assumptions around the flexibility of inputs to construct a number of moment conditions. These can then be solved using Generalised Method of Moments (GMM) to calculate the coefficients on the different terms in the production function, and therefore the output elasticities.

For the estimation of mark-ups, I use the output elasticity on intermediate inputs. I choose this in place of labour as it is likely to be more flexible. I also experiment with using an aggregate measure of intermediate and labour inputs, as is done in De Loecker and Eeckhout (2018). When I bundle the two, mark-ups still appear to increase. But the magnitude of the increase appears to be a bit smaller. This suggests that, at least in the Australian case, bundling leads to a potential understatement of the degree of mark-up by assuming labour and intermediate inputs are perfect complements.

In my preferred specification, I use a translog production function. This allows for the fact that large and small firms in a given industry could have different production technologies. Most papers use a simpler Cobb-Douglas production function that imposes a common production technology, and note that translog function does not lead to substantially different results.

When I instead use a Cobb-Douglas production function the trends are quite similar, though the levels are quite different, especially for the weighted metrics (Appendix C). The weighted metrics, particularly the input-weighted metric, are quite low, and tend to be lower than the unweighted metrics, indicating that large firms have lower mark-ups. Moreover, the level of the unweighted and input-weighted are very high and low, respectively. Nevertheless, it is best not to read too much into the levels differences given concerns about interpretation of the levels of mark-ups.

Consistent with other papers, I exclude fixed costs from the estimation as these fixed outlays are not directly used in production. The paper and Appendix B provide robustness testing around this treatment. In general, mixing fixed costs with intermediate inputs, and allowing fixed costs to enter as an additional variable in the production function, lead to smaller estimated increase in mark-ups. This suggests increases in fixed costs and changing technologies can explain some of the increase in mark-ups.

As noted in the text, Bond et al (2020) argue that in using industry deflators rather than firm-level prices, and therefore effectively estimating a revenue elasticity and not an output elasticity, the mark-up is no longer defined. This reflects the fact that the mark-up estimate:

$$\hat{\mu}_i = \alpha_i^{rev} \Big/ \frac{P_m M_i}{P_y Y_i} = \frac{\alpha_i(1 + \varepsilon_i)}{\frac{P_m M_i}{P_y Y_i}} = \mu_i(1 + \varepsilon_i) = 1$$

Where ε_i is the demand elasticity, and therefore $\mu_i = (1 + \varepsilon_i)^{-1}$. In practice, researchers use an estimate of the revenue elasticity $\hat{\alpha}_i^{rev}$, so the measured mark-up captures the difference between the estimated revenue elasticity and the true one, which may or may not relate to the mark-up.

Looking at log changes in the estimated mark-up we get the following expression:

$$\Delta \ln(\hat{\mu}_i) = \Delta \ln\left(\frac{\alpha_i}{\frac{P_m M_i}{P_y Y_i}}\right) + \Delta \ln\left(\frac{\hat{\alpha}_i^{rev}}{\alpha_i}\right) = \Delta \ln(\mu_i) + \Delta \ln\left(\frac{\hat{\alpha}_i^{rev}}{\alpha_i}\right)$$

Assuming that the estimated and true production functions do not change, which is non-trivial but fairly standard assumption, the final term becomes zero. Therefore, the percentage change in the estimated and true mark-ups are the same, suggesting we can interpret changes in the estimated mark-ups.

In practice, in the preferred estimates we estimate a translog production function, where the elasticity can change as the firm changes its size or input mix. Doing so reduces potential mismeasurement associated with assuming that the output elasticity stays the same as size changes, but could introduce some mismeasurement to the extent that the demand elasticity changes with size, as both will feed into the estimated revenue elasticity. Which is worse is an empirical questions. But in either case the results using a Cobb-Douglas production function are very similar in terms of the increase in mark-ups, suggesting that this modelling choice is not substantially affecting the results (Appendix C). Moreover, as increases are evident even in the unweighted measures, it seems highly unlikely that the results are being driven by changing firm sizes.

APPENDIX B: DATA

As discussed in the test, I use data from the ABS BLADE database. The particular data I use come from firms' Business Income Tax forms and PAYG employment forms.

Regarding the key data variables:

- Gross output: Measured as firm income. This will include some income not directly related to production, such as interest. However, for most firms this item is small.

- Labour expense: labour costs plus superannuation expenses

- Fixed costs: Rental and leasing expenses, bad debts, interest, royalties, external labour and contractors

- Intermediate inputs: Total expenses, less labour, depreciation and fixed costs

- Labour input: FTE derived from PAYG statements, using the methodology laid out in Hansell (2015)

- Wage rate: Labour expense divided by FTE

- Capital: Book-value of non-current assets[21]

All of these metrics apart from FTE are measured in nominal terms. To construct real measures for the inputs into the production functions, I deflate using division level output, intermediate input and capital deflators. The wage rate is deflated using the output deflator.

The measure of fixed costs is as close as possible to the measure used in De Loecker et al (2020), and other papers, of 'Selling and General Administration' expenses. However, it likely excludes a number of expenses included as fixed in this paper, such as some advertising expenses. As robustness, I also estimated mark-ups using a narrower measure of variable costs (cost of sales), which lead to fairly similar results (Appendix C). However, this is not used as my preferred metric as it includes some labour costs.

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21   I experimented with capital stock measures, including adopting a perpetual inventory method (PIM). The results were generally similar. However, given the short sample available for many firms, I preferred not to use the PIM measures which can be heavily influenced by the starting values.

While BLADE has data on the (near) universe of Australian firms, I have to make some exclusions. First, I focus on the market sector, and so exclude the Health, Education, and Public administration divisions of the economy. Government plays a large role in these divisions, and so focusing on market power is potentially questionable. I also exclude the Finance division, given conceptual difficulties in measuring output in this sector (e.g. Brassil Forthcoming; La Cava 2019).

Second, I have to exclude all non-employing firms, given these firms will have undefined (log) labour inputs and costs.[22] I also choose to exclude all firms with less than one FTE as is common in the literature, as they introduce a large amount of noise into the estimation. Finally, I also exclude all sole proprietors, as they do not report information on their balance sheets, and so on their capital stock.[23] Finally, I exclude industries that have very few firms for privacy reasons, and due to difficulty in estimating production functions with little data. This mainly affects the mining and utilities divisions.

Even with these exclusions, I capture a very large proportion of the non-mining non-finance sector. Table B1 show the coverage in terms of sales for all divisions.[24] Coverage is generally larger than is common in the literature, and so my results should be highly representative.

As noted, part of the loss of coverage reflects the requirements for mark-up estimates at the firm level. But part also reflects the fact that I have to exclude industries with too few firms or observations. To get around this latter issue, I also produce mark-up estimates where I estimate productions functions at the 3-digit ANZSIC industry level, rather than the 4-digt level. This ameliorates the small industry issue and leads to better coverage in some industries, such as Mining, Arts, Manufacturing and Utilities (Table B1). But it potentially requires stronger assumptions about the similarities across different industries. As such, these are not my preferred estimates. Nevertheless, the board trends in mark-ups are similar, suggesting the main finding are robust to this choice (see Appendix C).

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22   An alternative would be to treat these firms as having one employee — the owner manager — and assuming the average industry wage. However, as I require a firm-specific wage rate to identify the labour coefficient in the gross output production function (Gandhi et al 2017; De Locker and Scott 2017), I don't take this approach.

23   Using a PIM would allow me to construct an estimate of the capital stock. However, strong assumptions regarding similarities between sole traders and other firm types would be needed to construct starting values for these firms. This could affect the results, especially given many firms are only observable for short samples, making the starting value for the capital stock very important.

24   I exclude any industry with too few firms to estimate a production function. This leads to the exclusion of a number of industries in the mining and utilites divisions. However, this does not substantially effect of my results (see Appendix C on estimation with broader industry definitions).

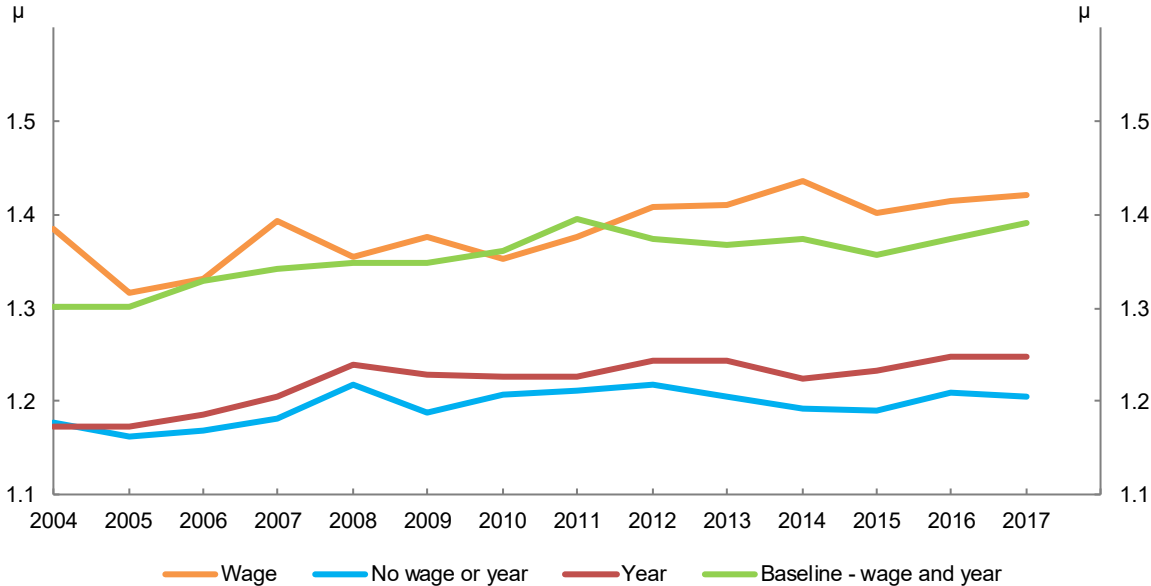## Table B1: Share of industry sales covered by mark-up estimates

	Agri	Mining	Manuf.	Utilities	Constr.	Whole. Trade	Retail Trade	Accom.	Transp.	Info & Media	Rental	Prof. Serves	Admin. Services	Arts	Other Services
Share	38.9	60.0	60.9	20.4	55.9	80.3	75.2	64.2	61.0	75.6	45.2	59.8	64.6	33.4	55.9
Share (3-digit ANZISC estimation)	41.9	87.7	81.9	40.2	56.0	80.3	75.2	64.3	69.1	88.0	45.2	59.8	64.6	60.1	55.9

APPENDIX C: ROBUSTNESS

Figure 11: Mark-ups Using Different First Step Estimation Methods

Panel A: Unweighted firm-level average

Legend: Wage — No wage or year — Year — Baseline - wage and year
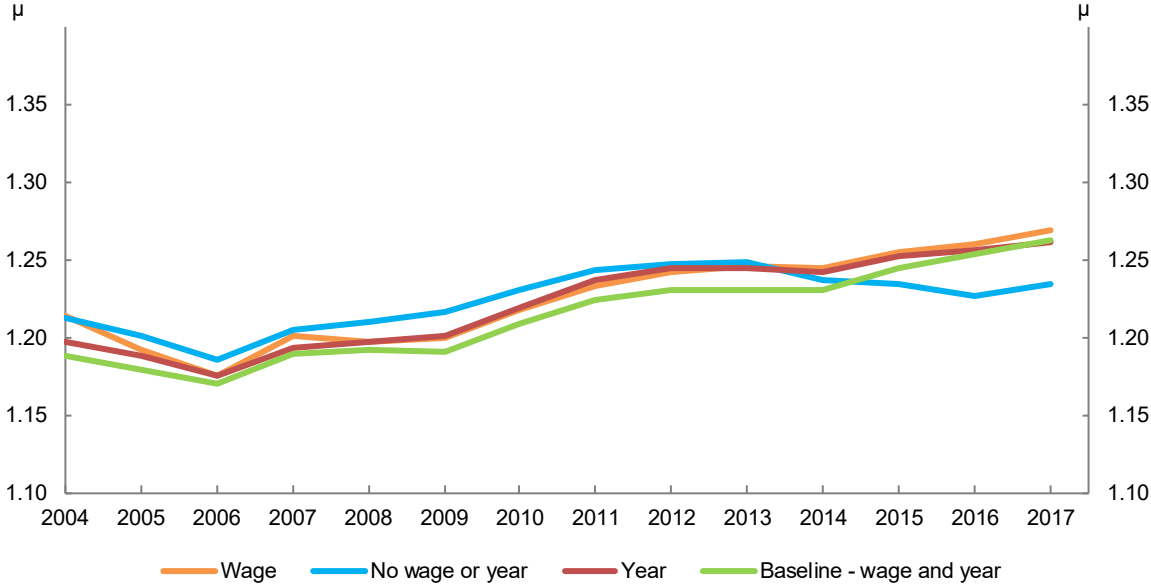
Panel B: Sales-weighted firm-level average

Legend: Wage — No wage or year — Year — Baseline - wage and year

Notes: These charts show average firm-level mark-ups estimated including different terms in the first-stage polynomial regression in the Ackerberg et al (2016) approach. 'No wage or year' just includes the inputs into the production function. Year adds year effects. Wage includes firm-level wage estimates, to address the identification issue highlighted in Gandhi et al (2017). Baseline is the preferred specification and includes both. Treasury calculations based on ABS BLADE

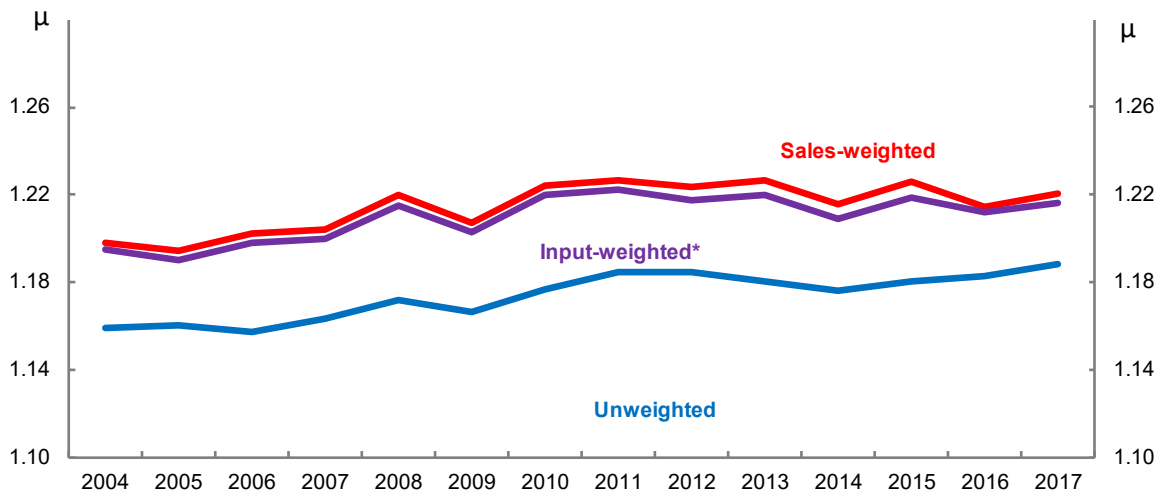## Figure 12: Average Firm-level Mark-ups — Stricter Trimming
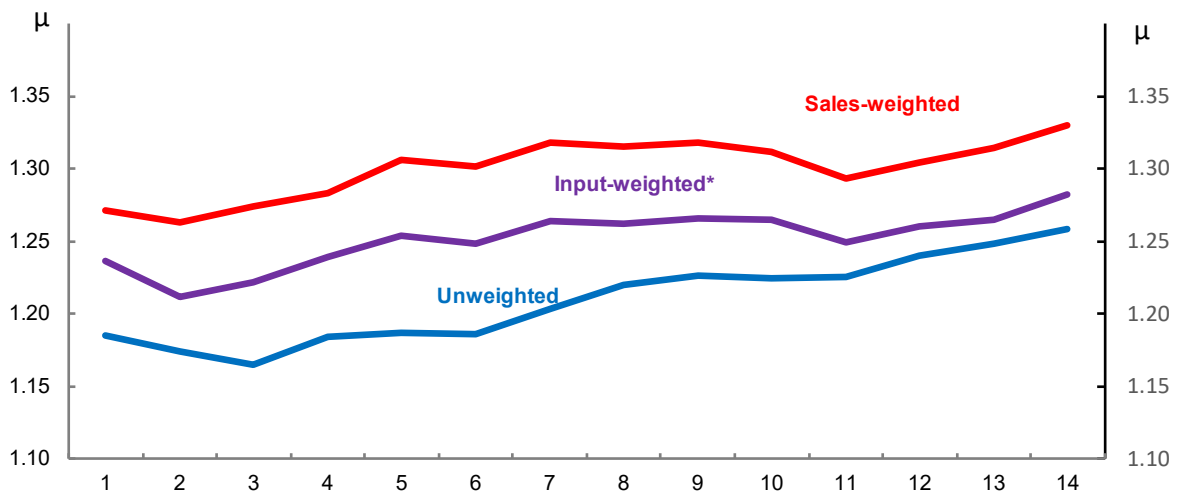
Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Remove firms that ever enter top and bottom percentile. Treasury calculations based on ABS BLADE

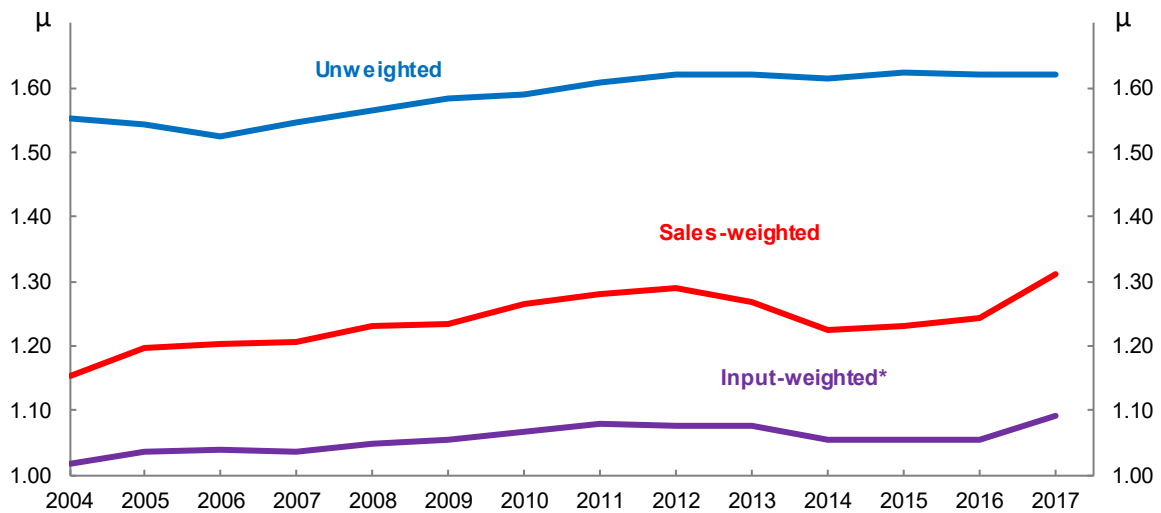## Figure 13: Average Firm-level Mark-ups — Narrower Variable Input Measure
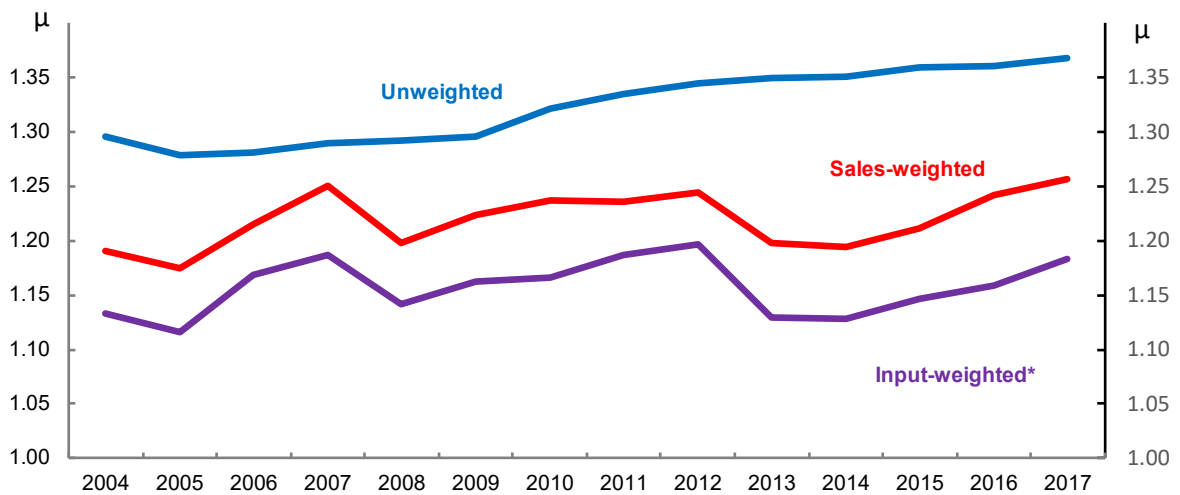
Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Measure of intermediate expenses is a narrower cost of sales metric. Treasury calculations based on ABS BLADE

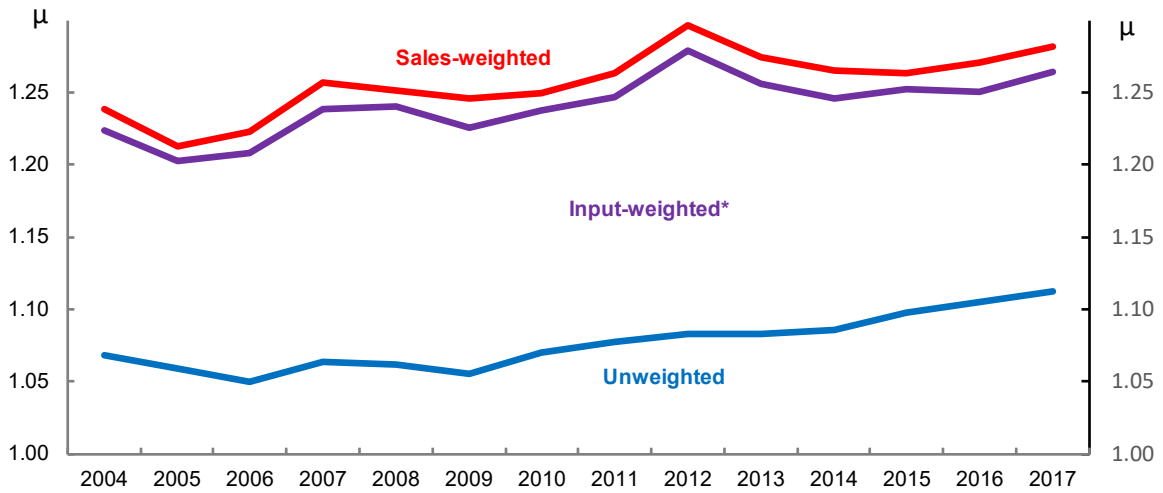## Figure 14: Average Firm-level Mark-ups — Labour and Intermediate Inputs Bundled

Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Labour costs included as an intermediate input in the estimation and calculation of mark-ups. Treasury calculations based on ABS BLADE

Figure 15: Average Firm-level Mark-ups — Cobb-Douglas Production Function
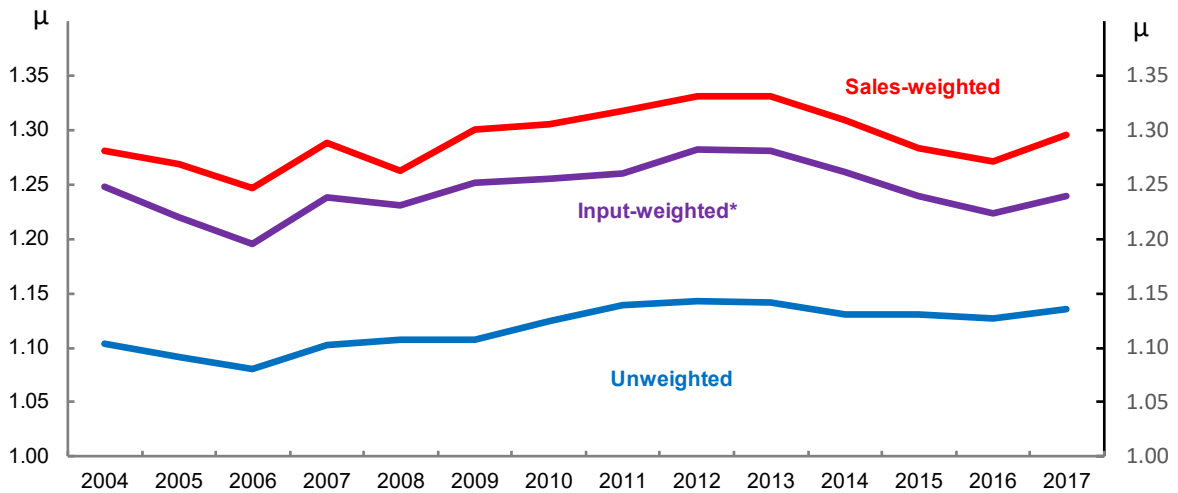

Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Estimates constructed using a Cobb-Douglas production function instead of a translog function. Treasury calculations based on ABS BLADE

Figure 16: Average Firm-level Mark-ups — Fixed Costs Bundled with Intermediate Inputs
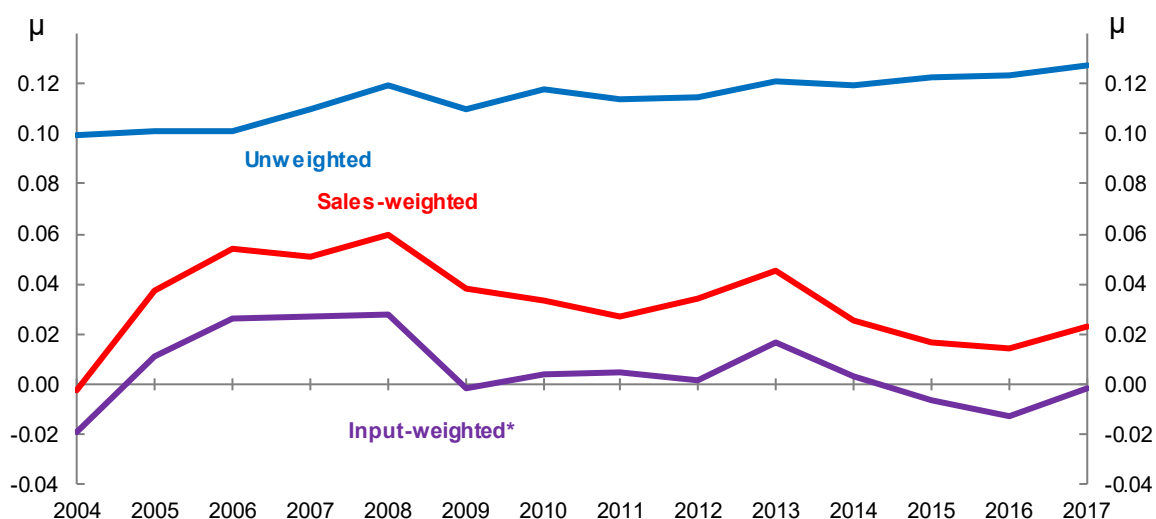

Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Fixed costs included as an intermediate input in the estimation and calculation of mark-ups. Treasury calculations based on ABS BLADE

Figure 17: Average Firm-level Mark-ups — Fixed Costs Included as Separate Input

Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Fixed costs included as an extra input in production function in the estimation and calculation of mark-ups. Treasury calculations based on ABS BLADE

Figure 18: Average Firm-level Excess Mark-ups

Note: Input-weighted measures uses intermediate input measure used in constructing mark-up estimates. Treasury calculations based on ABS BLADE .

Table C1: Mark-up correlates

	No FE (1)	Industry FE (2)	Firm FE (3)
Share of industry sales	2.62***	4.15***	2.60***
Fixed input share	0.16***	0.05***	0.10***
Productivity	0.32***	0.85***	1.15***
Observations	~3m	~3m	~3m

Notes: *** p<0.01, ** p<0.05, *p<0.1. All specifications have year fixed effects. Errors robust to autocorrelation and heteroscedasticity. Productivity if MFP from the production function estimation. Results robust to using labour productivity.

Table C2: Variable input cost share correlates

	No FE (1)	Industry FE (2)	Firm FE (3)
Share of industry sales	0.91***	-0.08	-0.363***
Fixed input share	-0.29***	-0.21***	-0.23***
Productivity	-0.14***	-0.38***	-0.53***
Observations	~3m	~3m	~3m

Notes: *** p<0.01, ** p<0.05, *p<0.1. All specifications have year fixed effects. Errors robust to autocorrelation and heteroscedasticity. Productivity if MFP from the production function estimation. Results robust to using labour productivity.

Table C3: Profit rate correlates

	No FE (1)	No FE (2)	Firm FE (3)	Firm FE (4)
Mark-up	0.05***	0.06***	0.004***	0.011***
Fixed input share	-	-0.26***	-	-0.378***
Observations	2,353,489	2,353,489	2,353,489	2,353,489

Notes: *** $p<0.01$, ** $p<0.05$, *$p<0.1$. All specifications have year fixed effects. Errors robust to autocorrelation and heteroscedasticity. Profit rate defined as net profits over sales.

Table C3: Summary of Changes in Mark-ups Using Different Fixed Cost Metrics

	Unweighted average				Sales-weighted average			
	Mark-up	Excess Mark-up	Mark-up (Traina)	Mark-up (De Loecker)	Mark-up	Excess Mark-up	Mark-up (Traina)	Mark-up (De Loecker)
Change 2004-2017 (ppt)	7.4	2.8	4.4	3.3	9.0	2.6	4.3	1.4
Change 2004-2017 (%)	6.2	na	4.1	3.0	6.9	na	3.4	1.1

Note: Mark-up Traina is the model including fixed costs as variable. Mark-up (De Loecker) is the approach including fixed costs as a separate input into the production function. Excess mark-ups exclude agriculture, mining and utilities divisions.

APPENDIX D: MARKET CONCENTRATION

As discussed in the text, there might be some concerns about the ability to identify the levels of mark-ups without having access to firm-level prices. I deal with this by focusing on changes, rather than levels, which should not be subject to the same concerns. But to provide further evidence, I also reproduce some of the analysis looking at measures of industry concentration.

I construct measures of industry concentration using sales data from firms' Business Activity Statements from 2001/02 to 2015/16. Industries are defined as 4-digit ANZSIC industries. The measure of concentration is the share of sales accruing to the largest 4 firms in an industry. I exclude the public sector, and the financial sector, and remove some extreme outliers.

Figures 2 and 3 in the main text show the key takeaways. Concentration has, on average, increased over time by around 2 percentage points. Concentration increased in about 2/3 of the 4-digit ANZSIC industries. At the same time, the top firms have become more entrenched, and less likely to be replaced by other small firms at the top of the industry.

The results are generally consistent to using other industry definitions, using other concentration metrics, and to looking only at domestic sales. They are also not driven by industries such as manufacturing and mining, which are highly tradeable on the global market, and so for which domestic concentration metrics may not be particularly relevant

If we use the concentration of employment, rather than sales, the concentration metrics are lower (Figure 19). They also appear to increase by slightly less, particularly since the mid-2000s when our measure of mark-ups increased. As discussed in Edmond et al (2019), this is indicative of rising variable mark-ups.

Figure 19: Share of Sales in Industries Made by Largest 4 Firms
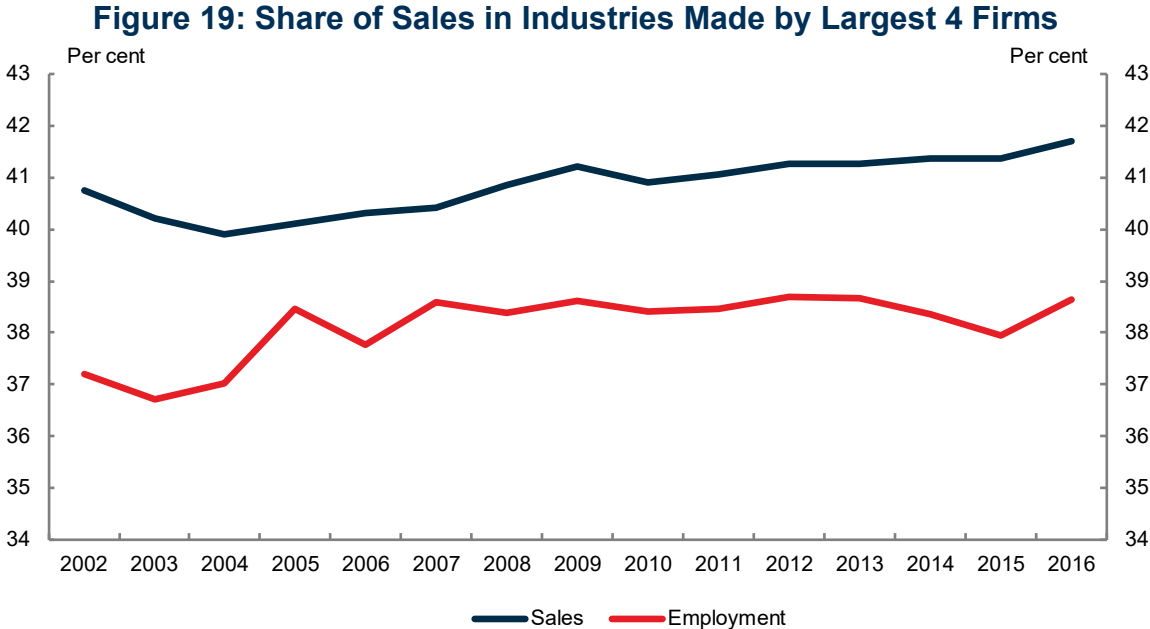
Note: Unweighted average of industry-level shares. Employment measure is FTE employees. Treasury calculations based on ABS BLADE.

As discussed in the text, concentration is not a perfect metric of market power, and it could increase due, for example, to change returns to scale, or even increasing competition that benefits the best firms (though this explanation would be inconsistent with the increasing entrenchment of the top firms). If, on the other hand, increasing concentration reflects decreasing competition, driven by less potential

competition of increasing barriers to entry, it should be associated with weaker selection effects, similar to mark-ups.

To examine this, and to provide additional support to the results in text, I run similar selection and growth models to those in Section 6.1, but replacing mark-ups with concentration. I focus on labour productivity, and remove the interaction between industry and productivity given I am less concerned with identifying the level of concentration, and for computational reasons.[25] I use gross output labour productivity, rather than value-added, as the measure of intermediate inputs in this data is likely to include a number of expenses that are treated as fixed in the mark-up analysis.[26]

The results of the regression are contained in Table D1. As in the main text, the coefficient on productivity in the exit the exit regression is negative and in the growth regression is positive, indicating that more productive firms are less likely to exit, and more likely to grow. The coefficients on the interaction of productivity and concentration are the opposite, indicating that the selection effects are weaker in more concentrated industries.

| Table D1: Results from Selection and Reallocation Regressions		
	Dependent variable: $Exit_{i,t+1}$	*Dependent Variable: $g^L_{i,t+1}$*
β	-0.009***	0.140***
(s.e.)	(0.001)	(0.007)
γ	0.006**	-0.089***
(s.e.)	(0.003)	(0.023)
Obs	~~$.9 million	~5.3 million

Notes: *** p<0.01, ** p<0.05, *p<0.1. All specifications have industry*year fixed effects, controls for size and past sales growth. Top and bottom percentile of productivity distribution drop trimmed. Errors clustered at the industry level.

To give a sense of the size of this effect, Figure 20 shows how the rate of employment growth, or probability of firm exit differs between high and low productivity firms in high and low concentration industries. In a highly concentrated industry, the gap in employment growth between high and low productivity firms is 7 percentage points larger, indicating that reallocation occurs more quickly in these industries. Similarly, the gap in probably of exit is one percentage point higher in high concentration industries, indicating that there is more selection on productivity.

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25   Including these interactions lowers the coefficients slightly, but does not substantially change the results.

26   The results are similar in the growth model if I use value-added. But in the exit model the coefficient on the interaction between productivity and concentration is no longer significant.

Figure 20: Employment growth and Exit Probability Gap between High and Low Concentration Industries
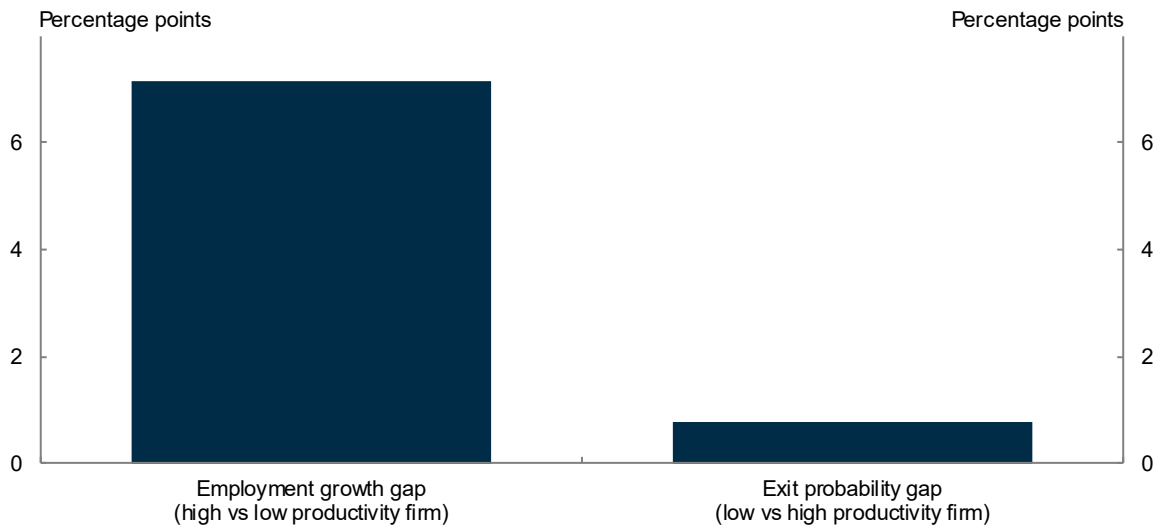
Note: Exit and employment growth gaps defined as difference in modelled probability of exit, and employment growth rate, respectively, for high and low productivity firms. High (low) productivity firms are firms one standard deviation above (below) the industry mean. Chart shows the difference in this gap between a high and low concentration firm. High (low) concentration firm is 75th (25th) percentile.