# How Costly are Mark-ups in Australia?
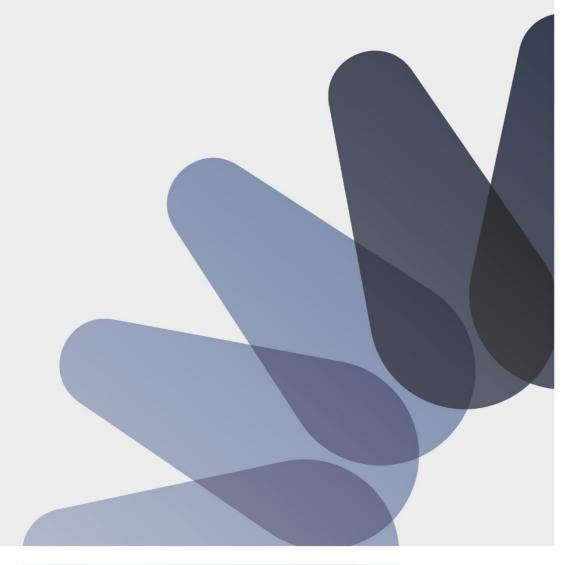
## The Effect of Declining Competition on Misallocation and Productivity

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## Acknowledgement and Disclaimer

# Abstract

There is substantial evidence that the degree of competition in the Australian economy has declined over the decade or so leading up to COVID. This has the potential to weigh on productivity, and in turn incomes and so the welfare of the Australian people. In this paper we calibrate the general equilibrium model from Edmond, Midrigan and Xu (2023) to Australian microdata to answer the following question: If the degree of competition had not declined from mid-2000s levels, how much higher would aggregate productivity and GDP be due to resources being better allocated across firms throughout the economy? The answer, according to this model, is 1-3 per cent. The model also suggests even larger economic costs once we account for other channels through which rising mark-ups affect the economy, though these are less precisely estimated.

# Contents

# 1. Introduction

There is substantial evidence that the degree of competition in the Australian economy declined over the decade or so leading up to the COVID-19 pandemic. This is evident when looking at a number of different proxies for competition: industries became more concentrated, with the few biggest firms accounting for a larger share of sales in their industries; industry leaders became more entrenched, and less likely to be displaced by new and growing firms; and estimates of mark-ups (the ratio of price to marginal cost and the most theoretically sound measure of market power) increased (Andrews, Dwyer and Triggs 2023; Hambur 2023).

At the same time, productivity growth has slowed. This has significant implications for living standards, as productivity growth is the main source of increases in income, and so consumption and living standards, over the medium term.[1] Slower productivity growth also has implications for fiscal and monetary policy. Slower productivity growth means slower growth in government revenue, and so impacts fiscal sustainability. It also implies slower trend growth and a lower neutral rate of interest, meaning that monetary policy is more likely to be constrained by the effective lower bound on interest rates (all else equal).

Declining competition and productivity may be linked. A decline in the degree of competition has the potential to weigh on productivity through a number of channels. It can blunt firms' incentives and ability to invest, innovate, improve, and adopt new technologies (Gutiérrez and Philippon 2017; Andrews, Criscuolo and Gal 2019; Andrews and Hansell 2021; Andrews *et al* 2022;).[2] Declining competition can also reduce the rate at which inputs are reallocated to more productive uses, which lowers aggregate productivity in the economy (De Loecker, Eeckhout and Unger 2020; De Loecker, Eeckhout and Mongey 2021; Hambur 2023). And more generally, theory states that higher mark-ups (which reflects lower competition) are a distortion that mean the economy is smaller, and prices higher, than it otherwise would be if there was perfect competition and no mark-ups.

A number of recent papers have highlighted that its not just the level of competition and mark-ups that matter, but how they differ across firms (Baqaee and Farhi 2020; Edmond, Midrigan and Xu 2023). In particular, if some firms (or industries) have higher mark-ups, they will be producing too little at too high a price, relative to other firms with lower mark-ups. It would be a more productive use of resources to have them produce a little more, and another firm to produce less. So, this dispersion in mark-ups represents a misallocation of resources and production in the economy across firms. This means lower aggregate productivity in the economy.

Understanding to what extent declining competition has led to lower productivity is important, as it can improve our understanding of the structural drivers of slowing productivity growth. In turn, this can help us to think about future productivity outcomes, and therefore potential growth and neutral interest rates, as well as future government revenues and fiscal position. And it can also help us think about the effects of future reforms.

Some previous work has tried to assess the effects of declining competition on productivity and output in Australia using simple, back-of-the-envelope approaches. These included looking at how reallocation of resources between high- and low-productivity firms, and the pace of firm-level productivity improvement, changed as mark-ups rose (Andrews *et al* 2022; Hambur 2023). Such approaches can provide some useful insights, but have a number of shortcomings. They tend to take a partial equilibrium approach (just looking at one piece of the puzzle and not the flow-on effects), be subject to noise, and, while they might be motivated by theory, they often lack a fully fleshed out model to motivate them. As a result of these shortcomings, they can be hard to express in terms of aggregate costs, such as the effect on the level of productivity and GDP.

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1    For a discussion of the Australian productivity slowdown, and its relationship to household consumption and incomes, see Plumb (2025) and Duretto, Hambur and Majeed (2022)

2    It is important to note that theoretically greater competition can lead to more or less innovation and investment, depending on the exact market structure. For example, market power can raise the potential profits from innovation and therefore incentivise innovative activity (Agion et al 2005). Though empirically in Australia it has been found to weigh on innovation.

In this paper, we take a more systematic approach, using the seminal general equilibrium model from Edmond, Midrigan and Xu (2023) (EMX) calibrated to the Australian economy. We use this model to answer the following question: If the degree of competition in the Australian economy had not declined from the mid-2000s, how much higher would aggregate productivity and GDP be due to resources being better allocated across firms throughout the economy?

We choose the EMX model for this exercise because it has a strong theoretical link between competition and mark-ups on one hand and productivity on the other. It has clear and transparent mechanisms, making it easy to interpret. And these are well captured by a few key economic parameters and relationships, so it is easy to apply to the Australian data.

In assessing the effects of declining competition on productivity, we focus on one specific channel: the misallocation of resources between firms. Previous work has indicated that this is a first-order issue in Australia, and so it deserves direct investigation. Still, as a result the estimates should be thought of as a lower bound. For example, they abstract from the effects that weaker competition might have on the impetus to invest in improved technologies and approaches, as explored in Andrews *et al* (2022). We also estimate the overall effect that high levels of mark-ups could have on household welfare by reducing aggregate output and investment, and so the size of the economy (deadweight loss channel). But these are not the main focus of the paper as they rely on a broader set of modelling assumptions and are less precise.

Overall, we find that, as of 2017 (when our estimates end), if the economy could have returned to mid-2000s levels of competition, productivity would have been around 1–3 per cent higher. The upper end of this range equates to around $3,000 per person in today's dollars. The findings are robust to accounting for fixed costs, different ways of aggregating measures of industry concentration and mark-ups, and different competitive structures. Accounting for the broader costs of mark-ups, in particular the effect of the level of mark-ups on firm choices about how much to produce (deadweight loss channel), leads to much larger estimates in terms of lost economic activity, though the range of estimates is quite large. As such our main estimates may be seen as conservative.

A key innovation of this paper is that we exploit the rich administrative data in Australia to understand productivity costs for the whole economy, unlike most other papers like EMX and Baqaee and Farhi (2020) which focus just on either the manufacturing sector or large publicly listed firms. As such our estimates should be more representative of aggregate economic costs.

Moreover, this allows us to look beyond the aggregate and think about how the costs differ across sectors. This is an important dimension for two key reasons. First, it may provide some indication of where reforms might have the largest productivity impacts, at least by lowering misallocation. And second, because there is a growing literature showing that input-output linkages can play an important role in amplifying industry-level distortions, with distortions in upstream industries tending to have larger aggregate effects (e.g. Jones 2011; Liu 2019; Andrews *et al* 2025). So by identifying sectoral heterogeneity in productivity losses due to declining competition, we can potentially get a sense of whether the main aggregate results could be under or overstated based on their sectoral outcomes.

We find that there is significant heterogeneity in productivity losses across sectors. In general, these firm-to-firm distortion costs have grown the most in upstream sectors like manufacturing and wholesale trade. As such, the aggregate effects may be even larger, and this could be quantified in future work.

Overall then, while the range of estimates is large, these findings suggest that declines in the degree of competition have significantly dragged on aggregate productivity over the period – an important finding for policymakers. That said, at least through the lens of this model, this represents a level shift down in productivity and past declines in competition should not weigh on future productivity growth. But looking beyond the model, if weaker competition does weigh on firms' impetus to improve and converge to the global frontier (which is not accounted for in this model), or if competition continues to weaken, there could still be ongoing effects.

# 2. Related literature

There is a large and growing literature trying to quantify the effects of competition and (its inverse) market power on productivity. Most closely related to our work is the portion of this literature that focuses on how misallocation of resources across firms (i.e. some being too large and some too small) due to distortions like mark-ups can affect aggregate productivity.

This literature is often traced back to Harberger (1954). He explored these costs using industry-level data and concluded that the misallocation costs of monopoly, the so-called `Haberger triangle', were very small.

More recently though a number of papers have begun to re-examine this question, exploiting firm-level data to better capture firm heterogeneity. Two early papers in this literature were Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), which argue that misallocation of resources across firms due to various 'wedges' (such as mark-ups) can lead to significant productivity and output losses. The latter paper measured these distortions as the dispersion of capital and labour productivity at a firm level.[3] They argued that dispersion in measured productivity, which they took as an indicator of dispersion in marginal productivity, meant there was a loss in productivity due to misallocation: it would increase aggregate productivity if the economy shifted resources and output towards those firms with high marginal productivity. They found that such misallocation could account for a large share of the gap in productivity between the United States and both China and India.

In a similar vein, Baqaee and Farhi (2020) derive a general non-parametric set of formulas for decomposing productivity into technical efficiency (i.e. the technological progress) and allocative efficiency (i.e. whether resources were being put to their most productive use) in the presence of wedges and distortions like mark-ups, which they take to be exogenous. Applying these to US data, they find that allocative efficiency rose (and so misallocation fell) from 1997 to 2015 as resources reallocated towards high mark-up, high (marginal) productivity firms. But eliminating mark-up dispersion in 2015 would still have raised productivity, specifically total factor productivity (TFP), by around 15 per cent. These costs are around two orders of magnitude larger than those found by Harberger (1954).

Most closely related to our paper is EMX, whose model we calibrate to Australia. They construct a heterogeneous firm model under general competition structures. They calibrate it to the US manufacturing sector and find that the TFP costs of misallocation are around 2–6 per cent. These estimates of costs are lower than Baqaee and Farhi (2020), in large part because EMX focus only on variation in mark-ups (and so misallocation) that can be explained by variation in firm size, noting that the rest could capture other factors such as mismeasurement, rather than true misallocation.[4] In this sense they have endogenous mark-ups that are micro-founded, unlike the exogenous mark-ups in Baqaee and Farhi (2020). They also apply the model to calculate the overall welfare costs of mark-ups, accounting for deadweight losses associated with the level of mark-ups, as well as flow-on effects of distortions into investment and the size of the economy. They find these to be quite large, reflecting both the misallocation channel and the level of mark-ups.

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3    More precisely, they used a revenue, rather than quantity-based measure of productivity.
4    This is similar to the argument made by Haltiwanger, Kulick and Syverson (2018) that much of the distortions in the Hsieh and Klenow (2009) may not be true sign of inefficiency, but rather, for example, demand shifts.

Some papers have looked at these questions in Australia in a more reduced-form, dynamic sense, using empirical regressions rather than full models. Andrews and Hansell (2021) show that the pace of reallocation of labour towards more productive firms within industries (dynamic rather than static allocative efficiency) has slowed since the mid-2000s, and that this reflects structural rather than cyclical factors. Taking a simple back-of-the-envelope calculation, they found that this slowing could account for a moderate portion of the slowdown in labour productivity growth in Australia. Hambur (2023) shows that this slowdown in reallocation is worse in sectors with rising mark-ups, thus linking slower reallocation and productivity growth to rising mark-ups in the Australian context.[5] He also found that mark-up increases in Australia have tended to reflect within-firm increases, rather than reallocation of resources to high-productivity firms as in the United States (De Loecker *et al* 2020). Moreover, dispersion in mark-ups increased significantly. Both of these findings suggest that the level of misallocation due to mark-ups is likely to have risen in Australia. Finally, Elkington (2022) applied the Baqaee and Farhi (2020) approach to Australia. He found that the misallocation costs were significant and of an order of magnitude similar to Baqaee and Farhi (2020) for the United States. This provides strong motivation for analysis of these dynamics in the EMX framework.

# 3. Model

Below we outline a very high-level sketch of the EMX model and its key mechanisms. A more detailed description of the model follows. We focus on the components needed to study the misallocation effects and leave the reader to refer to EMX for a fuller account of the model.

In the model there are heterogeneous firms that differ in terms of their productivity. In the baseline model, firms compete in a monopolistically competitive market, giving rise to mark-ups. Unlike some models, where all firms have equal mark-ups, in this model firms' mark-ups endogenously differ based on their size. In turn, their size relates to their productivity. How mark-ups vary with firm size is dictated by the 'superelasticity'. This is an important parameter in the model, and captures how demand elasticiticities (and so mark-ups) change as firm size changes. If the superelasticity is positive, larger firms tend to have higher mark-ups, which is a standard finding in the literature. If it is zero, there is no variation in firm mark-ups, and we are back in the standard model with equal mark-ups and no misallocation across firms.

In the model, mark-ups create costs in the economy via three mechanisms:

1. When average mark-ups are higher, decisions around consumption, investment and output are distorted, so the economy is smaller than it would be in the first best case, *for a given level of aggregate productivity* (the traditional deadweight loss channel).

2. Mark-ups lead to inefficient rates of entry, and so an inefficient number of varieties in the economy (entry channel).

3. Dispersion in mark-ups creates misallocation. So, the level of aggregate productivity is lower than it could be, as resources could be moved between firms in ways that could raise aggregate productivity (misallocation channel).

As noted, while the model contains several important channels, it abstracts away from others. For example, it does not consider the dynamic effects of competition on firms' incentives to innovate, improve, and adopt technologies.[6] Moreover, our main focus is on the final channel though we return to the other channels briefly at the end of the paper.

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5    Hambur and Andrews (2023) make a similar finding for capital and total-factor productivity.
6    That said, it does capture some dimensions of innovation, particularly through firm entry and related gains from new varieties.

## 3.1 Consumer

The model has a representative consumer. Their utility function has the following form:

$$\sum_{t=0}^{\infty} \beta^t \left( \log C_t - \varphi \frac{L_t^{1+\nu}}{1+\nu} \right) \tag{1}$$

subject to the budget constraints:

$$C_t + I_t = WL_t + RK_t + \Pi_t \tag{2}$$

where $C_t$, $I_t$, $W_t$, $L_t$, $R_t$, $K_t$, $\Pi_t$ are consumption, investment, wages, labour hours, the return on capital, the capital stock and aggregate profits, respectively. $\beta$ is the discount factor, and $\nu$ is the elasticity of labour supply. The price is taken to be the numeraire $P_{(t)} = 1$

Capital follows the law of motion (with $\delta$ being the depreciation rate):

$$K_{t+1} = (1 - \delta)K_t + I_t \tag{3}$$

As is standard, households have the static labour supply decision:

$$\varphi C_t L_t^{\nu} = W_t \tag{4}$$

## 3.2 Intermediate goods producers

In the baseline model, there is a continuum of monopolistically competitive firms $i \in [0, n(s)]$ working within each industry $s$ producing differentiated goods.

Firms pay a fixed cost **κ** to enter and then get a random TFP draw $z_{it}(s) \sim G(z)$ where in practice this distribution is taken to be a Pareto distribution. Each firm produces $y_i(s)$ using a gross output production function:

$$y_i(s) = z_i(s) \left[ \phi^{\theta} v_i(s)^{\frac{\theta-1}{\theta}} + (1-\phi)^{\theta} x_i(s)^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{5}$$

where $z_i(s)$ is the firm's TFP, $x_{it}(s)$ is intermediate materials, $y_{it}(s)$ is the value-added of firm $i$, and $\theta$ is the elasticity of substitution between value-added and materials. Value-added is constructed using capital and labour via a Cobb-Douglas production function:

$$v_i(s) = k_i(s)^{\alpha} l_i(s)^{1-\alpha} \tag{6}$$

where $\alpha$ is the capital share of income.

Within each sector, output is aggregated using a Kimball aggregator of the form:

$$\int_0^{n(s)} \Upsilon\left(\frac{y_i(s)}{y(s)}\right) di \tag{7}$$

where the function $\Upsilon: R_+ \to R_+$ is strictly increasing and strictly concave.

The assumption about the aggregator implies that firms face an inverse demand curve $f(q)$, demand elasticity $\sigma(q)$, and mark-up $\mu(q)$ of the following form:

$$f(q) = \Upsilon'(q), \quad \mu(q) := \frac{\sigma(q)}{\sigma(q) - 1}, \quad \sigma(q) := -\frac{\Upsilon'(q)}{\Upsilon''(q)q} \tag{8}$$

where $q$ is the firm's share of industry output.

Unlike under the standard constant elasticity of substitution (CES) aggregator, this means that a firm's mark-up over marginal cost depends on its size (or market share $q$). Dispersion in mark-ups, and therefore marginal revenue products, leads to lower productivity within the sector, as discussed extensively elsewhere, such as (Hsieh and Klenow 2009). This is because aggregate productivity could be raised by shifting resources and output from one firm to another. So the endogenous dispersion in mark-ups leads to misallocation and lower productivity in the industry, compared to a version of the model with CES aggregators.

How the elasticity of demand, and so mark-ups, change with firm size is referred to as the superelasticity of demand. The superelasticity (along with the firm size distribution) pins down the dispersion in mark-ups in the model, and so the degree of misallocation. If the superelasticity is zero, we return to the CES case with constant mark-ups. But there may still be aggregate mark-ups in the economy, and so costs through other channels (e.g. the deadweight loss channel).

EMX also consider other competitive structures in their fairly general set-up. This includes an oligopoly model, where non-atomistic firms compete within industries. We return to this in Section 6.

## 3.3   Final goods producers

The products of the industries are aggregated into a final good *Y*. This final good is used for consumption, investment and as an intermediate good. So there is a fairly simple input-output structure, sometimes referred to as a 'roundabout' structure.

The final good is produced by perfectly competitive firms who aggregate industry inputs, leading to the following form:

$$Y_t = \left(\int_0^1 y_t(s)^{\frac{\eta-1}{\eta}} ds\right)^{\frac{\eta}{\eta-1}} \tag{9}$$

where $\eta > 1$ is elasticity of substitution across sectors.

## 3.4 Aggregate mark-ups and productivity

As shown in EMX, sector and aggregate productivity can be written as sales-weighted harmonic averages of firm and industry productivity, respectively:[7]

$$z_t(s) = \left( \int_0^{n(s)} \frac{q_{it}(s)}{z_{it}(s)} \, di \right)^{-1}, \qquad Z_t = \left( \int_0^1 \frac{q_t(s)}{z_t(s)} \, ds \right)^{-1} \tag{10}$$

Similarly, sector and aggregate mark-ups are sales-weighted harmonic averages:

$$\mu_t(s) = \left( \int_0^{n(s)} \frac{1}{\mu_i(s)} \cdot \frac{p_i(s) y_i(s)}{p_t(s) y_t(s)} \, di \right)^{-1} \tag{11}$$

$$M_t = \left( \int_0^1 \frac{1}{\mu_t(s)} \cdot \frac{p_t(s) y_t(s)}{Y_t} \, ds \right)^{-1} \tag{12}$$

Each industry's share of aggregate sales is a function of its mark-up and productivity:

$$q_t(s) = \left( \frac{\mu_t(s)}{M_t} \cdot \frac{Z_t}{z_t(s)} \right)^{-\eta} \tag{13}$$

Inputting this in into Equation (10), aggregate productivity takes the form:

$$Z_t = \left( \int_0^1 \left( \frac{\mu_t(s)}{M_t} \right)^{-\eta} z_t(s)^{\eta-1} \, ds \right)^{\frac{1}{\eta-1}} \tag{14}$$

As discussed, dispersion in mark-ups leads to lower industry-level productivity, and therefore lower aggregate productivity. We can see this from Equation (14) (at an industry level): as if $\mu_t(s) = M_t$ the first term in the integral will be 1, so there will be no distortion down in aggregate productivity coming through via Jensen's inequality.

Note that we can also consider the case of value-added productivity, which relates more directly to GDP, as GDP is measured on a value-added basis. The value–added productivity in the economy (or industry) can be written as:

$$Z_{va} = \phi^{1/(\theta-1)} \cdot \frac{1 - (1-\phi) Z^{\theta-1} M^{-\theta}}{[1 - (1-\phi) Z^{\theta-1} M^{1-\theta}]^{\theta/(\theta-1)}} \cdot Z \tag{15}$$

While only the dispersion of mark-ups influences gross-output productivity, the level of mark-ups in aggregate does affect value-added productivity. This is because it distorts the choice of materials relative to value-added, leading to too many intermediate inputs being used relative to what would be efficient.

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7    Alternatively they can be expressed as labour- or input-weighted arithmetic averages.

# 4. Model calibration

The model has three key parameters that bed down the amount of misallocation in the economy, and therefore the cost of mark-ups:

1. Productivity dispersion: How different are firms in terms of their productivity? This pins down differences in firm size (or more precisely market shares).

2. Superelasticity: How do firms' mark-ups vary with their market shares? This, together with the dispersion in size, pins down the dispersion in mark-ups.

3. The average elasticity of demand: How willing are consumers to switch between different producers, and so how much market power do firms have (on average)? This pins down the aggregate mark-up in the economy.

To estimate the cost of mark-ups, we need to figure out reasonable values for these three parameters for the Australian economy. To do so, we calculate real-world counterparts to each using firm-level microdata from the ABS BLADE database. We then match the model to their values.

More details on the data are contained in Appendix A. But at a high level, BLADE is a large administrative database with tax data on the near universe of firms in Australia. As well as tax information on their sales, employment and expenses, it contains demographic information on their industry, firm age, and other dimensions. This information can be used to estimate firm-level outcomes, including mark-ups, but also sector-level variables, such as superelasticities and industry concentrations.

The specific metrics we use for the model calibration are:

- The share of sales accruing to the top 5 per cent of firms in an average industry. This pins down the productivity dispersion, as it pins down the dispersion in firm sizes.

  – We calculate concentration metrics at a very detailed 4-digit ANZSIC industry level (e.g. bakery product manufacturing) and take an unweighted average across industries.

- As in EMX, we assume the Klenow-Willis form of the Kimball aggregator. This implies that the superelasticity can be estimated using a nonlinear regression of mark-ups on market shares (see Appendix A).

  – Regressions are run for each detailed 4-digit ANZSIC industry, including firm fixed effects (and so identifying off changes in mark-ups and size). They are then aggregated across industries using industry sales-weights. Estimates are the same as in Champion, Edmond and Hambur (2023).

- The aggregate mark-up in the economy, which directly relates to the elasticity of demand.

  – We construct this both as a cost-weighted average of firm-level mark-ups and as a harmonic sales-weighted average, as suggested by EMX, using mark-up estimates from Hambur (2023).[8]

Values for each of these calibration targets are shown in Table 1. The degree of concentration increased by around 2 percentage points from the mid-2000s to the mid-2010s, while mark-ups increased by around 5 per cent. We assume the superelasticity remains unchanged due to the relatively short sample, but the sensitivity of the results to this assumption is tested in the robustness section.

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8   EMX argue that the input-weighted and harmonic sales-weighted averages should be identical. This relies on certain assumptions, including a common elasticity of output with respect to value-added and wage rate, which may not actually hold in the data and mark-up estimation.

## Table 1: Model Calibration Targets

Baseline model

| | Mark-up Harmonic sales-weighted | Mark-up Cost-weighted | Concentration[a] Top 5 per cent share | Superelasticity |
|---|---|---|---|---|
| Mid-2000s | 1.18 | 1.25 | 68 per cent | 0.13 |
| Mid-2010s | 1.25 | 1.33 | 70 per cent | 0.13 |

Note: (a) Concentration based on unweighted average of industry-level shares. Sources: Author's calculations; Hambur (2023).
Sources: Authors' calculations; Hambur (2023).

Table 2 shows the calibrated parameters to meet these targets. We can see that to meet the higher mark-ups in the later period, the average demand elasticity declines moderately.

## Table 2: Model Parameters

Baseline model

| | Harmonic sales-weighted | | Cost-weighted | |
|---|---|---|---|---|
| | Pareto tail $\xi$ | Demand elasticity $\sigma$ | Pareto tail $\xi$ | Demand elasticity $\sigma$ |
| Mid-2000s | 5.59 | 9.45 | 4.00 | 7.26 |
| Mid-2010s | 4.04 | 7.02 | 3.05 | 6.03 |

Table 3 shows the other parameters in the model. For most other parameters we take them directly from EMX, as they are broadly in line with equivalent measures for Australia (e.g. the labour share of income).[9] However, we change the materials share of gross output to better align with the Australian economy.

## Table 3: Other Parameters

Baseline model

| Parameter | Value |
|---|---|
| Discount rate $\beta$ | 0.96 |
| Depreciation rate $\delta$ | 0.06 |
| Exit rate | 0.04 |
| Labour share of value-added $(1 - \alpha)$ | 2/3 |
| Elasticity of labour supply | 1 |
| Elasticity of substitution between value added and materials $\theta$ | 0.5 |
| Materials share of gross output | 0.47 |

Sources: Authors' calculations; Edmond, Midrigan and Xu (2023).

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9 The exit rate is significantly below the actual overall exit rate for the Australian economy, which tends to be around 10-15 per cent (depending on if non-employing firms are included). But EMX target an employment weighted metric – the share of employment by previously existing firms. Using ABS Counts of Australian Businesses data on exits by firm size and taking firms to be in the middle of each employment size bucket, leads to quite a similar number to EMX.

# 5. Cost of mark-ups in Australia

## 5.1 Aggregate productivity costs

We use the model to calculate how much lower productivity, specifically TFP, was relative to the economy where there was no dispersion in mark-ups and therefore misallocation. We show this both for the mid 2000s and late 2010s, and consider how these costs changed. These calculations reflect a 'static' assessment of the costs, as they do not consider flow-on effects in terms of investment choices and firm entry (the static social planner problem). They capture, all else equal, how much could we raise TFP by shifting resources and output across firms to offset the mark-up distortion.

We show three measures of these potential TFP improvements. The first is gross output misallocation cost. The second is value-added misallocation cost, which is more relevant in considering the impact on GDP. Finally, we also show a value-added measure excluding input distortions (which EMX refer to as 'Value-added, $\mu = 1$'). This latter measure is similar to the overall value-added measure but is narrower and only includes the cost of misallocation across firms, whereas the main value-added measure also includes 'input misallocation'. Input misallocation captures the fact that there is too much 'churning' of intermediate inputs, and so too much intermediate input use relative to final consumption. We calculate all three measures for both cost-weighted, and harmonic sales-weighted mark-ups.

Focusing on the cost-weighted mark-up we can see that the cost went up by 1.54 percentage points when focusing on the narrower value-added loss measure, and 3.67 percentage points for the broader measure (Table 4). Using the harmonic sales weighted mark-ups the increases were slightly smaller, at around 1.12 and 2.52 percentage points, respectively. So had competition not declined, this suggests that productivity would be around 1-3 per cent higher due to a better allocation of resources across the economy.

The increase in the cost of mark-ups coming from misallocation reflects an increase in the dispersion of mark-ups across firms. In the cost-weighted case the gap between the 90th percentile and 25th percentile mark-up rose from 21 index points to 30 index points (Table 5). These are broadly in line with the change in dispersion seen in the actual data, where the cost-weighted gap went from 77 to 91 index points. Notably, the level of dispersion is much lower in the model than in the data. While we could use the observed dispersion in mark-ups to calibrate the model, EMX caution against this, noting that some of the dispersion in measured mark-ups may reflect noise and other factors. As such, we should only incorporate the amount of dispersion that the model itself can justify based on theory.[10]

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10    It's also worth noting that in the data, a non-negligible share of firms have very low or zero mark-ups. The model does not allow for this.

## Table 4: Productivity Cost of Mark-ups

Baseline model

| | Harmonic sales-weighted mark-up | | | Cost-weighted mark-up | | |
|---|---|---|---|---|---|---|
| | Gross output | Value added | Value added (no input) | Gross output | Value added | Value added (no input) |
| Mid-2000s – % | 1.06 | 3.60 | 2.15 | 1.60 | 6.21 | 3.33 |
| Mid-2010s – % | 1.59 | 6.11 | 3.31 | 2.27 | 9.89 | 4.87 |
| Change – ppt | 0.53 | 2.52 | 1.16 | 0.67 | 3.67 | 1.54 |

Note: Shows percentage loss in productivity relative to the efficient static planner's problem allocation.

## Table 5: Dispersion of Mark-ups – Cost-weighted Model

Baseline model

| | Model Mid-2000s | Model Mid-2010s | Data Mid-2000s | Data Mid-2010s |
|---|---|---|---|---|
| 25th percentile | 1.18 | 1.22 | 1.00 | 1.04 |
| 50th percentile | 1.23 | 1.30 | 1.18 | 1.24 |
| 75th percentile | 1.31 | 1.40 | 1.38 | 1.46 |
| 90th percentile | 1.39 | 1.52 | 1.77 | 1.95 |

Note: Shows percentiles of the model and observed mark-up distribution. Sources: Authors' calculations; Hambur (2023).

It's important to keep in mind that these results suggest a level shift down in productivity due to misallocation. Whether or not these costs continue to rise will depend on whether or not mark-up and mark-up dispersion continue to rise. Existing work suggests that this was not the case over the two years to COVID-19 (Andrews *et al* 2023; Champion *et al* 2023, Appendix A). Further work could consider post-COVID-19 outcomes once data become available.

Robustness: We consider a number of robustness tests to these main results. One small concern may be that in estimating the superelasticity we trim some firms, for example firms with only one year of mark-up estimates (as the regressions include firm fixed effects), and those with mark-ups below one (due to model assumptions). But our mark-up estimates are taken from the full sample in Hambur (2023). Focusing on the sub-sample of firms feeding into our superelasticity measure leads to higher mark-up estimates, and so higher productivity costs in levels terms. But the changes in costs across time are of a similar magnitude (Table B3). The results are also very similar if we use the sales-weighted average concentration measures, rather than the unweighted average.

A further robustness that can be considered is to allow the superelasticity to change over time, exploiting the time-series dimension of the data. A key decision that needs to be made in doing so is how to split the sample when allowing the superelasticity to vary. There is no clear optimal window size to use, and any choice represents a trade-off between flexibility over time, and noise coming from using a smaller sample. We consider the case of a three-year window for an, admittedly arbitrary, starting point

Doing so, the superelasticity estimates have varied moderately over time. They increased moderately over the 2000s, peaked around 2010, then fell back slightly. Taking the start and end points (consistent with the rest of the paper), the superelasticity falls from around 0.11 in the mid-2000s to 0.09 in the mid-2010s. Incorporating this into the model leads to slightly smaller estimates of the change in the productivity cost of misallocation, but they are not substantially different and remain of the order of 1-3 per cent (Appendix B Table B6).

## 5.2  Industry results

As discussed, one advantage of the Australian data is that we are able to estimate the key model parameters for a broad range of industries. This is valuable, as there may be significant heterogeneity in the key parameters, including mark-ups, superelasticity and concentration, across industries. Given the growing literature showing how input-output linkages matter, drawing out these differences can be informative. It can also help us understand more generally where these dynamics may account for more of the productivity slowdown.

Table 6 shows the key parameters, and their changes, across most 1-digit ANZSIC industry divisions.[11] The first thing to note is that there is a very large range of superelasticity estimates across sectors, as noted in Champion et al (2023). In particular, those sectors that are downstream, and deal more directly with households, such as retail trade, tend to have superelasticities that are near zero (or even moderately negative). As such, the correlation between size and mark-ups is lower in these sectors. In accommodation & food services the estimated superelasticity is actually notably negative, indicating that smaller firms have higher mark-ups, rather than larger firm. Intuitively this makes sense. These downstream consumer-facing sectors are likely to have more small niche providers that have substantial market power due to quality and branding. That said, a full examination of the drivers of differences in superelasticities across sectors is beyond the scope of this paper.

In those sectors with near-zero superelasticities, taking the model at face value there will be no systematic misallocation across firms, and so no misallocation costs (though the welfare cost from having a positive aggregate mark-up still exists). As such, we abstract from industries with superelasticity below 0.05 in absolute terms. We also abstract from the accommodation & food services. This is because the particular Klenow-Willis form of Kimball aggregator is not well behaved for a negative superelasticity.[12] That said, its change in mark-ups and superelasticity are quite similar to the aggregate economy (in absolute terms), so the costs in this sector may look broadly similar to the aggregate.

Table 7 shows the costs across the remaining divisions, and how they change. Again, the results suggest that the increase in cost has mainly been in upstream industries, as well as in professional services, which likely is an input into many other sectors.[13] Recent papers have argued distortions in upstream input industries can be larger in terms of their impact on aggregate productivity, as the distortion gets amplified through creating further inefficiencies in the production network (e.g. Jones 2011; Liu 2019). As such, at face value it suggests that the earlier results may provide somewhat of a lower bound on the misallocation effects of decreasing competition. But alternative modelling frameworks would be needed to quantify this.

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11  Note that value-added shares are also allowed to vary across sectors. These are taken from the ABS 'Estimates of Multifactor Productivity'.

12  More precisely, quantities go very quickly towards infinity as mark-ups go towards zero.

13  Some caution should be taken in interpreting the value-added cost estimates, as despite using different material shares, we have not allowed the elasticity of output with respect to value add to differ as estimates do not currently exist by sector.

## Table 6: Model Calibration Targets

Division-level model

| | Superelasticity | Mark-up [a] | | Concentration[b] | |
|---|---|---|---|---|---|
| | | Mid-2000s | Mid-2010s | Mid-2010s | Mid-2010s |
| Agriculture | -0.02 | 1.21 | 1.29 | 0.53 | 0.58 |
| Mining | 0.21 | 1.98 | 1.94 | 0.73 | 0.77 |
| Manufacturing | 0.14 | 1.2 | 1.32 | 0.74 | 0.73 |
| Utilities | 0.02 | 1.53 | 1.25 | 0.71 | 0.79 |
| Construction | -0.03 | 1.12 | 1.19 | 0.6 | 0.62 |
| Wholesale trade | 0.26 | 1.25 | 1.3 | 0.72 | 0.74 |
| Retail Trade | -0.01 | 0.95 | 1.06 | 0.6 | 0.67 |
| Accom. & Hospitality | -0.11 | 1.17 | 1.24 | 0.59 | 0.6 |
| Transport | 0.02 | 1.31 | 1.44 | 0.81 | 0.79 |
| Rental, hiring and real estate | 0.09 | 1.36 | 1.35 | 0.69 | 0.69 |
| Prof. Services | 0.09 | 1.14 | 1.19 | 0.65 | 0.7 |
| Admin. Services | 0.03 | 1.17 | 1.35 | 0.71 | 0.74 |
| Arts & Recreation | 0.19 | 1.24 | 1.49 | 0.68 | 0.66 |
| Other Services | -0.02 | 1.05 | 1.24 | 0.55 | 0.57 |

Note: (a) Mark-ups are harmonic sales-weighted.
(b) Concentration based on unweighted average of industry-level shares.  Sources: Authors' calculations; Hambur (2023).

## Table 7: Productivity Cost of Mark-ups Change

Division-level model

| | Gross output | Value-added | Value-added (no input) |
|---|---|---|---|
| Agriculture | na | na | na |
| Mining | -0.76 | -3.78 | -1.72 |
| Manufacturing | 0.99 | 32.69 | 5.84 |
| Utilities | na | na | na |
| Construction | na | na | na |
| Wholesale trade | 0.67 | 3.23 | 1.65 |
| Retail Trade | na | na | na |
| Accom. & Hospitality | na | na | na |
| Transport | na | na | na |
| Rental, hiring and real estate | -0.12 | -1.4 | -0.33 |
| Prof. Services | 0.3 | 1.69 | 0.69 |
| Admin. Services | na | na | na |
| Arts & Recreation | 3.08 | 39.91 | 11.55 |
| Other Services | na | na | na |

Note: Shows change in percentage loss in productivity relative to the efficient static Planner's problem allocation across periods. Based on harmonic sales-weighted mark-ups.

It is important to keep in mind that these results do not suggest that declining competition has not had a negative effect on activity in other sectors. For example, rising mark-ups would weigh on output in levels terms, not just due to misallocation. And they may have effects on incentives to improve. And we did see the average level of mark-ups increase in some of those sectors with near zero superelasticities, like retail trade. Here though we are only focusing on this one channel – misallocation across firms.

# 6. Cost of mark-ups – Oligopoly model

One final question is: How much does the assumption of monopolistic competition drive the findings? Many sectors in Australia are highly concentrated with a few small dominant firms. As such, a model of oligopoly might be a better description of the economy. To explore this, we use the oligopolistic version of the model which is also outlined in EMX.

## 6.1 Set-up

For the oligopoly model, we follow EMX and assume Cournot competition within industry, with standard CES demand within each industry.

More precisely, we assume that each industry $s$ consists of $n$ firms. Output is aggregated within an industry $s$ using a CES aggregator that is a power function:

$$\sum_{i=1}^{n(s)} \Upsilon\big(q_{it}(s)\big) \tag{16}$$

$$\Upsilon\big(q_{it}(s)\big) = q_{it}(s)^{\frac{\gamma-1}{\gamma}} \tag{17}$$

where $\gamma$ is the elasticity of substitution within the industry and $q_{it}(s)$ is again the share of output accruing to firm $i$ in industry $s$. This implies that the inverse demand function takes on the following form:

$$f(q) = \Upsilon'(q) = \frac{\gamma-1}{\gamma} q^{-\gamma} \tag{18}$$

Under Cournot competition, this will mean the elasticity of demand facing each firm is:

$$\sigma\big(q_{it}(s)\big) = \left[\frac{1}{\eta}\omega_{it}(s) + \frac{1}{\gamma}\big(1 - \omega_{it}(s)\big)\right]^{-1} \tag{19}$$

where $\eta$ is the elasticity of substitution between industries, $\gamma > \eta > 1$ and $\omega_{it}(s) = q_{it}(s)^{\frac{\gamma-1}{\gamma}}$ is the market share of the firm within the industry in terms of sales (rather than output).

This implies the mark-up takes the form:

$$\frac{1}{\mu_{it}(s)} = \left(1 - \frac{1}{\gamma}\right) - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right)\omega_{it}(s) \tag{20}$$

so the inverse of the mark-up is related to the market share. The strength of the relationship between the mark-up and market share depends on the gap between the within and between sector elasticities of substitution. Intuitively, when households are just as willing to switch consumption between industries as they are between firms within an industry, a firm's market share in its industry doesn't really matter in terms of their market power and mark-up.

Multiplying Equation (20) by $\omega_{it}(s)$ and summing over all firms in an industry gives us the following relationship between industry mark-ups and the sum of squared market shares:

$$\frac{1}{\mu_t(s)} = \left(1 - \frac{1}{\gamma}\right) - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right)\sum_{i=1}^{n(s)} \omega_{it}(s)^2 \tag{21}$$

So there is a linear relationship between the inverse mark-up in the industry and the sum of the squared-sales shares in the industry. This latter measure is often referred to as a Herfindahl-Hirschman index (HHI), and it is a

common measure of market concentration. As the labour share is linearly related to the inverse mark-up too, this means that there should be a linear relationship between the industry labour share and the HHI, where the slope of this relationship can tell us about the gap between the within and across-industry elasticity of substitution parameters $\eta$ and $\gamma$.[14]

# 6.2  Calibration

Again for this model we need to pin down the shape of the productivity distribution. In this case as well as pinning down the within-industry elasticity of substitution, we also need to pin down the across industry elasticity.

To calibrate the parameters, we again target a number of moments. To pin down the shape of the productivity distribution (i.e. the tail of the Pareto distribution $\xi$ ) we again target measures of industry concentration. In this case we target the top 4 and top 20 share of firm sales within industries, taking the unweighted average across industries (Table 8). This is similar to the approach taken in the monopolistic model but using two moments in the firm size distribution instead of one. The top 4 share is similar to the EMX calibration, but the top 20 share is a bit lower at around 60 per cent, compared to 75 per cent. This reflects, at least in part, the use of the whole economy, rather than the manufacturing sector as in EMX.

## Table 8: Model Calibration Targets
### Oligopoly model

| | Mark-up[a] | Concentration[b] | | Coefficient | Firm number |
| --- | --- | --- | --- | --- | --- |
| | | Top 4 share | Top 20 share | | |
| Mid-2000s | 1.25 | 39 per cent | 59 per cent | -0.15 | 3,440 |
| Mid-2010s | 1.33 | 41 per cent | 63 per cent | -0.15 | 3,884 |

Note:   (a) Mark-ups are harmonic sales-weighted.
          (b) Concentration based on unweighted average of industry-level shares.
Source:   Authors' calculations; Hambur (2023)

To pin down the elasticities we target two moments. One is again the observed mark-ups. We focus on the harmonic sales-weighted measures for parsimony. The second is the coefficient from a regression of the labour share of income in the industry on the sector HHI. As discussed above, this helps to pin down the difference between the within- and between-industry elasticities of substitution. Under our preferred specification (run on an annual rather than long-difference model) the coefficient is around –0.15. This is slightly lower than the value used in EMX of –0.21.

One other notable difference in the calibration compared to EMX is that the average number of firms in each industry is much larger in our sample, closer to 3,500 compared to around 350 in EMX. In part this likely reflects the use of slightly more aggregated industries (4-digit ANZSIC instead of 6-digit NAICS industry definitions). It also likely reflects again the use of the entire economy, rather than the manufacturing industry, as the average number of firms per industry in the manufacturing sector in our data is closer to EMX.

Table 9 shows the calibrated parameters to meet these targets. We can see that to meet the higher mark-ups in the later period, the demand elasticity declines moderately.

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14   In practice, mark-ups could increase without the labour share declining if the share of income accruing to capital declines. As discussed in Barkai (2020), while people tend to measure the capital share as the residual from the labour share, this calculation actually captures two components: the true return to capital and excess profits (or mark-ups).

## Table 9: Model Parameters

Oligopoly model

|  | Pareto Tail ξ | Between-industry elasticity η | Within-industry elasticity γ |
|---|---|---|---|
| Mid-2000s | 6.419 | 1.678 | 8.60 |
| Mid-2010s | 4.596 | 1.499 | 6.53 |

Note:    Using harmonic sales-weighted mark-ups.

## 6.3   Cost of mark-ups

Turning now to the misallocation costs, we can see that the results under the oligopoly model are actually extremely similar to those under the equivalent monopolistic competition model (Table 10). This indicates that the earlier findings are not particularly sensitive to the choice of competitive structure for the economy.

## Table 10: Productivity Cost of Mark-ups

Oligopoly model

|  | Gross output | Value-added | Value-added (no input) |
|---|---|---|---|
| Mid-2000s – % | 1.82 | 5.10 | 3.67 |
| Mid-2010s – % | 2.35 | 7.62 | 3.31 |
| Change – ppt | 0.52 | 2.52 | 1.18 |

Notes:    Shows percentage loss in productivity relative to the efficient static planner's problem allocation. Based on harmonic sales-weighted mark-ups.

# 7. Broader cost of mark-ups

So far we have focused on the negative impact that mark-ups, and in particular dispersion in mark-ups, has on productivity via misallocation of resources across firms. But, as discussed above, this is only one channel through which rising mark-ups could have economic costs. We now turn to the broader economic costs.

To consider these costs, we solve the full EMX model with the mark-up distortions and without them (often referred to as the social planner problem). This will capture the three different channels through which mark-ups and market power will affect the economy: the traditional deadweight loss channel; the inefficient entry channel; and the misallocation channel. It will also capture the full dynamic costs, instead of just the 'static' allocation costs noted above.

Table 11 shows the results, again focusing on the baseline model. The columns show the gains that could be achieved by eliminating mark-ups and returning to the first-best allocation in the economy, in terms of output, consumption, labour inputs and total consumer welfare. In all cases we compare the steady states to the first-best, and ignore any transition dynamics in moving from one to the other.

## Table 11: Economic Costs of Mark-ups

Baseline model

| | Output | Consumption | Hours | Welfare |
|---|---|---|---|---|
| **Harmonic sales-weighed mark-up measures** | | | | |
| Mid-2000s, relative to first-best | 82 | 61 | 23 | 35 |
| Mid-2010s, relative to first-best | 141 | 106 | 31 | 61 |
| Mid-2010s, relative to mid-2010s | 32 | 28 | 7 | 20 |
| **Cost-weighed mark-up measures** | | | | |
| Mid-2000s, relative to first-best | 144 | 108 | 31 | 63 |
| Mid-2010s, relative to first-best | 247 | 187 | 41 | 108 |
| Mid-2010s, relative to mid-2010s | 42 | 38 | 7 | 28 |

Note: Shows percentage total gain from moving from one equilibrium to another (i.e. ignoring transition dynamics).

We can see that, relative to the first-best, mark-ups create large economic costs. These costs are on a similar scale to those documented in EMX. Removing all mark-ups in the mid-2000s would have raised GDP by 82 per cent, and household welfare by 35 per cent (for the harmonic sales-weighted version).

That said, this is not a particularly feasible and useful benchmark.[15] A more interesting comparison is to compare outcomes between the mid-2000s and mid-2010s. The results suggest that output and consumption would have been around 30-40 per cent higher if the economy was in the more competitive mid-2000s state, compared to the less competitive mid-2010s state. Household welfare would have been around 20-30 per cent higher. These losses are an order of magnitude larger than those noted earlier.

These larger costs reflect two factors. First, we are capturing the additional channels through which mark-ups can affect economic outcomes. As shown in Table B9, incorporating the deadweight loss channel accounts for a large share of the additional costs, and removing this distortion (via a uniform subsidy for production) removes much of the cost of mark-ups in the model. Second, these calculations account for the dynamic effects that, for example, lower productivity has on choices around the capital stock and firm entry, and therefore the overall size of the economy.

That said, it is important to keep in mind that these broader costs are more reliant on a larger set of modelling assumptions and parameters, compared to the misallocation costs. Moreover, they are more reliant on having an accurately estimated level of mark-ups. Some papers have argued that mark-ups estimated using production function approaches, such as those in Hambur (2023), can have difficulty accurately identifying the level of mark-ups (e.g. Bond *et al* 2021). Focusing on changes in the level of mark-ups over time can limit these issues, as the change in the mark-up may be well identified even if the level is not. However, EMX show that the full welfare costs of mark-ups increase nonlinearly as mark-ups rise in their model. So the starting level of mark-ups still matters for these welfare calculations.

All this is to say that these results suggest that the costs of declining competition are potentially significantly larger than those identified through the productivity misallocation channel we have focused on for most of the paper. But it is harder to create precise estimates of these costs. Even focusing on the two different ways of aggregating firm-level mark-ups, we get welfare gains ranging from 20 to 28 per cent.

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15 Assessing against a no mark-up benchmark is also difficult, given some amount of mark-ups might be needed to recoup fixed costs, or incentivise innovation.

# 8. Conclusions

Over the past few decades we have seen productivity growth slow in Australia. This has profound implications for the welfare of the Australian people, and for fiscal and monetary policy. At the same time, there has been evidence that the degree of competition in the Australian economy has declined. Previous work has linked these two dynamics, but it has been hard to quantify the effects.

In this paper, we have begun to quantify these effects, by bringing Australian data to an existing frontier theoretical model. We have used this to quantify the extent to which declining competition has weighed on productivity by causing resources to be less effectively allocated across firms in the economy.

Our key finding is that, if we were we able to return to mid-2000s levels of competition, productivity would be 1-3 per cent higher as a result of better allocated resources. This shows that, declining competition has been a significant drag on productivity, and therefore GDP and incomes. And this is before we consider other channels through which competition might affect productivity, such as incentives to adopt technologies and improve processes. Moreover, we show that the broader economic costs of declining competition are potentially much larger, though harder to precisely estimate.

These are important findings. They suggest that declining competition in the Australian economy can account for a significant portion of the slowdown in productivity growth, and therefore growth in incomes and living standards. That said, they do not give an indication of whether these costs will continue to grow from here, which is an important avenue for future work.

Moreover, they do not point to the ultimate source of the decline in competition in Australia. This could reflect a myriad of factors from regulatory burdens, to competition enforcement, to availability of finance, along with many others. Further work to understand the ultimate causes of declining competition and therefore productivity would be extremely valuable.

# Appendix A: Data, and mark-up and superelasticity estimation

## A.1 Data

The firm-level data used in this paper come from the ABS's Business Longitudinal Analysis Data Environment (BLADE). This is a longitudinal dataset of administrative tax data matched to ABS surveys and other data for (almost) the entire population of firms in Australia.

While BLADE has data on the (near) universe of Australian firms, our analysis focuses on the non-financial market sector, given difficulty measuring outputs and inputs in these sectors. As is common in the literature we remove any firms with less than one full-time employee. Even with these exclusions the data cover a very large and representative sample of economic activity in the sectors analysed.[16]

The data used for mark-up estimation 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. The PAYG statements contain information on headcount and full-time equivalent (FTE) worker numbers, which are used as the labour input for mark-up estimation.

## A.2 Mark-ups

Mark-up estimates are taken from Hambur (2023). This paper estimates mark-ups using a gross-output production function, of a translog form, using the production function approach pioneered in De Loecker and Warzynski (2012).

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, Nguyen and Soriano 2015).

- Capital: Book value of non current assets

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

As discussed in a number of papers, the use of industry deflators can make it difficult to identify the level or mark-ups (e.g. Bond *et al* 2021). That said, while the levels might be affected, the changes are unlikely to be overly affected, assuming that the production function and its estimates remain broadly constant (De Loecker

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16   Hambur (2023) shows that for the non mining, non finance market sector, that the mark-ups estimates we use cover on average about 60 per cent of the sales in each constituent industry divisions analysed.

and Warzynski 2012). As such, the lack of firm-level prices is unlikely to substantially affect the results on changes in the mark-ups.

# A.3 Superelasticity

As in EMX, for the baseline model we use the Klenow and Willis version of the Kimball aggregator.

This implies that the inverse demand function facing the firm $f(q)$ is given by

$$\Upsilon'(q_i) = \frac{\overline{\sigma} - 1}{\overline{\sigma}} \exp\left(\frac{1 - q_i^{\varepsilon/\overline{\sigma}}}{\varepsilon}\right), \qquad \overline{\sigma} > 1 \tag{A1}$$

where $\overline{\sigma}$ is a measure of the aggregate average demand elasticity.

The parameter $\varepsilon/\overline{\sigma}$ is the superelasticity of demand. It controls how demand elasticity $\sigma(q_i)$ varies with relative size $q_i$ CES demand is the special case where $\varepsilon = 0$, so demand elasticity is $\sigma(q_i) = \overline{\sigma}$ constant and independent of $q_i$, and hence there is no dispersion in mark-ups (at least no systematic variation).

This demand system will imply a one-to-one non-linear relationship between the mark-up $\mu_i$ and its sales share $\omega_i$ that can be written

$$F(\mu_i) = a + b \ln \omega_i, \qquad b = \frac{\varepsilon}{\overline{\sigma}} \tag{A2}$$

where the function

$$f(\mu_i) := \frac{1}{\mu_i} + \ln\left(1 - \frac{1}{\mu_i}\right) \tag{A2}$$

is strictly increasing and free of other parameters. So, the slope coefficient $b$ in this relationship is the superelasticity of the demand system.

To estimate this variable, we take out mark-ups estimates and transform them. We then regress them on the observed sales share $\omega_i$ We do so for each 4-digit detailed industry. We include firm fixed effects and so just identify off how mark-ups change as sales shares change. We then aggregate these industry-level superelasticities into division-level or aggregate superelasticities using industry sales-weights.

# Appendix B: Robustness

## B.1 Mark-ups based on superelasticity sample only

### Table B1: Model Calibration Targets

Smaller sample model

| | Mark-up | Mark-up | Concentration [a] | Superelasticity |
|---|---|---|---|---|
| | Harmonic sales-weighted | Cost-weighted | Top 5 per cent share | |
| Mid-2000s | 1.37 | 1.59 | 68 per cent | 0.13 |
| Mid-2010s | 1.25 | 1.46 | 70 per cent | 0.13 |

Note:     Smaller model using only firms feeding into superelasticity calculation.
          (a) Concentration based on unweighted average of industry-level shares.
Source:   Authors' calculations; Hambur (2023)

### Table B2: Model Parameters

Smaller sample model

| | Harmonic sales-weighted | | Cost-weighted | |
|---|---|---|---|---|
| | Pareto tail $\xi$ | Demand elasticity $\sigma$ | Pareto tail $\xi$ | Demand elasticity $\sigma$ |
| Mid-2000s | 2.706 | 5.493 | 2.121 | 4.697 |
| Mid-2010s | 2.184 | 4.884 | 2.000 | 4.577 |

Note:     Smaller sample model using only firms feeding into superelasticity calculation.

### Table B3: Productivity Cost of Mark-ups

Smaller sample model

| | Harmonic sales-weighted mark-up | | | Cost-weighted mark-up | | |
|---|---|---|---|---|---|---|
| | Gross output | Value-added | Value added (no input) | Gross output | Value added | Value-added (no input) |
| Mid-2000s – % | 2.64 | 12.17 | 5.73 | 3.67 | 18.91 | 8.23 |
| Mid-2010s – % | 3.53 | 17.93 | 7.90 | 3.98 | 21.09 | 9.02 |
| Change – ppt | 0.89 | 2.72 | 0.51 | 0.32 | 2.18 | 0.80 |

Note:     Shows percentage loss in productivity relative to the efficient static planner's problem allocation. Smaller sample model using only firms feeding into superelasticity calculation.

## B.2  Time-varying superelasticity

### Table B4: Model Calibration Targets

Time-varying superelasticity model

| | Mark-up | Mark-up | Concentration [a] | Superelasticity |
|---|---|---|---|---|
| | Harmonic sales-weighted | Cost-weighted | Top 5 per cent share | |
| Mid-2000s | 1.37 | 1.59 | 68 per cent | 0.11 |
| Mid-2010s | 1.25 | 1.46 | 70 per cent | 0.09 |

Note:     (a) Concentration based on unweighted average of industry-level shares.
Sources:  Authors' calculations, Hambur (2023).

### Table B5: Model Parameters

Time-varying superelasticity model

| | Harmonic sales-weighted | | Cost-weighted | |
|---|---|---|---|---|
| | Pareto tail ξ | Demand elasticity σ | Pareto tail ξ | Demand elasticity σ |
| Mid-2000s | 5.64 | 8.91 | 4.03 | 6.83 |
| Mid-2010s | 4.10 | 6.62 | 3.09 | 5.37 |

Note:     Shows estimated parameters. Time-varying superelasticity model.

### Table B6: Productivity Cost of Mark-ups

Time-varying superelasticity model

| | Harmonic sales-weighted mark-up | | | Cost-weighted mark-up | | |
|---|---|---|---|---|---|---|
| | Gross Output | Value-added | Value-added (no input) | Gross Output | Value-added | Value-added (no input) |
| Mid-2000s – % | 0.85 | 3.17 | 1.72 | 1.29 | 5.59 | 2.69 |
| Mid-2010s – % | 1.02 | 4.98 | 2.14 | 1.49 | 8.31 | 3.20 |
| Change – ppt | 0.17 | 1.81 | 0.42 | 0.20 | 2.72 | 0.51 |

Note:     Shows percentage loss in productivity relative to the efficient static planner's problem allocation.

# B.3  Division-level parameterisation

## Table B7: Model Parameters

Division-level model

|  | Mid-2000s | | Mid-2010s | |
|---|---|---|---|---|
|  | Pareto tail ξ | Demand elasticity σ | Pareto tail ξ | Demand elasticity σ |
| Agriculture | na | na | na | na |
| Mining | 1.03 | 13.27 | 1.06 | 16.26 |
| Manufacturing | 4.95 | 9.39 | 3.18 | 6.63 |
| Utilities | 5.85 | 7.18 | 5.75 | 7.69 |
| Construction | na | na | na | na |
| Wholesale trade | 4 | 10.73 | 3.35 | 9.64 |
| Retail Trade | na | na | na | na |
| Accom. & Hospitality | na | na | na | na |
| Transport | 5.41 | 7.37 | 5.35 | 7.27 |
| Rental, hiring and real estate | 2.8 | 4.99 | 2.95 | 5.19 |
| Prof. Services | 7.63 | 10.63 | 5.37 | 8.33 |
| Admin. Services | 6.78 | 8.3 | 6.7 | 8.63 |
| Arts & Recreation | 4.24 | 8.78 | 2.05 | 5.25 |
| Other Services | na | na | na | na |

## Table B8: Productivity Cost of Mark-ups Change

Division-level model

|  | Mid-2000s | | | Mid-2010s | | |
|---|---|---|---|---|---|---|
|  | Gross output | Value-added | Value-added (no-input) | Gross output | Value-added | Value-added (no-input) |
| Agriculture | na | na | na | na | na | na |
| Mining | 14.9 | 64.61 | 32.44 | 14.14 | 60.83 | 30.72 |
| Manufacturing | 1.39 | 18.96 | 6.07 | 2.37 | 51.65 | 11.92 |
| Utilities | na | na | na | na | na | na |
| Construction | na | na | na | na | na | na |
| Wholesale trade | 2.86 | 9.97 | 6.43 | 3.53 | 13.2 | 8.08 |
| Retail Trade | na | na | na | na | na | na |
| Accom. & Hospitality | na | na | na | na | na | na |
| Transport | na | na | na | na | na | na |
| Rental, hiring and real estate | 1.7 | 14.02 | 4.33 | 1.58 | 12.62 | 4 |
| Prof. Services | 0.47 | 2.02 | 1.01 | 0.78 | 3.71 | 1.7 |
| Admin. Services | na | na | na | na | na | na |
| Arts & Recreation | 2.08 | 12.73 | 6.13 | 5.16 | 52.63 | 17.68 |
| Other Services | na | na | na | na | na | na |

Note:     Shows percentage loss in productivity relative to the efficient static Planner's problem allocation.

# B.4 Full economic Costs

## Table B9: Economic Costs of Mark-ups Decomposition

Baseline model

|  | Output | Consumption | Hours | Welfare |
|---|---|---|---|---|
| **Gains from moving to first-best** | | | | |
| Mid-2000s – % | 82 | 61 | 23 | 35 |
| Mid-2010s – % | 141 | 106 | 31 | 61 |
| **Gains from uniform subsidy (remove deadweight loss)** | | | | |
| Mid-2000s – % | 73 | 50 | 21 | 27 |
| Mid-2010s – % | 122 | 86 | 29 | 48 |

Note:     Show percentage total gain from moving one equilibrium to another (i.e. ignores transition dynamics). Mark-ups are harmonic sales-weighted.

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