Competition, Markups, and Inflation: Evidence From Australian Firm-Level Data*

Preliminary Draft

Monique Champion† Chris Edmond‡ Jonathan Hambur§

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Abstract

Do variable profit margins play a substantial role in amplifying inflationary dynamics? Using detailed administrative micro data for Australia we find that: (i) there is some evidence that prices tended to increase by more in industries that had increasing markups over the 2004-2017 period, but (ii) passthrough from cost shocks to prices appears to be incomplete with no statistically significant increase in passthrough in the recent period, and (iii) there is evidence that passthrough is *lower* in less competitive industries. Viewed through the lens of macroeconomic models with variable markups, these facts are inconsistent with substantial inflation amplification. To generate substantial inflation amplification requires both that average passthrough is higher than is observed in Australian data and that passthrough is higher in less competitive industries. We calibrate a model with variable markups to match key facts from the Australian data. For our benchmark parameterization we find that, if anything, variable markups are predicted to dampen inflation.

Keywords: competition, profits, inflation, firm dynamics.

JEL classifications: E3, L1.

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†University of Melbourne, mechampion@student.unimelb.edu.au

‡University of Melbourne, cedmond@unimelb.edu.au.

§Reserve Bank of Australia, hamburj@rba.gov.au

1 Introduction

Inflation increased sharply in Australia and overseas in the years following the COVID-19 pandemic. The consensus view is that the underlying source of these inflationary dynamics was some combination of strong demand coming out of the pandemic — reflecting a combination of pent-up demand and expansionary fiscal and monetary policies — along with reduced supply — reflecting a combination of supply chains issues stemming from the COVID disruption and Russia's invasion of Ukraine. A more contentious issue is to what extent have these underlying shocks been amplified by firms taking advantage of the economic conditions to increase profits by increasing their prices by more than the increase in their costs. In other words, to what extent are inflationary dynamics amplified by increases in profit margins?

In support of this view, a number of recent studies have pointed to observed increases in *aggregate*, economy-wide, profit shares as evidence that firms have passed on price increases more than one-for-one, and thus contributed to higher inflation (see e.g., Stanford, 2023; OECD, 2023; Legarde, 2023). Against this, others have argued that observed increases in the aggregate profit share reflect other factors, such as subsidies (Haskel, 2023), energy price shocks (RBA, 2023), or firms increasing prices now in anticipation of higher future higher costs (Glover, Mustre-del Río and von Ende-Becker, 2023), rather than a decrease competitive pressures that allowed firms to increase their profit margins.

Regardless, a key concern with these approaches is their focus on the aggregate, *macro*, profit share. Our contribution is to address the basic question of whether increasing profit margins have played a substantial role in amplifying Australian inflation dynamics using detailed administrative *micro* data. We provide evidence on two related but conceptually distinct hypotheses, one stronger and one weaker:

(1) **Stronger:** Firms have passed on cost increases more than one-for-one, directly pushing up inflation.

(2) **Weaker:** Market structure considerations, e.g., market concentration, have played a key role in amplifying the inflationary impulse and inflation would have been lower if markets were more competitive.[1]

Understanding whether these hypotheses are true, and more generally understanding the key drivers of recent inflation, is crucial for policy-makers. For example, if profits are going up because firms are responding to stronger current or expected demand, monetary policy, as a demand management tool, remains highly effective. If on the other hand firms are implicitly or explicitly coordinating to pass on costs more than one-for-one and competitive pressure

[1] This weaker hypothesis allows for the fact that, with sticky prices, adverse cost shocks will put downward pressure on profit margins as many firms will not be able to raise prices immediately. But the extent of the price changes for those firms that do change prices might still differ based on the degree of competition.

has somehow fallen, this may worsen the tradeoffs monetary policy faces in responding to cost shocks and make other kinds of policies more effective.

We assess these hypotheses using two complementary approaches. First, in Section 2, we use detailed administrative micro data to assess the extent to which the pattern of firm- and industry-level markup and price changes are in principle consistent with the above hypotheses. Specifically, we:

(i) Compare changes in industry-level prices to industry-level markups, as in Conlon, Miller, Otgon and Yao (2023).

(ii) Compare changes in firm-level prices and profits.

(iii) Estimate the *passthrough* from unexpected changes in firm costs to industry prices, as in Bräuning, Fillat and Joaquim (2023).

In these three exercises we impose essentially no theoretical structure, but at the cost of having less to say about what *causes* what and how things may differ if the economy had a different structure.

Second, in Section 3 we use a dynamic macroeconomic model calibrated to match key facts from the Australian data and ask whether, viewed through the lens of that model, there is reason to think that variable markups are likely to be a source of substantial inflation amplification. In this second approach we impose much more theoretical structure, which at least has the benefit of giving a more clear causal interpretation to our results. The model we use features heterogeneous firms with endogenously variable markups, as in Edmond, Midrigan and Xu (2023), with nominal rigidities, as in Baqaee, Farhi and Sangani (2023). These model features mean that it is in principle possible for firms to choose substantially higher markups that genuinely amplify inflationary dynamics.[2]

Our key finding is that neither the reduced form empirics nor the calibrated model suggests an important role for variable markups in amplifying inflationary dynamics. First, the evidence from Australian firm-level data suggests that (i) there is some evidence that prices tended to increase by more in industries that had increasing markups over the 2004-2017 period, but (ii) passthrough from cost shocks to prices appears to be incomplete – passthrough < 1 — and there is no statistically significant evidence that passthrough has risen in recent years, and (iii) there is some evidence that, in the cross-section of industries, passthrough is *lower* in less competitive industries. Second, when we calibrate our model to match key facts in the administrative microdata data, we find that variable markups do not amplify inflation dynamics. To the contrary, for our benchmark model we find that variable markups if anything slightly dampen inflation dynamics. To generate substantial inflation amplification in

[2] We focus on the amplification of adverse cost shocks, given, as discussed above, this is where amplification could increase the tradeoffs faced by the central bank in restoring inflation to target. We also briefly present results on the amplification of demand shocks and find broadly similar results.

the model requires both that average passthrough is higher than is observed in Australian data and that more specifically passthrough is *higher* in less competitive industries. In other words, in order for there to be substantial amplification, the underlying structure of the economy would have to be very different to what we actually observe.

Although this paper has a clear focus on the Australian economy, we also contribute to the broader literature by providing a heterogeneous firms model calibrated to administrative data that is able to match a much larger share of economic activity than is typical in the literature, which tends to focus either on larger, publicly listed firms, or the manufacturing sector (e.g., as in Amiti, Itskhoki and Konings, 2019; Baqaee, Farhi and Sangani, 2023). In this sense, our estimates provide a clear view of the range of potential variation in inflation amplification as a function of underlying industry characteristics, etc.

Related literature. The debate about inflation, profits and market power in the aftermath of the pandemic comes on top of a growing literature on the topic over the past decade. In particular, a number of papers have documented declines in measure of competitive pressures across a number of countries, and discussed the economic implications in terms of productivity and growth (see e.g., De Loecker and Eeckhout, 2018; Hambur, 2023; Diez, Duval, Chen, Jones and Villegas-Sanchez, 2019). A growing number of papers have also started to consider the role of competition in more cyclical dynamics, such as passthrough of cost shocks (Amiti, Itskhoki and Konings, 2019), or of monetary policy or demand shocks (see e.g., Wang and Werning, 2022; Ueda, 2023; Menezes and Quiggin, 2022; Fujiwara and Matsuyama, 2022; Baqaee, Farhi and Sangani, 2023; Duval, Furceri, Lee and Tavares, 2021).

2 Evidence from Australian Firm-Level Data

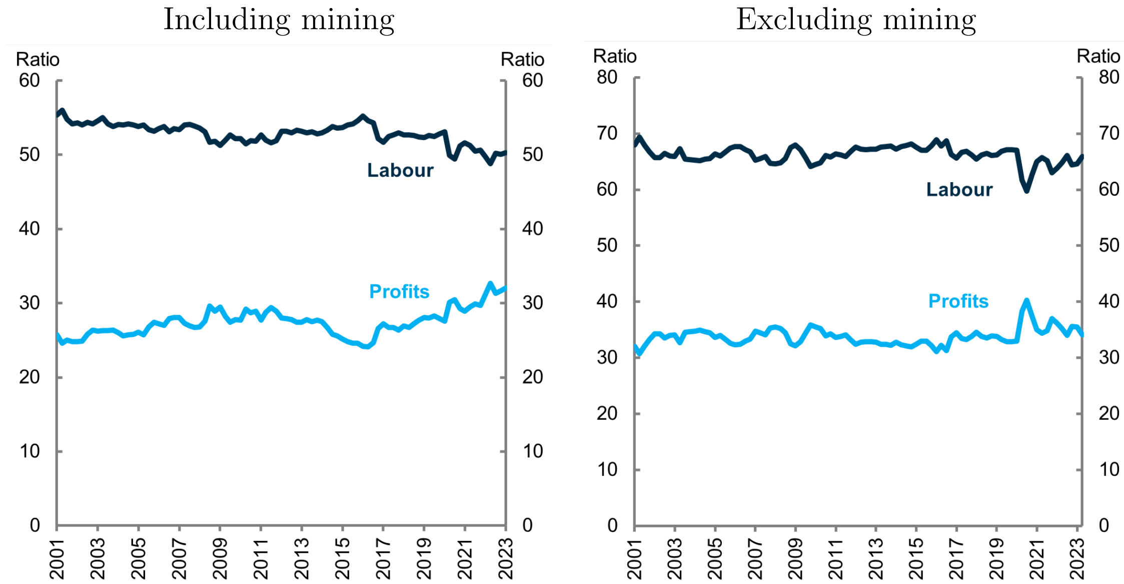
In this section we first present some basic facts from the Australian data.

2.1 Aggregate Markups and Profits

As noted above, the stronger hypothesis argues that firms have passed on cost increase by more than one-for-one, leading to higher profits and profit margins. In Australia, aggregate data are inconsistent with this thesis. As shown in Figure 1, outside of the mining sector the aggregate profit share — i.e., non-labour income share — is broadly unchanged compared to the pre-COVID period.[3] Similarly, average profit margins across much of the distribution of firms have been broadly unchanged (see e.g., RBA, 2023).

[3] Stanford (2023) comes to quite different conclusions. These differences are driven in large part due to the effective inclusion of exported mining and energy prices. These prices are set globally and so domestic firms have little control over them. Moreover, since for the most part these goods are exported and so do not directly feed into domestic prices, interpreting the role of these prices in contributing to domestic inflation is not straightforwards.

Figure 1: Aggregate Labour Share



Note: Profit share (excluding mining) defined as Gross Operating Surplus/(Gross Operating Surplus + Wages and Salaries) from Business Indicators release. Source: ABS National Accounts and Business Indicators; Authors' calculations.

That said, there are a number of weaknesses with this aggregate approach. For example, a key concern is that the profit margin and profit share measures conflate the 'normal' or 'warranted' return to capital *and* the 'excess' return to capital associated with *economic profits*. It is of course the latter concept that is more relevant when thinking about lack of competition. Measures of profit shares and excess profits can diverge significantly both when thinking about longer run movements in profit shares, as in Barkai (2020), and when examining shorter-run movements such as during COVID, as in Yotzov, Manuel and Piton (2023).

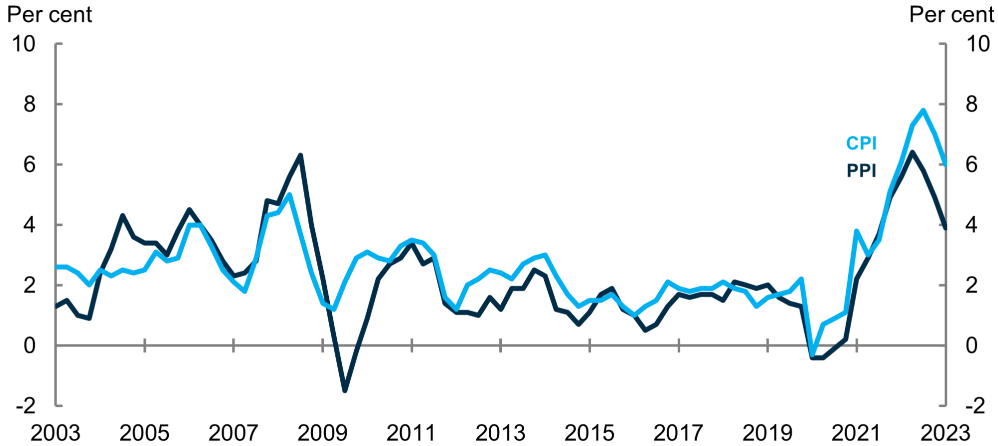
In what follows we build on the existing evidence by taking two alternative approaches to examine whether firms may be passing on price increases more than one-for-one. The first is to compare changes in markups to changes in output prices at an industry level for a moderately large sample of firms and industries. The second is to compare firm-level prices to firm-level profits for a narrower set of firms.

2.2 Industry Markups and Prices

In this section we take an approach similar to Conlon, Miller, Otgon and Yao (2023). We construct industry-level sales-weighted average markups, and compare these to changes in ABS producer price indexes (PPI) for various industries (ABS, 2023).

As a baseline, we use the measures of markups constructed in Hambur (2023) to see

Figure 2: Through-the-Year PPI and CPI Growth, 2003–2023



Source: ABS Producer Price Index and Consumer Price Index

whether there is a relationship between industry-level markup changes and industry-level output prices pre-COVID. This allows us to consider whether, at least historically, we have seen evidence that times of large changes in industry-level prices are associated with large changes in industry-level markups. Firm-level markups are estimated from administrative tax data using the production function approach advocated by De Loecker and Warzynski (2012), which amounts to comparing observed intermediate input shares to an estimated output elasticity for intermediate inputs. The elasticity is estimated using the approach from Ackerberg, Caves and Frazer (2015) assuming a translog production function. The sample is highly representative, covering around 60 per cent of sales in each industry considered.[4] To consider the more recent period we then extend the markup series using administrative data. Unfortunately, data are only available to 2020–2021, which means we cannot examine the entire period of interest. But it does let us look at outcomes during the early COVID period.[5]

Compared to Conlon, Miller, Otgon and Yao (2023), we have the advantage of being able to construct markup measures using a much more representative sample, as they focus on listed firms only. However, a disadvantage we face is that detailed industry-level PPI data for Australia are only available for a subset of around 1/3 of Australian industries, with the majority tending to be in the manufacturing sector. In this sense our analysis is deeper, but narrower. That said, despite the limited coverage, as shown in Figure 2, the PPI does track the Consumer Price Index (CPI) data quite closely in Australia, so the industry exclusions may not be a major concern.

To examine the relationship, we do a simple regression of growth in the industry-level

[4]The financial and public sector are excluded. For more details see Hambur (2023) and Appendix A.
[5]This analysis will be updated when the relevant data are available.

sales-weighted markup on growth in the industry's PPI from the start to the end of our analysis period, i.e., the specification is in long-differences.[6] Focusing on the 2004–2017 period, we see a moderate and significant positive relationship, with industries that saw larger increases in their mark-ups tending to have larger increases in prices. The elasticity is around 1/3, so in industries where markups rose by 1 percentage point more over the sample, prices tended to increase by 1/3 percentage point more. As shown in Figure 3, this is also evident in a simple scatter plot of industry markup growth against PPI price growth.[7]

This finding contrasts with the findings in Conlon, Miller, Otgon and Yao (2023) for the US, where they find no evidence of a relationship. The difference could reflect the more representative dataset we have, at least for the set of industries considered. Alternatively, it could reflect differences in the underlying causes of the increased mark-ups. For example, De Loecker, Eeckhout and Mongey (2021) show that a moderate portion of the increase in markups in the US reflected a reallocation of resources towards high markup firms. As these firms tended to be larger and more productive, this would be accompanied by higher aggregate productivity, putting offsetting downward pressure on prices. By contrast, Hambur (2023) documents that most of the increase in markups in Australia has reflected increased firm-level markups, which would not tend to be associated with an offsetting productivity improvement and so might have more inflationary impact.

As shown in Figure 4, the relationship appears to have weakened during the early COVID period potentially reflecting greater noise in the construction of markups, for example due to the role of subsidies in influencing measured inputs.[8] Future data will allow us to assess the relationship between markups and prices in the post-COVID period.

2.3 Prices and Profits

A second approach to assessing whether firms tend to pass on cost increases more than one-for-one is to use newly integrated firm-level prices and activity data. Web-scraped price data have recently been integrated to administrative firm tax data for around 60 retailers for a sample from 2016–2022.[9] These data have the advantage of giving us direct measures of firm prices that we can compare to profits, removing any concerns about mismeasurement of markups. But these data are only available for a much smaller sub-set of firms and industries.

To consider whether firms have tended to pass on price increases more than one-for-one we use a simple regression of firm-level average price changes on the firm-level gross operating

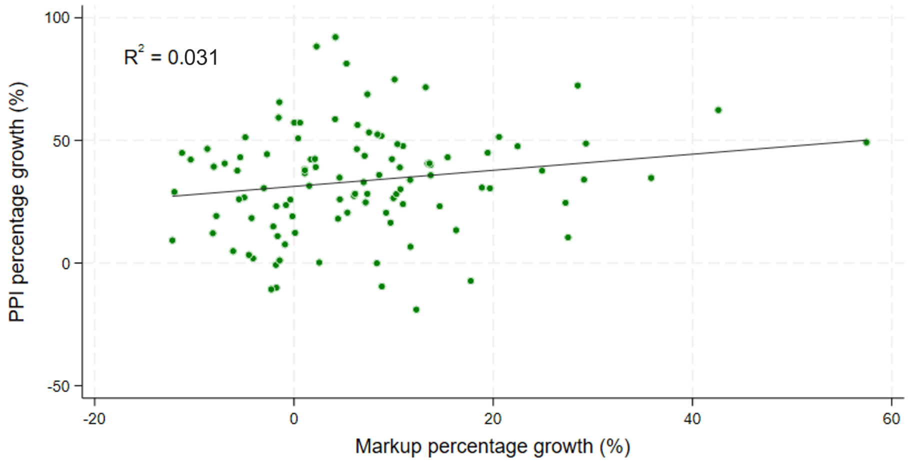
[6] Robust standard errors are used. Regressions are also weighted using an industry's share in aggregate sales as weights to bring us closer to the 'macroeconomic' effect.

[7] Results are similar whether we use all industries, or trim the top and bottom 1 per cent of growth rates.

[8] We construct markups for the longer sample by estimating output elasticities using data up to 2018/19 and using these for the COVID period. This assumes that production functions remained stable during the pandemic. As a result, we do not remove noise in the first stage of the estimation from the mark-up estimates.

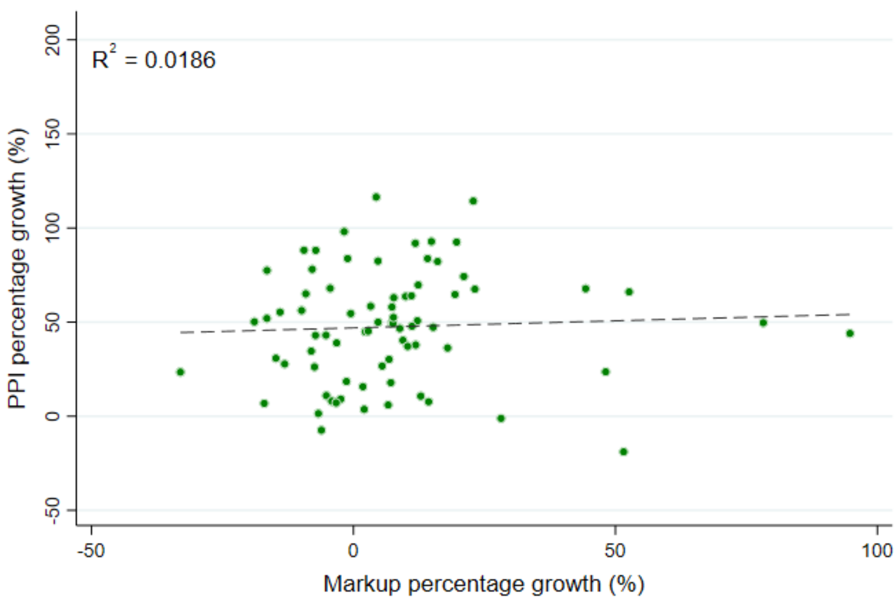
[9] These data are outlined in more detail in Fink, Hambur and Majeed (2023) and Appendix A

Figure 3: Markup and price growth by 4-digit ANZSIC industry, 2004–2017



Note: Full line indicates results are statistically significant at 5% level.
Source: ABS; Authors' calculations.

Figure 4: Markup and price growth by 4-digit ANZSIC industry, 2004–2021



Note: Full line indicates results are statistically significant at 5% level.
Source: ABS; Authors' calculations.

Table 1: Firm-Level Regressions of Profits on Prices

	Full sample	Sample split
price change	-0.147^{***}	-0.137
	(0.044)	(0.225)
price change×2019		0.0235
		(0.261)
price change×2020		0.056
		(0.245)
price change×2021		-0.178
		(0.241)
price change×2022		0.102
		(0.234)
R-squared	0.011	0.047
Observations	742	742

Quarterly firm-level regression of gross profit margin on average price change for continuing items. Includes year fixed effects, excludes small firms below threshold for expense reporting. Standard errors in brackets.

margin at a quarterly frequency. The former is an unweighted average of price changes for items that the firm sells in both quarters. While a sales-weighted average price changes would be preferable, sales weights are not available in the web-scraped price data.

Table 1 shows the results. Focusing on the full sample period in column 1, we see that increases in prices tend to be associated with lower profits. This is consistent with incomplete passthrough of price increases – when costs go up, firms pass on only part of the increase into prices and so profit margins fall. The coefficient equates to passthrough of around 0.85. This is somewhat higher than found for Amiti, Itskhoki and Konings (2019) for larger manufacturing firms, though the two approaches are not directly comparable.[10] But, reassuringly, this reduced-form passthrough of around 0.85 is also what we find for our sales-weighted average passthrough coefficients backed out of the structural model calibrated to other Australian microdata, as discussed in Section 3 below.

Column 2 allows the coefficient to vary over time. The first row shows the coefficient in 2018, and all other coefficient show the changes relative to that period. The coefficient on price changes in 2022 is positive, though the overall relationship between prices and profits remains negative (in practice very close to zero). While the point estimates suggest that

[10]Further work will explore the relationship over multiple quarters to consider the longer-term relationship.

passthrough from costs to prices may have increased during the post COVID period, none of these changes are statistically significant and there is no evidence that passthrough has ever been more than one-for-one.[11]

2.4 Passthrough from Cost Shocks

In the previous section we considered the stronger hypothesis – that firms passed on price increases more than one-for-one and actually raised profits. In this section we consider the weaker hypothesis: could, as argued by Bräuning, Fillat and Joaquim (2023), passthrough of cost shocks tend to be stronger in less competitive and more concentrated markets?

To consider this we take a similar approach to Bräuning, Fillat and Joaquim (2023). In particular, we construct 'exogenous' cost shocks at an industry level. We use these in a local projection framework to trace out the effect of shocks on the log PPI. We also interact the shocks (and other controls) with various measures of the degree of competitive pressure to see whether the shocks have a larger or smaller effect on prices where competition is weaker.

More precisely, we estimate the following regression:

$$\ln PPI_{t+h,i} = \alpha_i^h + \alpha_t^h + \beta_h \, GIV_{i,t} + \beta_{h,mu} \, GIV_{i,t} \, \mu_{i,t} + \gamma \, X_{i,t} + \epsilon_{i,t} \tag{1}$$

where $\ln PPI_{t+h,i}$ is industry i log PPI in h period's time, $GIV_{i,t}$ is the exogenous cost shock, $\mu_{i,t}$ is the industry's sales-weighted average markup, α_i^h and α_t^h are industry and time fixed effects, respectively, and $X_{i,t}$ is a battery of controls including linear industry time trends and the lagged PPI. The standard errors are clustered at the industry level to allow for serially correlated shocks, and the regressions are weighted using an industry's share in aggregate sales as weights to provide a sense of the macroeconomic effects.

The coefficient of interest is $\beta_{h,mu}$, which traces out for each horizon (measured in years), whether the passthrough of the cost shock to end prices is larger or smaller in industries with higher markups (or other measures of competition).

As in Bräuning, Fillat and Joaquim (2023) we construct our exogenous cost shocks using a granular instrumental variable (GIV) approach pioneered by Gabaix and Koijen (2022). This involves regressing firm-level input costs taken from administrative tax data (measured as total costs less fixed costs such as depreciation) on a number of controls outlined in Table 2, including sales, industry-by-time trends and firm fixed effects. The residuals are taken to be idiosyncratic firm-level cost 'shocks'.[12] We then recover the firm-level shocks and aggregate them to create industry-level shocks, using firms' (lagged) sales weights to create weighted averages. The idea behind this approach is to abstract from aggregate factors that could drive

[11] This is obviously a very simple approach, and is subject to a number of caveats in terms of the measurement of price increases, and in terms of other factors that could be influencing profit margins and therefore introducing noise and attenuation bias.

[12] The full specification used is equivalent to specification 4 from their paper, which is their baseline model.

Table 2: Controls used to Residualise Firm-Level Costs

Observations	2,937,331
Industry*Time FE	Yes
Firm FE	Yes
Firm×Time-Trend	Yes
Time×Log_Sales	Yes
Time×Log_Assets	Yes
Time×Lag_Log_Sales	Yes
Time×Lead_Log_Sales	Yes

Table 3: Summary of Industry-Level Cost Shocks

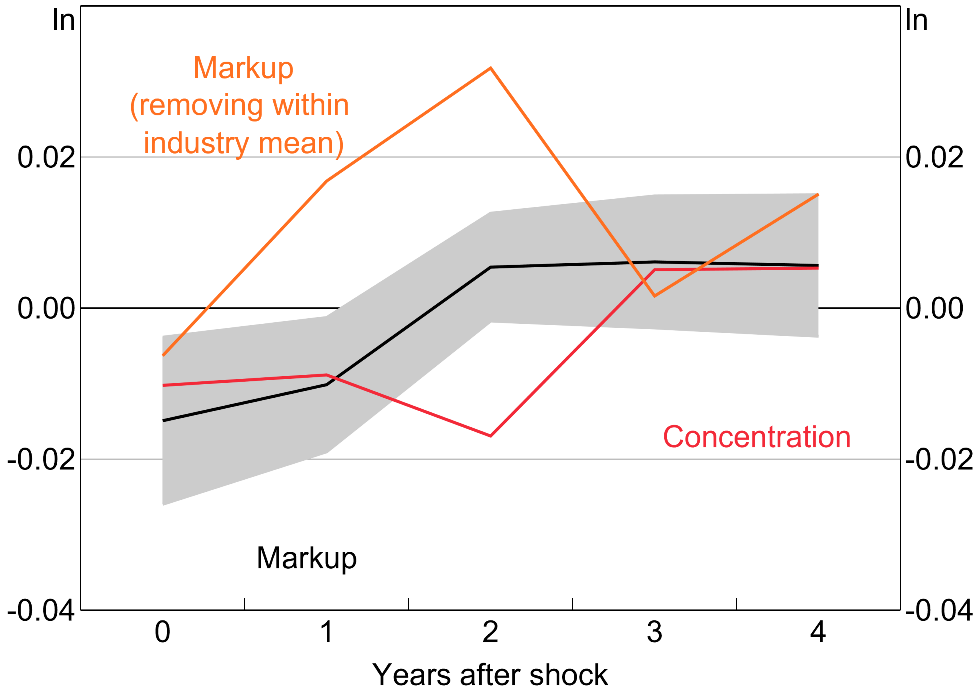
Number of industries	1416
Mean	0.00096
Standard deviation	0.041
Minimum	−0.23
5th percentile	−0.068
25th percentile	−0.018
Median	0.0011
75th percentile	0.021
95th percentile	0.064
Maximum	0.21

costs and prices, such as industry demand, and focus on (presumably) exogenous firm-level shocks. If all firms were small, and these shocks were random, the shocks should cancel out. But because some firms are larger, their random shocks will be more important in driving aggregate prices and we can exploit this to construct an exogenous instrument for aggregate prices. Table 3 reports summary statistics for the industry-level shocks. By construction they are near mean zero, but there is a moderate amount of variation, with the standard deviation being around 0.04.

Figure 5 shows the coefficient on the interaction between various measures of competitive pressures and pass-through $\beta_{h,mu}$, scaled to capture the effect of a one standard deviation shock. Focusing first on the sales-weighted markup measure (grey), we see that in industries with higher markups the pass-through of the shocks to prices tends to be significantly lower.

Figure 5: Competition and Passthrough

Change in log PPI after one standard deviation shock.



Note: Shaded region shows 90 per cent confidence interval.

To give some sense of these coefficients, the median (firm-level) markup in 2017 was around 1.3, while the 75th percentile was 1.4 (Hambur, 2023). A one standard deviation GIV shock equates to around 0.04. So in the year a one standard deviation shock occurs $h = 0$, aggregate prices increase by 0.15 percentage points less (0.04*0.347*0.1 log points) in an industry with markups at the 75th percentile, compared to an industry at the median markup. This is a moderate difference in outcomes, though not extremely large.

The results are broadly similar when markups are replaced with a measure of market sales concentration, specifically the Herfindahl-Hirschmann index (HHI), though the coefficients are not statistically significant. By contrast Bräuning, Fillat and Joaquim (2023) find, for the US, that passthrough of cost shocks is larger in more concentrated industries as measured by the HHI.[13] However, it is broadly consistent with standard models of endogenously variable markups, such as the one we discuss in Section 3 below.

That said, we should note that these findings are sensitive to the details of our empirical specification. For example, if we *de-mean* our sales-weighed markup measures, and therefore focus on whether passthrough is stronger or weaker when industries are becoming less

[13] This difference could reflect the more representative data we have, at least for the set of industries considered. It could also reflect the fact we are limited by the frequency of data (annual rather than quarterly as in Bräuning, Fillat and Joaquim (2023).

competitive, there is no statistically significant evidence that passthrough varies as markups change.[14] Such an approach might be preferred if we are concerned about the ability of the production approach to estimate the level of markups, as it is constructed using a revenue based production function (as discussed in Bond, Hashemi, Kaplan and Zoch (2021)), but we are more comfortable interpreting changes (which are less prone to such issues). Using lagged markups or HHIs also leads to weaker evidence. Using lags might be preferred as increases in concentration might inherently make the GIV a stronger instrument, with larger firms now having a higher weight in both the aggregate PPI and in the GIV.

Taken together, we find some empirical evidence that cost shocks are passed through less to final prices in less competitive industries, though the evidence is sensitive to the details of the empirical specification.

All told, the evidence from Australian firm-level data suggests that (i) while there is some evidence that prices tended to increase by more in industries that had increasing markups over the 2004-2017 period, (ii) passthrough from cost shocks to prices appears to be incomplete – passthrough < 1 — with no statistically significant evidence that passthrough has risen in recent years, and (iii) there is some evidence that, in the cross-section of industries, passthrough is lower in less competitive industries.

To help interpret these facts we now turn to a more structural economic model. As we will see, the model predicts that variable markups can amplify inflationary shocks but only if, within a given industry, the firms with relatively high markups are relatively *small* and passthrough is relatively high — passthrough > 1. Perhaps not surprisingly given our empirical findings above, for our benchmark model calibrated to administrative tax data from the ABS Business Longitudinal Analysis Data Environment (BLADE), we find that variable markups *do not* amplify inflation dynamics. To the contrary, for our benchmark model we find that variable markups if anything slightly *dampen* inflation dynamics.

3 Model

The model is a simplified version of Edmond, Midrigan and Xu (2023) augmented with nominal rigidities as in Baqaee, Farhi and Sangani (2023). In particular, there is a representative consumer with preferences over final consumption and labour supply and who owns all the firms. The final good is produced by perfectly competitive firms using a bundle of intermediate inputs. The inputs are produced by heterogeneous imperfectly competitive firms using labour and a special factor that is in inelastic supply. The intermediate input producers are subject to nominal rigidities in price setting, specifically a Calvo (1983) pricing friction. There is no entry or exit.

[14] More precisely, we allow for a time-invariant industry-specific coefficient for the shock variable $\beta_{h,i}$. The coefficient on the markup variable therefore only captures changes relative to the industry-level average markup over time. Removing the industry-level mean gives a similar pattern.

Representative consumer. Time is discrete $t = 0, 1, 2, ...$ The representative consumer maximizes

$$\mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \big(\log C_t - \frac{L_t^{1+\varphi}}{1+\varphi} \big) \right\} \tag{2}$$

subject to the budget constraints

$$P_t C_t + Q_t B_{t+1} = W_t L_t + R_t X_t + \Pi_t + B_t \tag{3}$$

where C_t denotes real consumption of the final good, L_t denotes labour supply, P_t denotes the ideal price index, Q_t denotes the nominal price of a bond B_{t+1} paying one unit of account in one period's time, W_t denotes the nominal wage, and Π_t denotes nominal profits. The representative consumer also has an endowment of a special factor X_t with nominal rental rate R_t. Fluctuations in the exogenous supply of X_t will be the underlying source of *cost shocks* in this model.[15]

The key first order conditions for the representative consumer are the consumption Euler equation

$$Q_t = \mathbb{E}_t \left\{ \beta \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}} \right\} \tag{4}$$

and the static labour supply condition

$$C_t L_t^{\varphi} = \frac{W_t}{P_t} \tag{5}$$

Firms are owned by the representative consumer and use the consumer's nominal stochastic discount factor to discount future profit flows.

Final good producers. The final good is produced by perfectly competitive firms using a bundle of intermediate inputs. The technology for transforming the bundle of intermediate inputs y_{it} for $i \in [0, 1]$ into the final good Y_t is represented by a *Kimball aggregator* of the form

$$\int_0^1 \Upsilon\big(\frac{y_{it}}{Y_t}\big)\, di = 1 \tag{6}$$

where the function $\Upsilon : \mathbb{R}_+ \to \mathbb{R}_+$ is strictly increasing and strictly concave. The textbook setup with CES aggregation corresponds to the special case where Υ is a power function.

Taking as given input prices p_{it}, each period t, the representative final food producer chooses input demand y_{it} for $i \in [0, 1]$ to maximize profits

$$P_t Y_t - \int_0^1 p_{it} y_{it}\, di \tag{7}$$

subject to the Kimball aggregator (6) above.

[15] It may be helpful to think of this X_t factor as an inflexible energy input, for example. In the New Keynesian literature it is common to introduce cost shocks as exogenous *markup shocks*. But in our model markups are *endogenous*. Our alternative specification in terms of X_t makes it easier to distinguish between the primitive source of changes in costs and prices from the role of markups as an amplifying mechanism.

Kimball demand system. The implied inverse demand curve facing intermediate producer $i \in [0,1]$ is then given by

$$\frac{p_{it}}{P_t} = \Upsilon'(q_{it})\, D_t, \qquad q_{it} := \frac{y_{it}}{Y_t} \tag{8}$$

where P_t is the ideal price index, D_t is the Kimball demand index, and $q_{it} := y_{it}/Y_t$ is a measure of the relative size of $i \in [0,1]$. The price index P_t is given by the usual size-weighted average price

$$P_t = \int_0^1 p_{it}\, q_{it}\, di \tag{9}$$

The Kimball demand index D_t works out to be the inverse of the size-weighted average of marginal productivities

$$D_t = \left(\int_0^1 \Upsilon'(q_{it})\, q_{it}\, di \right)^{-1} \tag{10}$$

In the special case where Υ is a power function, the price index reduces to the usual CES price aggregator and the demand index is a constant that drops out of the analysis. But outside of this special case, the demand index D_t is another endogenous aggregate variable that needs to be determined in solving the model.

For future reference, note that this demand system implies that a firm's sales share ω_{it} is pinned down by its relative size q_{it}, namely

$$\omega_{it} := \frac{p_{it}y_{it}}{P_t Y_t} = \Upsilon'(q_{it}) q_{it} D_t \tag{11}$$

Intermediate input producers. The intermediate input producers are *monopolistically competitive*. Each firm $i \in [0,1]$ has a time-invariant productivity draw $z_i \sim G(z_i) := \text{Prob}[z \leq z_i]$ and uses labour l_{it} and other factors x_{it} to produce their output y_{it} using the Cobb-Douglas production technology

$$y_{it} = z_i\, x_{it}^{\alpha}\, l_{it}^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{12}$$

Taking as given the nominal wage W_t and rental rate R_t, the nominal cost of producing y_{it} units of output is given by

$$\frac{\Psi_t}{z_i}\, y_{it} \tag{13}$$

where the aggregate component of nominal marginal cost is given by

$$\Psi_t := \min_{x,l} \Big[\, R_t x + W_t l \;\; \Big| \;\; x^{\alpha} l^{1-\alpha} = 1 \Big] = \left(\frac{R_t}{\alpha}\right)^{\alpha} \left(\frac{W_t}{1-\alpha}\right)^{1-\alpha} \tag{14}$$

The static profits of firm $i \in [0,1]$ with nominal price p_{it} and output y_{it} are given by

$$\pi_{it} = \left(p_{it} - \frac{\Psi_t}{z_i}\right) y_{it} \tag{15}$$

The objective of an intermediate input producer is to maximize their expected discounted profits subject to the demand curve (8) and pricing frictions they face.

Flexible-price markups. Absent pricing frictions, firms maximize profits by setting nominal prices p_{it} that are a markup $\mu_{it} \geq 1$ over their nominal marginal cost

$$p_{it} = \mu_{it} \frac{\Psi_t}{z_i} \tag{16}$$

With the Kimball aggregator, the flexible-price markup μ_{it} can be written as a function of a firm's relative size q_{it}, specifically

$$\mu_{it} = \mu(q_{it}) \tag{17}$$

where the markup function $\mu(q)$ depends on the demand elasticity $\sigma(q)$ facing a firm of relative size q, namely

$$\mu(q) := \frac{\sigma(q)}{\sigma(q) - 1}, \qquad \sigma(q) := -\frac{\Upsilon'(q)}{\Upsilon''(q)q} \tag{18}$$

The second order conditions for the firm's problem imply that it will operate on the relatively elastic portion of its demand curve where $\sigma(q) > 1$, and hence $\mu(q) \geq 1$.

For future reference, let ρ_{it} denote a firm's *passthrough coefficient*, i.e., the elasticity of the firm's price with respect to its marginal cost, absent pricing frictions

$$\rho_{it} := -\frac{\partial \ln p_{it}}{\partial \ln z_i}$$

As with the markups $\mu_{it} = \mu(q_{it})$, the amount of passthrough ρ_{it} can be written as a function of a firm's relative size, $\rho_{it} = \rho(q_{it})$, where the passthrough coefficient $\rho(q)$ for a firm of relative size q works out to be

$$\rho(q) = \frac{1}{1 + \sigma(q)\frac{\mu'(q)q}{\mu(q)}} = \frac{1}{1 - \mu(q)\frac{\sigma'(q)q}{\sigma(q)}} \tag{19}$$

Importantly, the passthrough coefficient is strictly less than unity, i.e., there is *incomplete passthrough*, whenever the markup function $\mu(q)$ is increasing in relative size, $\mu'(q) > 0$. In the special case of CES demand, $\mu'(q) = 0$ and hence $\rho(q) = 1$, i.e., in the CES special case there is complete passthrough.

In equilibrium, the endogenous cross-sectional distribution of relative size is pinned down by the exogenous distribution of productivities, $q_{it} = q_t(z_i)$. This in turn determines the equilibrium cross-sectional distribution of markups, $\mu_{it} = \mu(q_t(z_i))$, passthrough coefficients $\rho_{it} = \rho(q_t(z_i))$, etc. See Edmond, Midrigan and Xu (2023) for further details.

Aggregate markup and aggregate profits. As in Edmond, Midrigan and Xu (2015, 2023) the aggregate markup $\mathcal{M}$ is given by a *sales-weighted harmonic average* of firm-level markups

$$\mathcal{M}_t = \left(\int_0^1 \frac{\omega_{it}}{\mu_{it}} \, di \right)^{-1}, \qquad \omega_{it} := \frac{p_{it} y_{it}}{P_t Y_t} \sim \Upsilon'(q_{it}) q_{it} \tag{20}$$

where in equilibrium the endogenous cross-sectional distribution of sales shares ω_{it} are likewise determined by the exogenous distribution of productivities

$$\omega_{it} = \Upsilon'(q_t(z_i))q_t(z_i)D_t \tag{21}$$

With this expression for the aggregate markup in hand, we can then compute aggregate profits

$$\Pi_t = \int_0^1 \pi_{it}\, di = \int_0^1 \left(p_{it} - \frac{\Psi_t}{z_i}\right) y_{it}\, di = \left(1 - \frac{1}{\mathcal{M}_t}\right) P_t Y_t \tag{22}$$

The aggregate profit share moves one-for-one with the aggregate markup.

Sticky prices. We introduce nominal rigidities through a simple Calvo (1983) pricing friction. Specifically, each period any given firm has an exogenous probability $\theta \in [0,1]$ of being *stuck* with its price from the previous period. With complementary probability $1-\theta$ any given firm has the opportunity to *reset* its price. Firms that have the opportunity to reset their price do so to maximize their expected discounted profits, taking into account their expected future opportunities to reset prices. The flexible price benchmark is the special case where $\theta = 0$.

As is standard in the New Keynesian literature, we log-linearize the model around a deterministic zero inflation steady state. Let $\bar{q}_i$ denote the steady-state distribution of relative size and let $\bar{\mu}_i = \rho(\bar{q}_i)$, $\bar{\rho}_i = \rho(\bar{q}_i)$, etc denote the implied steady state distribution of markups, passthrough coefficients, etc.

Reset price. In this log-linear model the optimal reset price p^*_{it} for firm $i \in [0,1]$ is given by the difference equation

$$\ln p^*_{it} = (1-\theta\beta)\left[\bar{\rho}_i \ln \Psi_t + (1-\bar{\rho}_i)(\ln P_t + \ln D_t)\right] + \theta\beta\mathbb{E}_t\left[\ln p^*_{it+1}\right] \tag{23}$$

Iterating forward we get

$$\ln p^*_{it} = (1-\theta\beta)\,\mathbb{E}_t \left\{ \sum_{k=0}^{\infty} (\theta\beta)^k \left[\bar{\rho}_i \ln \Psi_{t+k} + (1-\bar{\rho}_i)(\ln P_{t+k} + \ln D_{t+k})\right] \right\} \tag{24}$$

In the CES special case where desired (flexible-price) markups are constant and there is complete passthrough, $\bar{\rho}_i = 1$, this optimality condition implies that the reset price is set to equal the current value of expected discounted future nominal marginal costs. In this special case there are no strategic interactions in price setting in the sense that, if $\bar{\rho}_i = 1$, the optimal reset price p^*_{it} does not depend on the path of the aggregate price level P_t. But if $\bar{\rho}_i > 1$, i.e., if the markup function is decreasing in relative size, $\mu'(q) < 0$, then there are *strategic complementarities* in price setting in the sense that an increasing path for the aggregate price level P_t increases the optimal reset price p^*_{it} for any individual firm.

Inflation dynamics. Aggregating over firms $i \in [0,1]$, Baqaee, Farhi and Sangani (2023) show that this characterization of reset prices plus the definition of the aggregate price index implies that inflation dynamics are given by

$$\Delta \ln P_t = \beta \mathbb{E}_t\big[\Delta \ln P_{t+1}\big] + \lambda \left(\mathbb{E}_\omega[\bar{\rho}_i](\underbrace{\ln \Psi_t - \ln P_t}_{\text{real marginal cost}}) + \big(1 - \mathbb{E}_\omega[\bar{\rho}_i]\big) \ln D_t \right) \tag{25}$$

where λ denotes the composite parameter

$$\lambda := \frac{(1-\theta)(1-\theta\beta)}{\theta}$$

and where $\mathbb{E}_\omega[\bar{\rho}_i]$ denotes the steady-state sales-weighted average passthrough

$$\mathbb{E}_\omega[\bar{\rho}_i] := \int_0^1 \bar{\rho}_i \, \bar{\omega}_i \, di \tag{26}$$

Again, if there are constant desired markups and hence complete passthrough, $\bar{\rho}_i = 1$, this collapses to the usual New Keynesian Phillips Curve written in terms of real marginal cost. If there is, on average, incomplete passthrough, $\mathbb{E}_\omega[\bar{\rho}_i] < 1$, then the effects of fluctuations in real marginal cost on current inflation are *dampened* relative to a benchmark New Keynesian model with constant desired markups. Only if $\mathbb{E}_\omega[\bar{\rho}_i] > 1$ will fluctuations in real marginal cost *amplify* inflation dynamics. In this sense, the magnitude of the moment $\mathbb{E}_\omega[\bar{\rho}_i]$ will be crucial for the quantitative properties of the model.

Aggregate TFP dynamics. In this model with variable desired markups, relative price dispersion has first-order effects on aggregate TFP even local to the zero-inflation steady state. These effects on aggregate TFP reflect the cross-sectional dispersion in markups, i.e., *misallocation* — that part of the dispersion in relative prices that is not warranted by dispersion in relative marginal costs. Specifically, the log-deviation of aggregate TFP can be written

$$\ln Z_t = \ln \mathcal{M}_t - \mathbb{E}_\omega\big[\ln \mu_{it}\big] \tag{27}$$

Baqaee, Farhi and Sangani (2023) show that, for this setup, aggregate TFP dynamics are given by

$$\Delta \ln Z_t = \beta \mathbb{E}_t\big[\Delta \ln Z_{t+1}\big] - \lambda \ln Z_t + \lambda \bar{\mathcal{M}} \frac{\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]}{\mathbb{E}_\omega[\bar{\sigma}_i]} \big(\ln \Psi_t - \ln P_t - \ln D_t\big) \tag{28}$$

In the CES special case where desired markups are constant and there is complete passthrough $\bar{\rho}_i = 1$, the covariance term is zero, there are no forcing dynamics, and hence the unique solution to this difference equation is $\ln Z_t = 0$. In this case there are no endogenous TFP dynamics because, local to the zero-inflation steady state, relative price dispersion due to nominal rigidities has only second-order effects on aggregate TFP.

But with variable desired markups, there are potentially more substantial endogenous TFP dynamics. The properties of such endogenous TFP dynamics depend crucially on (i) the sign of the covariance term $\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]$, i.e., on whether firms with low demand elasticities and hence high markups have high passthrough or not, and (ii) the magnitude of the covariance term relative to the average demand elasticity $\mathbb{E}_\omega[\bar{\sigma}_i]$. We discuss in detail below how we use Australian firm-level data to pin down these crucial moments.

Rest of the model. The rest of the model is fairly standard. To first order, local to the zero-inflation steady state the aggregate production function can be written

$$\ln Y_t = \ln Z_t + \alpha \ln X_t + (1-\alpha) \ln L_t \tag{29}$$

Using the representative consumer's labour supply condition and imposing goods market clearing $C_t = Y_t$ gives

$$\ln W_t - \ln P_t = \ln Y_t + \varphi \ln L_t \tag{30}$$

Letting $i_t := -\ln Q_t$ and imposing goods market clearing gives the Euler equation

$$\mathbb{E}_t\big[\Delta \ln Y_{t+1}\big] = i_t - \mathbb{E}_t\big[\Delta \ln P_{t+1}\big] \tag{31}$$

Finally, monetary policy is given by a simple interest rate rule

$$i_t = \phi_\pi \, \Delta \ln P_t + \phi_y \, \ln Y_t \tag{32}$$

4 Model Results

In this section we first explain how we use Australian firm-level data to pin down the crucial cross-sectional moments that enter the coefficients of our log-linear model. We then use the model, calibrated to Australian data, to assess the extent to which endogenous markup variation can generate quantitatively substantial amplification of cost or demand shocks.

4.1 Quantification

We begin by outlining how we parameterize the model. We adopt the Klenow and Willis (2016) form of the Kimball aggregator. Following Edmond, Midrigan and Xu (2023), we estimate the key parameters of the Klenow and Willis specification using the cross-sectional relationship between markups and firm size implied by the model. To implement this approach we need estimates of firm-level markups. We estimate markups using the production function methods advocated by De Loecker and Warzynski (2012) as applied to Australian firm-level data by Hambur (2023).

Key cross-sectional moments. Relative to a benchmark New Keynesian model with constant desired markups, the key quantitative properties of this model are driven by the magnitudes of three cross-sectional moment

$$\mathbb{E}_\omega[\,\bar{\sigma}_i\,], \qquad \mathbb{E}_\omega[\,\bar{\rho}_i\,], \qquad \mathrm{Cov}_\omega[\,\bar{\sigma}_i\,,\,\bar{\rho}_i\,]$$

To estimate these moments using firm-level data we use the structure of the demand system to back out (unobservable) firm-level demand elasticities and passthrough coefficients from (observable) firm size, as explained below.

Kimball-Klenow-Willis specification. The Klenow and Willis (2016) specification of the Kimball aggregator gives inverse demand curves of the form

$$\Upsilon'(q_i) = \frac{\bar{\sigma}-1}{\bar{\sigma}}\,\exp\Big(\frac{1-q_i^{\varepsilon/\bar{\sigma}}}{\varepsilon}\Big), \qquad \bar{\sigma} > 1 \tag{33}$$

For this specification, the implied demand elasticity and passthrough coefficients are

$$\sigma(q_i) = \bar{\sigma}\,q_i^{-\varepsilon/\bar{\sigma}}, \qquad\qquad \rho(q_i) = \frac{1}{1+\frac{\varepsilon}{\bar{\sigma}}\mu(q_i)} \tag{34}$$

The parameter $\varepsilon/\bar{\sigma}$ is known as the '*superelasticity*' of demand. It governs the extent to which the demand elasticity $\sigma(q_i)$ varies with relative size, i.e., it governs the strength of the variable markups mechanism. CES demand is the special case where $\varepsilon = 0$ so that the demand elasticity is $\sigma(q_i) = \bar{\sigma}$, a constant independent of q_i, and hence the passthrough coefficient is $\rho(q_i) = 1$ independent of q_i, i.e., there is complete passthrough. If $\varepsilon > 0$, then relatively larger firms face less elastic demand, lower $\sigma(q)$, and hence have higher desired markups and lower passthrough $\rho(q) < 1$. Alternatively, if $\varepsilon < 0$ then larger firms face more elastic demand, have higher $\sigma(q)$ and hence have lower desired markups and higher passthrough $\rho(q) > 1$.

Estimating the superelasticity $\varepsilon/\bar{\sigma}$. Edmond, Midrigan and Xu (2023) show that this demand system implies a one-to-one relationship between a firm's markup and its sales share that can be written

$$f(\mu_i) = a + b\,\ln\omega_i, \qquad b = \frac{\varepsilon}{\bar{\sigma}} \tag{35}$$

where the function

$$f(\mu_i) := \frac{1}{\mu_i} + \ln\Big(1-\frac{1}{\mu_i}\Big) \tag{36}$$

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

This suggests the following strategy. First obtain preferred markup estimates, say $\hat{\mu}_i$, as discussed below. Then take the transformation $f(\hat{\mu}_i)$ and regress on the observed sales share ω_i. The estimated slope coefficient $\hat{b}$ is then the estimated superelasticity, $\varepsilon/\bar{\sigma} = \hat{b}$.

Table 4: Key Moments From BLADE

	$\varepsilon/\bar{\sigma}$	$\mathbb{E}_\omega[\hat{\rho}_i]$	$\mathbb{E}_\omega[\hat{\sigma}_i]$	$\mathrm{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i]$
preferred production function $\hat{\mu}_i$ estimates (Hambur 2023)				
weighted mean	0.11	0.87	2.56	0.010
weighted percentiles				
25	−0.01	0.75	2.14	−0.001
50	0.13	0.85	2.47	0.001
75	0.26	1.01	2.90	0.016
simple cost-share $\hat{\mu}_i$ estimates				
weighted mean	0.10	0.80	5.16	0.270

Recover passthrough coefficients and estimate key moments. Equipped with our preferred markup estimates $\hat{\mu}_i$ and an estimated superelasticity $\varepsilon/\bar{\sigma} = \hat{b}$ we can then recover the other key properties of the demand system. The implied demand elasticities are

$$\hat{\sigma}_i = \frac{\hat{\mu}_i}{\hat{\mu}_i - 1} \tag{37}$$

And the implied passthrough coefficients are

$$\hat{\rho}_i = \frac{1}{1 + \hat{b}\hat{\mu}_i} \tag{38}$$

We can then calculate the key cross-sectional moments that enter the log-linear model

$$\mathbb{E}_\omega[\hat{\sigma}_i], \qquad \mathbb{E}_\omega[\hat{\rho}_i], \qquad \mathrm{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i]$$

Key moments from BLADE. We report the results of this exercise in Table 4. The top panel reports estimates of the key moments when we use markups $\hat{\mu}_i$ estimated using the production function methods advocated by De Loecker and Warzynski (2012) as applied to Australian firm-level BLADE data by Hambur (2023). For the median Australian industry we find a superelasticity estimate $\varepsilon/\bar{\sigma} = \hat{b} = 0.13$, implying that, within a given industry, demand elasticities are decreasing in a firm's relative size and hence that, within that industry, relatively larger firms set larger markups, i.e., $\mu'(q) > 0$. Interestingly, this point estimate

Table 5: Benchmark Parameterization

superelasticity	$\varepsilon/\bar{\sigma}$	0.13
average passthrough	$\mathbb{E}_\omega[\bar{\rho}_i]$	0.85
average demand elasticity	$\mathbb{E}_\omega[\bar{\sigma}_i]$	2.47
covariance	$\text{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]$	0.001
aggregate markup	$\bar{\mathcal{M}}$	1.15
elasticity of output wrt nonlabour input	α	1/3
discount factor	β	0.99
Frisch elasticity	$1/\varphi$	1
Calvo probability no price change	θ	2/3
interest rate rule coefficient inflation	ϕ_π	1.5
interest rate rule coefficient output	ϕ_y	0.5/4

$\hat{b} = 0.13$ is quite close to the benchmark superelasticity 0.16 that Edmond, Midrigan and Xu (2023) estimate from US manufacturing data. We then use our markup estimates $\hat{\mu}_i$ and superelasticity estimate $\varepsilon/\bar{\sigma} = \hat{b}$ to infer demand elasticities $\hat{\sigma}_i$ and passthrough coefficients $\hat{\rho}_i$ using the structure of the Kimball-Klenow-Willis demand system, as outlined above. For the median Australian industry we find that the sales-weighted average passthrough coefficient is $\mathbb{E}_\omega[\hat{\rho}_i] = 0.85$, substantially lower than we would have with CES demand.[16] The corresponding sales-weighted average demand elasticity is $\mathbb{E}_\omega[\hat{\rho}_i] = 2.47$. Importantly, the sales-weighted covariance between demand elasticities and passthrough is, while positive, almost zero. In our calibrated model, this will imply that there is quite weak feedback from fluctuations in real marginal cost to the endogenous component of aggregate TFP. Only for the bottom quartile or so of Australian industries do we find a negative covariance, and even here the magnitude of the covariance is quite small. Finally, we have also experimented with alternative markup estimates based on simple cost shares, and find broadly similar results. We report these alternative estimates in the last row of Table 4.

Benchmark parameterization. For our benchmark parameterization we use the median BLADE estimates reported in Table 4, as discussed above. We later explore the sensitivity

[16]Interestingly, this median estimate of average passthrough $\mathbb{E}_\omega[\hat{\rho}_i] = 0.85$ corresponds exactly with the reduced-form passthrough we estimated from the narrow set of industries for which we have firm-level price data, see Table 1 above.

of our results to adopting parameterizations that reflect outlier industries, e.g., industries with negative superelasticities and/or average passthrough coefficients that exceed 1. As shown in Table 5, the rest of our benchmark parameterization is fairly standard. Given the difficulties in estimating markup *levels* we target an aggregate markup of $\mathcal{M} = 1.15$, a conventional number in the literature.[17] We set the elasticity of output with respect to labour to $1 - \alpha = 2/3$. We adopt a quarterly frequency and set the discount factor to $\beta = 0.99$. We set the Frisch elasticity of labour supply to 1. We set the Calvo probability of no price change to $\theta = 2/3$, implying a median duration of prices of 3 quarters of a year. We set the interest rate rule parameters to $\phi_\pi = 1.5$ and $\phi_y = 0.5/4$, again, both conventional numbers in the literature — see e.g., Galí (2015).

4.2 Implications for Inflation Dynamics

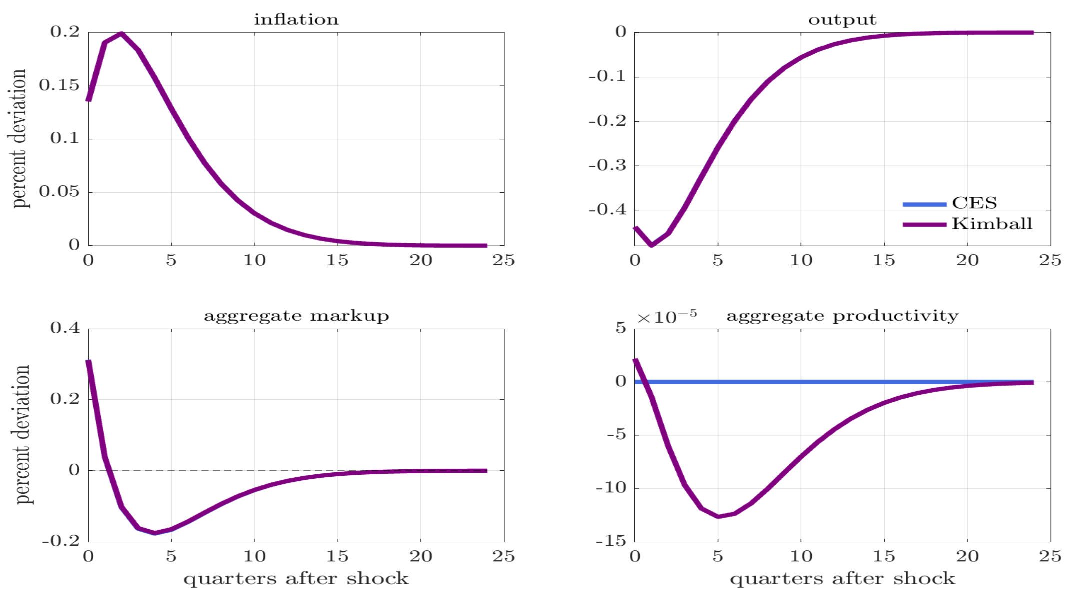
In this section we ask whether this model with variable desired markups and nominal rigidities, once calibrated to match key features of the Australian data on markups and the size distribution of firms, can generate quantitatively substantial amplification of inflation dynamics in response to cost and demand shocks. We find that it cannot.

How much amplification? In this model, with Kimball demand, firm heterogeneity, and nominal rigidities, within a given industry, markups vary in the cross-section of firms for two reasons: (i) the demand system creates endogenous variation in the desired (flexible price) markups of firms, and (ii) the nominal rigidity itself creates gaps between a firm's price (which may well have been set some time ago) and its current marginal costs. Our goal in this section is to assess how much *amplification* of inflation can be generated by the variable desired markups mechanism relative to a textbook New Keynesian model with constant desired markups. To do this, we compare our results to an otherwise identical model but with CES demand. To be clear, our model lacks the features that are known in the literature to be important in generating realistic impulse responses of inflation to cost and demand shocks. Our goal is simply to assess whether the variable desired markups mechanism, when calibrated to Australian firm-level data, is a plausible source of inflation amplification.

Response to cost shock: benchmark parameterization. Our basic exercise is to subject the model economy to a 1% reduction in the exogenous supply of the X_t factor. This exogenous reduction in supply in turn leads to rising prices and lower output. Figure 6 shows the impulse response functions for inflation, aggregate output, the aggregate markup, and aggregate productivity in response an exogenous 1% reduction in X_t with AR(2) dynamics.

[17] Hambur (2023) estimates a sales-weighted *arithmetic* average markup on the order of 1.4 for Australian data, but the aggregate markup $\mathcal{M}$ in the model is a sales-weighted *harmonic* average, as in (20). For Australian data the sales-weighted harmonic average markup is close to 1.15.

Figure 6: Response to Cost Shock: Median BLADE



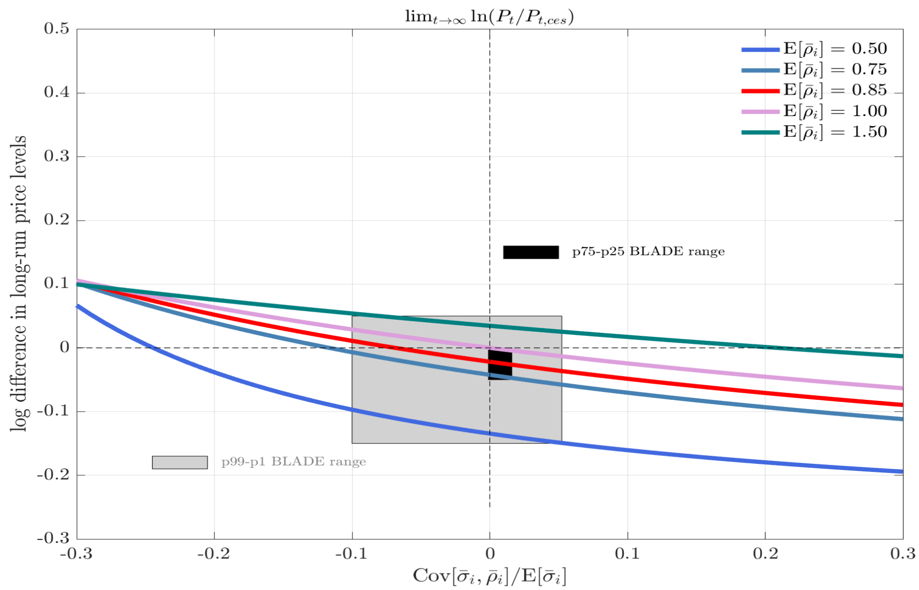
All variables are measured in % deviation from the non-deterministic steady state. In response to the adverse cost shock, inflation rises and output falls on impact, with each then reverting to their long run values. On impact the aggregate markup (and hence profit share) rises, then quickly falls, temporarily overshooting its long-run level. As can be seen, with our benchmark model parameterized to the median BLADE estimates, the model delivers quantitatively negligible amplification of inflation, output, and markup dynamics relative to the CES version of the model.[18] The counterpart CES version of the model features exactly zero endogenous TFP dynamics. The benchmark model with variable desired markups does deliver an endogenous fall in TFP, but this effect is also quantitatively tiny.

Response to cost shock: sensitivity to passthrough conditions. We now assess the sensitivity of this result to alternative passthrough conditions. Our benchmark parameterization matches an average passthrough coefficient $\mathbb{E}_\omega[\bar{\rho}_i] = 0.85$ with average demand elasticity $\mathbb{E}_\omega[\bar{\sigma}_i] = 2.47$ and $\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i] = 0.001$, chosen to match the median industry in the BLADE data. We now re-parameterize the model to match different industry configurations as represented by differing amounts of passthrough and differing amounts of covariance between passthrough coefficients and demand elasticities.

To quantify this sensitivity in a simple way, we first measure the amount of inflation

[18]In fact, for this benchmark parameterization the variable markups mechanism ever so slightly *dampens* the inflation response.

Figure 7: Inflation Amplification: Cost Shock



amplification by computing the long-run difference in price levels

$$\lim_{t\to\infty} \ln \frac{P_t}{P_{t,ces}} \tag{39}$$

relative to same model but with CES demand. Cumulating the impulse response function for inflation in Figure 6 we see that for our benchmark model this measure of inflation amplification is practically zero. We then examine how this long-run difference in price levels varies as a function of the two key moments

$$\frac{\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]}{\mathbb{E}_\omega[\bar{\sigma}_i]}, \qquad \mathbb{E}_\omega[\bar{\rho}_i]$$

Notice from (28) that the average demand elasticity $\mathbb{E}_\omega[\bar{\sigma}_i]$ only matters through the ratio $\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]/\mathbb{E}_\omega[\bar{\sigma}_i]$. For brevity, and in slight abuse of terminology, in what follows we refer to this ratio as the '*standardized covariance*' term.

We report the results of this exercise in Figure 7. Specifically, we plot the long-run difference in price levels as a function of the standardized covariance for different levels of average passthrough, from $\mathbb{E}_\omega[\bar{\rho}_i] = 0.5$ to 1.5. To highlight the empirical range of interest, we shade in black the region of outcomes that correspond to the 25^{th} to 75^{th} percentiles of BLADE estimates, as reported in Table 4. Similarly, we shade in grey the region of outcomes that correspond to the 1^{st} to 99^{th} percentiles of BLADE estimates.

As can be seen, within this range the specification that gives the greatest amount of inflation amplification features both (i) an average passthrough coefficient of $\mathbb{E}_\omega[\bar{\rho}_i] = 1.5$, and (ii) a standardized covariance of about -0.1, i.e., on the outer northwest corner of the 1^{st} to 99^{th} percentile range. In terms of the underlying primitives of the model, a negative covariance is possible if and only if the superelasticity of demand $\varepsilon/\bar{\sigma}$ is itself negative.[19] In turn, if the estimated superelasticity is negative, from (38) we see that the passthrough coefficients will exceed 1. In economic terms, this configuration corresponds to a type of industry where (i) the high-markup firms are relatively small, since $\mu'(q) < 0$ if the superelasticity $\varepsilon/\bar{\sigma} < 0$, and (ii) where within this industry firms face substantial strategic complementarities in price-setting. As can be seen from Table 4 this is a quite rare industry configuration.

Moreover, even granting this comparatively rare industry configuration, the actual amount of inflation amplification generated is quite modest. Even the parameterization most favorable to inflation amplification only generates a long-run log price level about 0.05 points higher than the textbook CES version of the New Keynesian model with constant desired markups. To put this in perspective, for the textbook CES version of the model it turns out that the long-run increase in the log price level in response to this cost shock is about 1.36 points. So even with this specification most favorable to the inflation amplifying properties of variable markups we would attribute about $0.05/(1.36 + 0.05) = 0.0355$, i.e., 3.55%, of the cumulative inflation to the variable markups mechanism,leaving the remaining $1.36/(0.05+1.36) = 0.9645$, i.e., 96.45%, of the cumulative inflation to be attributable to the textbook New Keynesian effects of an adverse cost shock.

In short, when calibrated to match Australian firm-level data the variable markups mechanism does not seem to be a plausible source of inflation amplification in response to cost shocks.

Response to demand shock: benchmark parameterization. We have conducted a similar set of exercises for the response of the model economy to an exogenous demand shock, modeled as a shock to the representative consumer's time discount factor. As shown in Figure 8, qualitatively the story is much the same as for the response to a cost shock. For our benchmark parameterization, using the median BLADE estimates, the variable markups mechanism has quantitatively negligible amplifying effects on inflation. As expected, the demand shock increases inflation, increases output, and decreases the aggregate markup, i.e., decreases the aggregate profit share. Moreover the amount of inflation generated in response to a 1% demand shock is an order of magnitude larger than in response to a 1% cost shock. But these responses are nonetheless very similar to what we get in a textbook CES version of the New Keynesian model with constant desired markups. As with the response to a cost shock, for our benchmark parameterization we find that the variable markups mechanism

[19] To see this, observe from (37) that the estimated demand elasticities are strictly decreasing in the estimated markups while from (38) the estimated passthrough coefficients are strictly increasing in the estimated markups, leading to a negative covariance, if and only if the estimated superelasticity $\hat{b} = \varepsilon/\bar{\sigma} < 0$.

has a very slight dampening effect on inflation relative to the textbook CES version of the model. As with a cost shock, the variable markups version of the model does lead to non-zero endogenous TFP dynamics, but these effects are again tiny.

Response to demand shock: sensitivity to passthrough conditions. The sensitivity of the inflation amplification in response to demand shocks is quite similar to the response to cost shocks. As shown in Figure 9, the specification that gives the greatest amount of inflation amplification again features an average passthrough coefficient of $\mathbb{E}_\omega[\bar{\rho}_i] = 1.5$, and a standardized covariance of about -0.1, i.e., again on the outer northwest corner of the 1^{st} to 99^{th} percentile BLADE range. The amount of amplification that can be generated by this specification is larger than in response to cost shocks. For demand shocks three is about a 1.75 point extra increase in the log price level for demand shocks, as opposed to a 0.05 point extra increase for cost shocks. However, once again this is a small share of the cumulative inflation response. The textboook CES version of the model generates a long-run increase in the log price level in response to this demand shock of about 13.50 points. So even with this specification most favorable to the inflation amplifying properties of variable markups we would attribute about $1.75/(13.50 + 1.75) = 0.1148$, say, 11.5%, of the cumulative inflation to the variable markups mechanism,leaving the remaining $13.50/(13.50 + 1.75) = 0.8852$, say 88.5%, of the cumulative inflation to be attributable to the textbook New Keynesian effects of the demand shock.

All told, these calculations suggest that, for our benchmark parameterization, calibrated to match the median BLADE estimates, the variable markups mechanism does not generate substantial inflation amplification in response to either cost or demand shocks. Indeed, for our benchmark parameterization we find that the variable markups mechanism leads to *dampening* effects on inflation. This implies that, for example, a temporary rise in costs temporarily reduces desired markups — squeezing profit margins — relative to what one would expect in a textbook CES version of the model.

Moreover, even for the specifications of the model most conducive to inflation amplification, representing industry configurations at the outer edge of the range that can be found in BLADE data, we still find at most quite modest amplification effects, e.g., adding at most something like 0.05 points to the long run log price level in response to a cost shock relative to the textbook CES version of the New Keynesian model.

Figure 8: Response to Demand Shock: Median BLADE

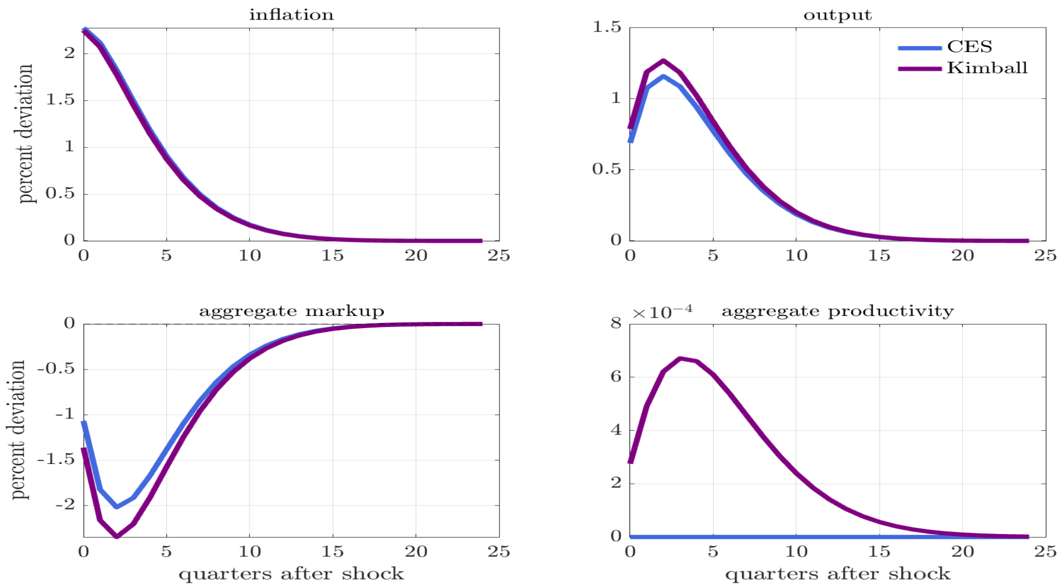
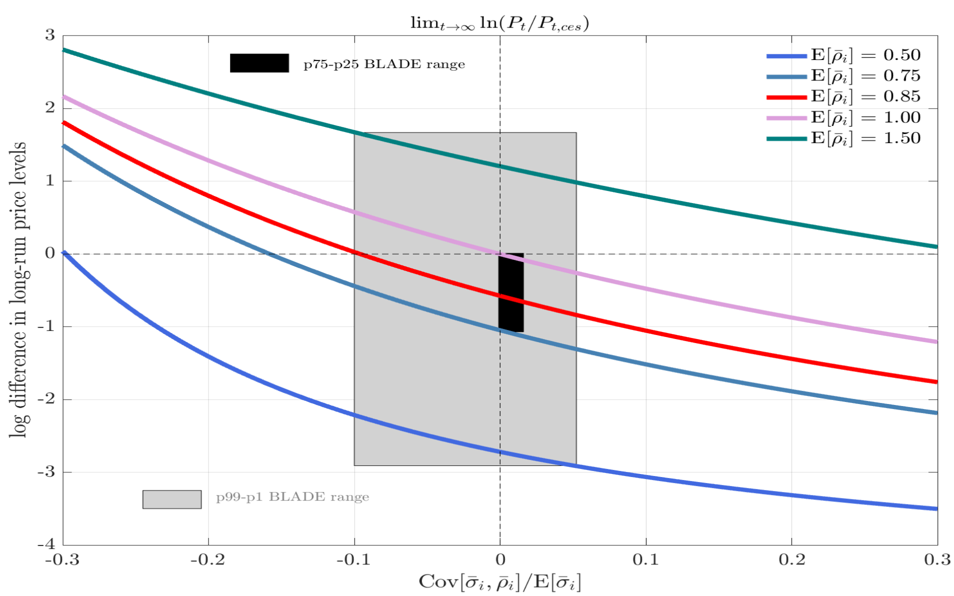


Figure 9: Inflation Amplification: Demand Shock



5 Summary and Conclusion

In this paper we ask whether variable markups, i.e., variable profit margins, might play a role in amplifying Australian inflationary dynamics. We answer this question using two complementary approaches. First, we use detailed administrative micro data to assess the extent to which the pattern of firm- and industry-level markup and price changes are in principle consistent with known inflation amplification mechanisms. In this first approach we impose essentially no theoretical structure, but at the cost of having less to say about what *causes* what, i.e., using these methods one cannot speak to *why* markups and prices may be moving together, to the extent that they do. Second, we use a dynamic macroeconomic model calibrated to match key facts from the Australian data and ask whether, viewed through the lens of that model, there is reason to think that variable markups are likely to be a source of substantial inflation amplification. In this second approach we impose much more theoretical structure, which at least has the benefit of giving a more clear causal interpretation to our results.

Neither approach suggests an important role for variable markups in amplifying inflationary dynamics. First, the evidence from Australian firm-level data suggests that (i) while there is some evidence that prices tended to increase by more in industries that had increasing markups over the 2004-2017 period, (ii) there is incomplete passthrough from cost shocks to prices — passthrough < 1 — and no statistically significant evidence that passthrough has risen in recent years, and (iii) there is some evidence that, in the cross-section of industries, passthrough is lower in less competitive industries. Second, when we calibrate our model to match key facts in the BLADE administrative tax data, we find that variable markups do not amplify inflation dynamics. To the contrary, for our benchmark model we find that variable markups if anything slightly dampen inflation dynamics.

Our model can produce inflation amplification, but only for parameterizations that are extreme outliers in the Australian data. In particular, our model produces inflation amplification only if, within a given industry, markup levels are negatively correlated with size, i.e., within a given industry, the firms with high markups are relatively small — in technical terms, only if the 'superelasticity' of demand is *negative*. This is certainly not true for the median industry. Indeed to get quantitatively substantial amplification we would need to use a superelasticity parameter at the lowest 1% of what we estimate across Australian industries. Put differently, to get substantial inflation amplification the model would need to use a calibration that is at odds with what we find is typically true for Australian industries.

Of course this model is hardly the last word on the subject. To keep things simple, we have abstracted from various model features that may in principle be important — e.g., state-dependence in pricing decisions, nominal rigidities in wage-setting, factor adjustment costs, etc. Understanding to what extent our benchmark results are robust to such modelling choices seems like a natural direction for future research.

And perhaps more important, we will have a much better sense of these issues once administrative data from the critical years 2022 and 2023 is more available. These data may of course lead us to revise our current findings. But so far as we can tell right now, neither the raw micro data nor quantitative economic models give much reason to think that variable markups are amplifying inflation dynamics.

Appendix

A Markups and Granular Instrumental Variables

The firm-level data used in this paper come from the ABS's Business Longitudinal Analysis Data Environment (BLADE).[20] This is a longitudinal data set 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. 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.[21]

The data used for markup estimation and estimation of granular instrumental variables (GIV) 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 worker numbers, which are used as the labour input for markup estimation.

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.

[20]The results of these studies are based, in part, on data supplied to the ABS under the Taxation Administration Act 1953, A New Tax System (Australian Business Number) Act 1999, Australian Border Force Act 2015, Social Security (Administration) Act 1999, A New Tax System (Family Assistance) (Administration) Act 1999, Paid Parental Leave Act 2010 and/or the Student Assistance Act 1973. Such data may only . used for the purpose of administering the Census and Statistics Act 1905 or performance of functions of the ABS as set out in section 6 of the Australian Bureau of Statistics Act 1975. No individual information collected under the Census and Statistics Act 1905 is provided back to custodians for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the Australian Taxation Office, Australian Business Register, Department of Social Services and/or Department of Home Affairs' core operational requirements.

Legislative requirements to ensure privacy and secrecy of these data have been followed. For access to MADIP and/or BLADE data under Section 16A of the ABS Act 1975 or enabled by section 15 of the Census and Statistics (Information Release and Access) Determination 2018, source data are de-identified and so data about specific individuals has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

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

- Labour input: Full-time equivalent workers derived from PAYG statements.
- Capital: Book value of non current assets.

All of these metrics apart from labour input are measured in nominal terms. To construct real measures to put into the production functions we deflate using division-level output, intermediate input and capital deflators. The labour expense 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* of markups (see e.g., Bond et al., 2021). Given the general difficulty of identifying markup levels, it is perhaps wiser to focus on *changes* in markups over time. Intuitively estimates of markup changes should be more robust so long as the estimated production function parameters themselves remain stable over time (see e.g., De Loecker and Warzynski, 2012) In this sense, we are confident in our estimates of markup changes over time despite the lack of firm-level prices.

B Price Microdata and Profit Margins

The data used for the analysis of firm-level prices and profit margins come from two sources that have recently been integrated by the ABS.

The first source is web-scraped prices microdata that have been collected by the ABS. These provide item-level prices at a high frequency (e.g., weekly) for 58 firms covering a period from 2016 to 2022 (though coverage is lower pre-2018). As discussed in Fink, Hambur and Majeed (2023), these data can be used to calculate the average price charged by a firm for a given item in each month or quarter. We can then then calculate the change for each item and take an unweighted average for each firm to construct a measure of firm-level price changes in each quarter.

Our measure of profit margins is constructed using data from firms' Business Activity Statements (BAS). These are reported on a quarterly basis and include data on a firm's sales, cost of goods sold and some other outlays. Since 2017/18 only firms over a certain size are required to report on their expenses in these forms, and so we exclude firms below the threshold for the analysis (though this excludes very few firms).

We measure profit margins as the gross profit margin: sales divided by cost of goods sold. We combine businesses that are part of a single consolidated entity into one firm.

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