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

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Abstract

We examine whether lack of competition can amplify inflationary cost shocks in a New Keynesian model with endogenous markups. We show that variable markups can amplify inflationary shocks if the 'superelasticity' of demand is negative, implying that passthrough from costs to prices is high. We pin down this key parameter using detailed administrative micro-data for Australia and find that the superelasticity is positive, implying that variable markups actually dampen passthrough. We supplement our structural model with reduced-form firm- and industry-level passthrough regressions and find that passthrough is low, and lower in less competitive industries, in line with the model.

Keywords: competition, profits, inflation, passthrough, firm dynamics.

JEL classifications: E3, L1.

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1 Introduction

Do variable profit margins play a substantial role in amplifying inflation dynamics? Has the recent rise in inflation been driven by firms with market power taking advantage of unusual disruptions to supply? We answer these questions using a New Keynesian model with heterogeneous firms and endogenously variable markups. In our model, the extent to which firms raise prices in response to shocks[1] — the amount of *passthrough* — is determined by the competitive conditions they face in their industry. If passthrough is sufficiently high, especially for firms with high existing markups, then this mechanism can generate inflation amplification. Our goal in this paper is to assess the plausibility of this mechanism using detailed administrative micro data from Australia's Business Longitudinal Analysis Data Environment (BLADE). Overall, we find that variable profit margins are *not* a plausible source of inflation amplification.

Our model features heterogeneous firms that differ in productivity and that engage in monopolistic competition subject to a Kimball (1995) demand system. This is a parsimonious way of allowing for non-constant demand elasticities, and hence variable markups, that nests the textbook constant elasticity demand system as a special case. We augment this Kimball demand system with nominal rigidities in the form of a Calvo (1983) pricing friction, as in Baqaee, Farhi and Sangani (2024). Relative to a textbook New Keynesian model, the key new parameter in this setup is the *superelasticity* of the demand system, which governs the extent to which the demand elasticity facing a firm depends on the *relative size* of the firm within a given narrowly-defined industry. In turn, the sign and magnitude of the superelasticity determines the amount of passthrough from shocks to changes in prices. In particular, if the superelasticity is positive, there is incomplete passthrough and price responses to the underlying shocks are *dampened* relative to a model with constant markups.[2] If instead the superelasticity is negative, price responses to the underlying shocks are *amplified*.

Why does a positive superelasticity lead to a dampened inflation response? First consider the textbook case with constant demand elasticity. Absent pricing frictions, an adverse cost shock leads to a 1-for-1 increase in prices that contracts sales while keeping the firm's profit margin intact. Now consider the case of a variable demand elasticity. If the superelasticity is positive, large firms face less elastic demand. These large firms have high initial markups but respond to an adverse cost shock by increasing prices less than 1-for-1 so that their markups fall from these high levels. By reducing markups, i.e., reducing profit margins, the sales of these firms contract by less than they otherwise would, allowing the *level* of profits these firms make, which is what they actually care about, to stay higher than they otherwise would. To get inflation amplification out of the variable markups mechanism requires the opposite

[1] We focus on the amplification of adverse cost shocks. We also briefly present results on the amplification of expansionary demand shocks and find broadly similar results.

[2] More precisely, constant *desired* markups, since markups also vary due to the Calvo (1983) friction.

parameter configuration, a negative superelasticity where an adverse cost shock leads to a more than 1-for-1 price response and a larger contraction in sales.

In short, the sign and magnitude of the superelasticity parameter is critical to the model's quantitative implications for inflation dynamics. To pin this parameter down we calibrate our model to match (i) facts on sales concentration within detailed 4-digit Australian industries, (ii) firm-level markup estimates using the production function methods advocated by De Loecker and Warzynski (2012), and (iii) measures of the within-industry covariation between firm-level sales shares and markups. As pointed out by Edmond, Midrigan and Xu (2023), this covariation is the key to identifying the sign and magnitude of the superelasticity of the demand system. If, within a given industry, firm-level sales shares and markups are positively correlated — i.e., relatively larger firms charge larger markups — then the estimated superelasticity is positive, passthrough is less than 1-for-1, and inflation dynamics will be dampened relative to a model with constant demand elasticity. But if, within a given industry, firm-level sales shares and markups are negatively correlated — i.e., relatively larger firms charge smaller markups — then the estimated superelasticity is negative, passthrough is greater than 1-for-1, and inflation dynamics are amplified.

We estimate the superelasticity for each 4-digit industry in our BLADE sample. We find that the majority of these Australian industries have a positive superelasticity. Specifically the median superelasticity is 0.11 and approximately 75 percent of these 4-digit industries have a positive superelasticity.[3] When calibrated to match a median superelasticity of 0.11, our model predicts average passthrough of about 0.86, i.e., a 10 percent increase in costs leads to a 8.6 percent increase in prices, so that in response to an adverse cost shock profit margins tighten but the contraction in sales is mitigated relative to a textbook New Keynesian model with constant demand elasticity. For these industries an adverse cost shock leads to an increase in prices that is *smaller* than would be predicted by a model with constant demand elasticity. While the variable markups mechanism could in principle amplify inflation, versions of the model consistent with the pattern of markups and market shares in Australian micro data predict that the variable markups mechanism instead *dampens* inflation.

To assess the sensitivity of our results to our parameterization of the superelasticity we have also solved the model with demand conditions that correspond to outlier industries with average passthrough on the order of 1.7, i.e., where a 10 percent increase in costs leads to a 17 percent increase in prices. This corresponds to a negative superelasticity estimate that is in the bottom 1 percent of our 4-digit industry estimates. In such industries, the firms with high markups are the relatively small firms — suggesting, perhaps, that the high markups of these firms reflect niche products or other unmeasured dimensions of product quality. In any case, this parameterization is at least *qualitatively* consistent with inflation amplification.

[3] Our median superelasticity estimate is 0.11, close to the pooled estimate of 0.16 reported by Edmond, Midrigan and Xu (2023) for 6-digit US manufacturing data and well within the range of 0.08 to 0.24 they report for 3-digit US manufacturing data. Importantly, all these estimated superelasticities are positive.

But even this parameterization, which gives the variable markups mechanism its best chance of delivering inflation amplification, turns out to give *quantitatively* modest amplification. In response to an adverse cost shock, this parameterization of the model implies a long-run price level (cumulative inflation) that is about 0.067 log points or 6.7 percent higher than it would otherwise be. This is not nothing, but it is at most modest amplification. The bulk of the inflation in this episode is attributable to the textbook New Keynesian dynamics, not to the variable markups mechanism. And recall, this is an outlier parameterization, at odds with the facts on markups and sales concentration in most Australian industries, chosen not because it is typical but because it gives the variable markups mechanism its best chance of delivering inflation amplification. For there to be substantial amplification, the underlying patterns in the data would have to be very different to what we actually observe.

A potential concern with our analysis to this point is that it makes heavy use of the structure of the model to estimate superelasticities and to back out (unobservable) firm-level demand elasticities and passthrough coefficients from (observable) measures of firm size. To address this concern we supplement the results from our structural model with results from several reduced-form exercises. First, following Fink, Hambur and Majeed (2023) we use newly available firm-level data on prices for a sample of retail firms to directly examine the correlation between firm-level prices and profits.[4] Reassuringly for our structural analysis, these reduced-form regressions imply passthrough of 0.85, almost exactly the same amount of passthrough, 0.86, that we back out of the benchmark parameterization of our model. Second, following Bräuning, Fillat and Joaquim (2023), we construct estimates of firm-level idiosyncratic variation in costs, aggregate these to the industry level, and examine passthrough of these industry-level cost shocks to industry-level prices. We find evidence that industry-level passthrough from these cost shocks is lower in industries with higher markups (and in more concentrated industries), again consistent with our structural model and inconsistent with variable markups being a substantial source of inflation amplification. Finally, following Conlon, Miller, Otgon and Yao (2023), we show that while there was a statistically significant positive correlation between industry-level markup changes and price changes pre-pandemic, that correlation has *not* become stronger during the pandemic period, if anything the industry-level correlation between markup changes and price changes is *negative* during the covid period.[5] In short, these reduced-form results offer no support for the kinds of parameterizations of our model that would be required for there to be substantial amplification of cost shocks.

[4] Our benchmark analysis using BLADE is limited by the lack of firm-level price data. For this exercise we use data from a narrower sample of retail firms for which we have product-level price data that can be aggregated to the firm-level.

[5] Our results on industry-level passthrough and the industry-level correlation between markup changes and price changes draw heavily on Champion (2023).

All told, neither the results from our structural model calibrated to match the facts on sales concentration and firm-level markups in 4-digit Australian industries nor our results from reduced-form firm- and industry-level passthrough regressions is consistent with variable profit margins being an important source of inflation amplification.

Earlier results on markups and inflation. This paper contributes to an established literature on the relationship between producer market power and inflation. For example, Bénabou (1988, 1992a) shows that in (s, S) pricing models higher trend inflation gives consumers an incentive to search harder, effectively making the demand facing firms *more elastic* and hence reducing their markups. In support of this, Bénabou (1992b) shows that the aggregate US retail sales markup is negatively correlated with inflation. Simon (2000) provides further evidence in support, showing that in the cross-section of US manufacturing industries inflation is negatively correlated with markups and that this relationship is stronger for more concentrated industries.

Renewed interest after the pandemic. With the sharp increase in inflation observed in many countries since the covid pandemic, there has been a renewed interest in the relationship between markups (or profit margins) and inflation — see e.g., Weber and Wasner (2023) and the literature reviewed in ACTU (2024). This literature argues that firms with market power have taken advantage of unusual conditions to increase profits by increasing prices by more than the increase in their marginal costs. In other words, this literature implicitly argues that firms are acting as if they suddenly face *less elastic* demand. Some argue that observed increases in *aggregate*, economy-wide, profit shares provide evidence that firms have passed on cost increases more than one-for-one, thereby contributing to higher inflation — see e.g., Legarde (2023), Stanford (2023) and OECD (2023). But these studies do not shed much light on whether increases in profit margins are driving inflation, for several reasons:

- They reflect a national income accounting decomposition that must hold regardless of what the underlying drivers of inflation are. For example, if high demand leads to both higher profits and higher inflation, this approach might lead one to mistakenly conclude that higher profits are causing higher inflation.

- They characterize changes in the GDP deflator not the CPI and hence include many changes in prices not directly relevant to consumers.

- They use a broad notion of *accounting profits*, i.e., non-labor income, rather than the *economic profits* that are the hallmark of firms taking advantage of market power.[6]

[6] 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.

In short, movements in the aggregate profit share alone are simply not informative about the role increases in profits may play in driving inflation. Given this, attention has turned to evidence from disaggregated data. For example, Konczal and Lusiani (2022) argue that there was a sharp increase in firm-level markups in 2021, consistent with market power contributing to the rise in inflation, while Leduc, Li and Liu (2024) argue that the rise in markups is confined to motor vehicles and petroleum industries and that more broadly markups do not appear to have contributed to the surge in inflation. Alvarez, MacKay, Cavallo and Mengano (2024) use product-level data to provide further evidence that markups have remained stable in US retail. Relative to this literature, our main contribution is to assess the extent to which variable markups amplify inflationary shocks through the lens of a dynamic general equilibrium model with heterogeneous firms and pricing frictions. Other related work in a similar spirit includes Bilbiie and Känzig (2023) and Giarda, Lu and Martner (2025).

Markups and firm size. Much of the interest in the possibility that rising markups have amplified inflationary shocks comes from the pre-pandemic literature on trend increases in market power and concentration, as documented by, e.g., Autor, Dorn, Katz, Patterson and Van Reenen (2020), Baqaee and Farhi (2020), De Loecker, Eeckhout and Unger (2020), and Hambur (2023). This literature consistently finds a positive relationship between markups and firm size. For further examples see Atkin, Chaudhry, Chaudhry, Khandelwal and Verhoogen (2015) and Gupta (2020).

Passthrough and firm size. Other closely related work considers the relationship between passthrough and firm size at short- and long-horizons, e.g., Alexander, Han, Kryvtsov and Tomlin (2024), Amiti, Itskhoki and Konings (2014, 2019), Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Genakos and Pagliero (2022), Li, Ma and Xu (2015), and Nakamura and Zerom (2010). See also Melitz (2018) and Sangani (2024). This literature consistently finds that larger, high markup firms have lower passthrough.

Markups and cyclical dynamics. Other related work considers the role of competition and markup variation in response to business cycle shocks, as in Wang and Werning (2022), Ueda (2023), Fujiwara and Matsuyama (2022), and Duval, Furceri, Lee and Tavares (2021).

2 Model

The model is a simplified version of Edmond, Midrigan and Xu (2023) augmented with nominal rigidities as in Baqaee, Farhi and Sangani (2024). There is a representative consumer with preferences over final consumption and labor 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 labor and a special factor that is in inelastic supply. The intermediate input producers are subject to nominal rigidities in the form of a Calvo (1983) pricing friction. There is no entry or exit.

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

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

subject to the budget constraints

$$P_t C_t + Q_t B_{t+1} = W_t L_t + R_t X_t + \Pi_t + B_t \tag{2}$$

where C_t denotes real consumption of the final good, L_t denotes labor 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.[7]

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

$$Q_t = \mathbb{E}_t \left\{ \beta \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}} \right\} \tag{3}$$

and the static labor supply condition

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

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

Final good. 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

$$\int_0^1 \Upsilon\big(\frac{y_{it}}{Y_t}\big)\, di = 1 \tag{5}$$

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

[7] 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.

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

$$P_t Y_t - \int_0^1 p_{it} y_{it} \, di \tag{6}$$

subject to the Kimball aggregator (5) above.

Kimball demand system. The profit maximization problem of the representative final good producer implies that the inverse demand curve facing the producer of intermediate input $i \in [0,1]$ can be written

$$\frac{p_{it}}{P_t} = \Upsilon'(q_{it}) \, D_t, \qquad q_{it} := \frac{y_{it}}{Y_t} \tag{7}$$

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

$$P_t = \int_0^1 p_{it} \, q_{it} \, di \tag{8}$$

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

$$D_t = \left(\int_0^1 \Upsilon'(q_{it}) \, q_{it} \, di \right)^{-1} \tag{9}$$

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

$$\omega_{it} := \frac{p_{it} y_{it}}{P_t Y_t} = \Upsilon'(q_{it}) q_{it} D_t \tag{10}$$

Since D_t is common to all firms, relative sales shares depend only on relative sizes. The expression for the demand index D_t in (9) ensures that the sales shares ω_{it} integrate to 1.

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 labor l_{it} and other factors x_{it} to produce their output y_{it} using the Cobb-Douglas technology

$$y_{it} = z_i \, x_{it}^{\alpha} \, l_{it}^{1-\alpha}, \qquad 0 < \alpha < 1 \tag{11}$$

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

$$\frac{\Psi_t}{z_i}\, y_{it} \tag{12}$$

where the aggregate component of nominal marginal cost is given by

$$\Psi_t := \min_{x,l}\left[R_t x + W_t l \quad \middle| \quad x^{\alpha} l^{1-\alpha} = 1 \right] = \left(\frac{R_t}{\alpha}\right)^{\alpha}\left(\frac{W_t}{1-\alpha}\right)^{1-\alpha} \tag{13}$$

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

$$\pi_{it} = \left(p_{it} - \frac{\Psi_t}{z_i}\right) y_{it} \tag{14}$$

The objective of an intermediate input producer is to maximize their expected discounted profits subject to the demand curve (7) and the 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

$$p_{it} = \mu_{it}\,\frac{\Psi_t}{z_i} \tag{15}$$

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

$$\mu_{it} = \mu(q_{it}) \tag{16}$$

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

$$\mu(q) := \frac{\sigma(q)}{\sigma(q)-1}, \qquad \sigma(q) := -\frac{\Upsilon'(q)}{\Upsilon''(q)q} \tag{17}$$

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

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

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

$$\rho(q) = \frac{1}{1+\sigma(q)\frac{\mu'(q)q}{\mu(q)}} = \frac{1}{1-\mu(q)\frac{\sigma'(q)q}{\sigma(q)}} \tag{18}$$

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 is given by a *sales-weighted harmonic average* of firm markups

$$\mathcal{M}_t = \left(\int_0^1 \frac{\omega_{it}}{\mu_{it}}\, di \right)^{-1}, \qquad \omega_{it} := \frac{p_{it} y_{it}}{P_t Y_t} \sim \Upsilon'(q_{it}) q_{it} \tag{19}$$

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

$$\omega_{it} = \Upsilon'(q_t(z_i)) q_t(z_i) D_t \tag{20}$$

Given this expression for the aggregate markup, we can then compute aggregate profits

$$\Pi_t = \int_0^1 \pi_{it}\, di = \int_0^1 \left(p_{it} - \frac{\Psi_t}{z_i} \right) y_{it}\, di = \left(1 - \frac{1}{\mathcal{M}_t} \right) P_t Y_t \tag{21}$$

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. 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 $\theta = 0$.

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 $\bar{\mu}_i = \mu(\bar{q}_i)$, $\bar{\rho}_i = \rho(\bar{q}_i)$, etc denote the implied steady state distribution of markups, passthrough coefficients, etc. To simplify notation, in the exposition below we drop constants that are absorbed by steady-state terms.

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

$$\ln p_{it}^* = (1-\theta\beta)\left[\bar{\rho}_i \ln \Psi_t + (1-\bar{\rho}_i)(\ln P_t + \ln D_t)\right] + \theta\beta\mathbb{E}_t\left[\ln p_{it+1}^*\right] \tag{22}$$

Iterating forward we get

$$\ln p_{it}^* = (1-\theta\beta)\,\mathbb{E}_t\left\{\sum_{k=0}^{\infty}(\theta\beta)^k\left[\bar{\rho}_i \ln \Psi_{t+k} + (1-\bar{\rho}_i)(\ln P_{t+k} + \ln D_{t+k})\right]\right\} \tag{23}$$

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}^* chosen by an individual firm 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 increasing 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 (2024) show that this characterization of reset prices plus the definition of the aggregate price index implies that inflation dynamics are given by

$$\Delta \ln P_t = \beta\mathbb{E}_t\left[\Delta \ln P_{t+1}\right] + \lambda\left(\mathbb{E}_\omega[\bar{\rho}_i](\underbrace{\ln \Psi_t - \ln P_t}_{\text{real marginal cost}}) + \left(1 - \mathbb{E}_\omega[\bar{\rho}_i]\right)\ln D_t\right) \tag{24}$$

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

$$\mathbb{E}_\omega[\bar{\rho}_i] := \int_0^1 \bar{\rho}_i\,\bar{\omega}_i\,di \tag{25}$$

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 TFP can be written

$$\ln Z_t = \ln \mathcal{M}_t - \mathbb{E}_\omega\big[\ln \mu_{it}\big] \tag{26}$$

and so reflects markup dispersion as measured by the difference between the log of the average markup and the average of log markups.

Baqaee, Farhi and Sangani (2024) show that aggregate TFP dynamics are then given by

$$\Delta \ln Z_t = \beta \mathbb{E}_t\big[\Delta \ln Z_{t+1}\big] - \lambda \ln Z_t + \lambda\, \bar{\mathcal{M}}\, \frac{\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]}{\mathbb{E}_\omega[\bar{\sigma}_i]} \big(\ln \Psi_t - \ln P_t - \ln D_t\big) \tag{27}$$

If there is *no heterogeneity in passthrough*, e.g., as in the CES special case where $\bar{\rho}_i = 1$, then 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

$$\ln Y_t = \ln Z_t + \alpha \ln X_t + (1-\alpha) \ln L_t \tag{28}$$

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

$$\ln W_t - \ln P_t = \ln Y_t + \varphi \ln L_t \tag{29}$$

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

$$\mathbb{E}_t\big[\Delta \ln Y_{t+1}\big] = i_t - \mathbb{E}_t\big[\Delta \ln P_{t+1}\big] \tag{30}$$

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

$$i_t = \phi_\pi \, \Delta \ln P_t + \phi_y \, \ln Y_t \tag{31}$$

3 Quantifying the Model

In this section we first outline our benchmark parameterization and then 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.

3.1 Benchmark parameterization

Overview. We adopt the Klenow and Willis (2016) form of the Kimball (1995) 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 sales shares 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 moments, namely the sales-weighted average demand elasticity, the sales-weighted average passthrough coefficient, and the sales-weighted covariance of demand elasticities and passthrough

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

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 sales shares, as explained below.

Kimball-Klenow-Willis demand. The Klenow and Willis (2016) form of the Kimball (1995) aggregator implies that the inverse demand facing a firm of relative size q_i is given by

$$\Upsilon'(q_i) = \frac{\bar{\sigma}-1}{\bar{\sigma}}\exp\left(\frac{1-q_i^{\varepsilon/\bar{\sigma}}}{\varepsilon}\right), \qquad \bar{\sigma}>1 \tag{32}$$

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

$$\sigma(q_i) = \bar{\sigma}\,q_i^{-\varepsilon/\bar{\sigma}}, \qquad\qquad \rho(q_i) = \frac{1}{1+\frac{\varepsilon}{\bar{\sigma}}\mu(q_i)} \tag{33}$$

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 q_i, 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 $\sigma(q_i)$, and hence have higher desired markups and lower passthrough $\rho(q_i) < 1$. Alternatively, if $\varepsilon < 0$ then larger firms face more elastic demand, have higher $\sigma(q_i)$, and hence have lower desired markups and higher passthrough $\rho(q_i) > 1$.

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 μ_i and its sales share ω_i that can be written

$$f(\mu_i) = a + b\,\ln\omega_i, \qquad b = \frac{\varepsilon}{\bar{\sigma}} \tag{34}$$

where the function

$$f(\mu_i) := \frac{1}{\mu_i} + \ln\left(1 - \frac{1}{\mu_i}\right) \tag{35}$$

is strictly increasing and free of other parameters. Importantly, the slope coefficient b in this relationship *is* the superelasticity of the demand system.[8]

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 this on the observed sales share ω_i. The estimated slope coefficient $\hat{b}$ is then the estimated superelasticity, $\varepsilon/\bar{\sigma} = \hat{b}$.

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

$$\hat{\sigma}_i = \frac{\hat{\mu}_i}{\hat{\mu}_i - 1} \tag{36}$$

And the implied passthrough coefficients are

$$\hat{\rho}_i = \frac{1}{1 + \hat{b}\hat{\mu}_i} \tag{37}$$

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

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

[8] In an extension of this framework with sector-level heterogeneity and additional firm-level time-invariant demand shifters, Edmond, Midrigan and Xu (2023) show that a correctly specified version of (34) should also include a full set of sector, sector-time, and time-invariant firm fixed effects.

Table 1: Key Moments From BLADE

	$\varepsilon/\bar{\sigma}$	$\mathbb{E}_\omega[\hat{\rho}_i]$	$\mathbb{E}_\omega[\hat{\sigma}_i]$	$\text{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i]$	$\frac{\text{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i]}{\mathbb{E}_\omega[\hat{\sigma}_i]}$
preferred production function $\hat{\mu}_i$ estimates (Hambur 2023)					
weighted mean	0.13	0.89	8.63	0.06	0.01
weighted percentiles					
01	−0.35	0.44	1.50	−2.72	−0.15
25	−0.00	0.69	3.78	0.00	0.00
50	0.11	0.86	6.17	0.04	0.01
75	0.26	1.00	9.39	0.10	0.02
99	0.56	1.71	45.52	0.45	0.07
simple cost-share $\hat{\mu}_i$ estimates					
weighted mean	0.08	0.84	5.87	0.29	0.05

ANZSIC 4-digit industry-level estimates of the superelasticity of demand $\varepsilon/\bar{\sigma}$ and the key cross-sectional moments of the demand system: the sales-weighted average passthrough, demand elasticity, and covariance of demand elasticities and passthrough. The first row reports the weighted average of these industry-level estimates, the next rows report key percentiles of the distribution of these industry-level estimates. The top panel reports results obtained using our preferred markup estimates $\hat{\mu}_i$ based on Hambur (2023). The last row reports analogous results for simple cost-share markup estimates.

Markup estimates. Our preferred markup estimates $\hat{\mu}_i$ are obtained using the production function methods advocated by De Loecker and Warzynski (2012) as applied to Australian firm-level BLADE data by Hambur (2023). This gives us estimated markup distributions for each 4-digit ANZSIC industry in our sample. Our sample excludes industries in the Health, Education, and Public Administration divisions and the Finance division and a small number of industries where there are too few firms to reliably estimate the production function. See Hambur (2023) and Appendix A for further discussion.[9]

3.2 Calibration results

Superelasticity $\varepsilon/\bar{\sigma}$ estimates. For each industry in our BLADE sample, we estimate the superelasticity using (34), i.e., regressing transformed firm-level markups $f(\hat{\mu}_i)$ on observed firm sales shares ω_i. In the first column of the top panel of Table 1 we summarize these

[9]For our benchmark results we focus on markups estimated on pre-covid data. As discussed in Section 5.4 below, our results are, if anything, stronger when we extend the sample to include covid and post-covid data.

estimates by reporting the weighted average superelasticity and key percentiles of the distribution of estimated superelasticities across industries. For the median Australian industry in our sample, we find a superelasticity estimate $\varepsilon/\bar{\sigma} = \hat{b} = 0.11$, 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., $\mu'(q_i) > 0$. Interestingly, this median estimate $\hat{b} = 0.11$ across all 4-digit industries is not far off the superelasticity 0.16 that Edmond, Midrigan and Xu (2023) estimate for 6-digit US manufacturing industries.[10]

Key moments from BLADE. Given our estimated superelasticity $\varepsilon/\bar{\sigma} = \hat{b}$ for each 4-digit ANZSIC industry in our sample, and our estimated markups $\hat{\mu}_i$ for each firm in that industry, we can then use the structure of the Kimball-Klenow-Willis demand system to infer firm-level demand elasticities $\hat{\sigma}_i$ and passthrough coefficients $\hat{\rho}_i$ for each firm within each 4-digit industry, as outlined above. For each of these 4-digit industries we then take sales-weighted averages across firms to compute the key cross-sectional moments $\mathbb{E}_\omega[\hat{\rho}_i]$, $\mathbb{E}_\omega[\hat{\sigma}_i]$, and $\mathrm{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i]$. We summarize these results in the remaining columns of the top panel of Table 1. For the median Australian industry we find that the sales-weighted average passthrough coefficient is $\mathbb{E}_\omega[\hat{\rho}_i] = 0.86$, substantially lower than we would have with CES demand.[11] The corresponding sales-weighted average demand elasticity is $\mathbb{E}_\omega[\hat{\rho}_i] = 6.17$. Importantly, the median sales-weighted covariance between demand elasticities and passthrough, while positive, is quite low, $\mathrm{Cov}_\omega[\hat{\sigma}_i, \hat{\rho}_i] = 0.04$. 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 lowest percentiles of Australian industries do we find a meaningfully negative covariance term. 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 1.

Benchmark parameterization. For our benchmark parameterization we use the median BLADE estimates reported in Table 1. We later explore the sensitivity of our results to adopting parameterizations that reflect outlier industries, e.g., industries with average passthrough coefficients that substantially exceed 1. As shown in Table 2, the rest of our benchmark parameterization is fairly standard. Given the difficulties in estimating markup *levels* we target

[10] Across 3-digit US manufacturing industries, Edmond, Midrigan and Xu (2023) estimate superelasticities ranging from 0.081 to 0.242. In recent work using Chilean administrative data, Giarda, Lu and Martner (2025) estimate a superelasticity of 0.27. Much larger estimates can be found in studies of specific industries, e.g., Nakamura and Zerom (2010) find a median superelasticity of 4.64 in the US retail coffee industry.

[11] Interestingly, this median estimate of average passthrough $\mathbb{E}_\omega[\hat{\rho}_i] = 0.86$ is almost exactly the same as the reduced-form passthrough 0.85 we estimate from the narrow set of retail firms for which we have firm-level price data, see Table 3 below.

Table 2: Benchmark Parameterization

superelasticity	$\varepsilon/\bar{\sigma}$	0.11
average passthrough	$\mathbb{E}_\omega[\bar{\rho}_i]$	0.86
average demand elasticity	$\mathbb{E}_\omega[\bar{\sigma}_i]$	6.17
covariance	$\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]$	0.04
aggregate markup	$\bar{\mathcal{M}}$	1.15
elasticity of output wrt nonlabor 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

For our benchmark parameterization we use the median of our 4-digit industry-level estimates of the superelasticity $\varepsilon/\bar{\sigma}$ and the key cross-sectional moments of the demand system, as reported in Table 1. We discuss the sensitivity of our results to these parameter choices at length below. The remaining parameters are assigned conventional values from the literature.

an aggregate markup of $\mathcal{M} = 1.15$, a conventional number in the literature.[12] We set the elasticity of output with respect to labor to $1 - \alpha = \frac{2}{3}$. We adopt a quarterly frequency and set the discount factor to $\beta = 0.99$. We set the Frisch elasticity of labor supply to 1. We set the Calvo probability of no price change to $\theta = \frac{2}{3}$, implying a median duration of prices of 3 quarters of a year. We set the interest rate rule parameters to conventional numbers, $\phi_\pi = 1.5$ and $\phi_y = 0.5/4$, as per Galí (2015).

4 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.

We first calculate our model's short-run and long-run responses to an exogenous *cost shock* for our benchmark parameterization and then explore the sensitivity of these results to alternative parameterizations chosen to represent industries with more extreme passthrough conditions. We then repeat these calculations for our model's short-run and long-run responses to an exogenous *demand shock*. We find that even for the specifications most conducive to inflation amplification, representing industry configurations at the outer edge of the range that we found in the BLADE data, our model predicts at most modest amplification effects.

[12] 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 (19).

4.1 Response to cost shocks

Our basic exercise is to subject the model economy to a 1 percent reduction in the exogenous supply of the X_t factor. This exogenous reduction in supply in turn leads to an economy-wide increase in marginal costs, hence rising prices and falling output.

Benchmark parameterization. Figure 1 shows, for our benchmark parameterization, the impulse response functions for inflation, aggregate output, the aggregate markup, and aggregate productivity in response an exogenous 1 percent reduction in X_t with AR(2) dynamics

$$\ln X_t = a_1 \ln X_{t-1} + a_2 \ln X_{t-2} + u_t$$

All variables are measured in percent 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. In fact, for this benchmark parameterization the variable markups mechanism ever so slightly *dampens* the inflation response. The counterpart CES version of the model features exactly zero endogenous TFP dynamics. The benchmark model with variable desired markups does deliver an endogenous rise in TFP, but this effect is tiny.[13]

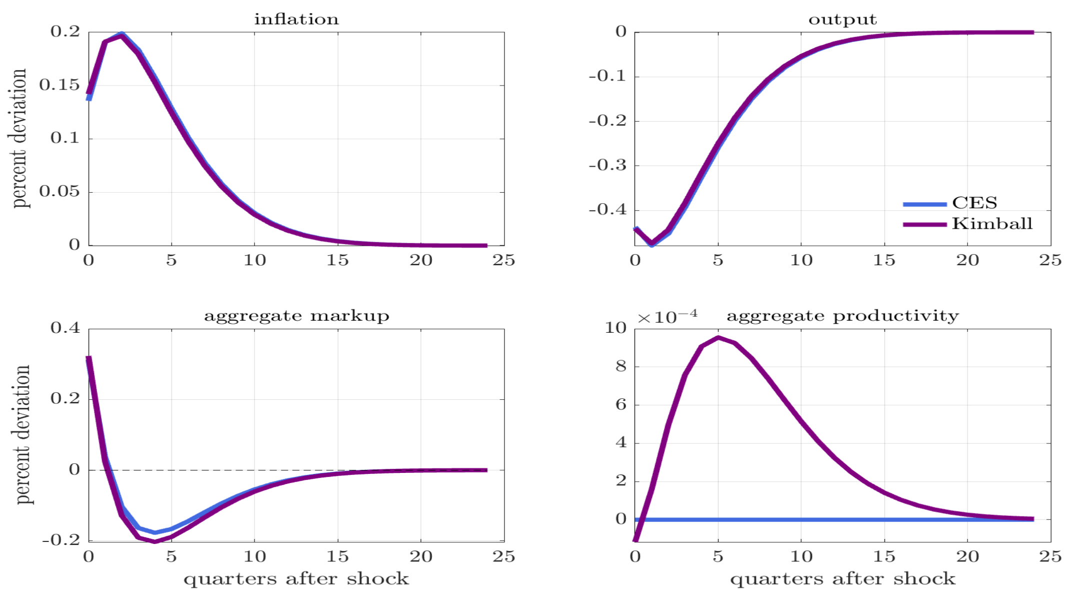
Sensitivity to passthrough conditions. Our benchmark model parameterized to the median BLADE estimates delivers negligible inflation amplification. We now assess the sensitivity of this result to alternative passthrough conditions. Our benchmark parameterization matches an average passthrough coefficient $\mathbb{E}_\omega[\bar{\rho}_i] = 0.86$ with average demand elasticity $\mathbb{E}_\omega[\bar{\sigma}_i] = 6.17$ and $\text{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i] = 0.04$, chosen to match the median industry in the BLADE data, as in Table 1. 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 amplification by computing the long-run difference in price levels

$$\lim_{t\to\infty} \ln \frac{P_t}{P_{t,\text{CES}}} \tag{38}$$

[13]The tiny *rise* in TFP in response to an adverse cost shock is because of a composition effect, specifically, that large firms shrink by less than small firms so that there is a relative reallocation of output towards large, more productive, firms, thereby increasing aggregate TFP. Similarly, the aggregate markup rises on impact because of the reallocation towards large, high markup, firms.

Figure 1: Response to Cost Shock: Median BLADE



Impulse response functions for our benchmark model with Kimball demand, parameterized to the median BLADE estimates, as given in Table 2 above. These impulse responses are to an exogenous 1 percent reduction in the supply of the X_t factor, with AR(2) dynamics [$a_1 = 1.4, a_2 = -0.5$]. All variables are measured in percent deviation from the non-deterministic steady state. Also shown are the impulse responses of an otherwise identical model with CES demand. Our benchmark model deliver quantitatively negligible amplification of inflation, output, and markup dynamics relative to the CES version of the model.

relative to same model but with CES demand. Cumulating the impulse response function for inflation in Figure 1 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

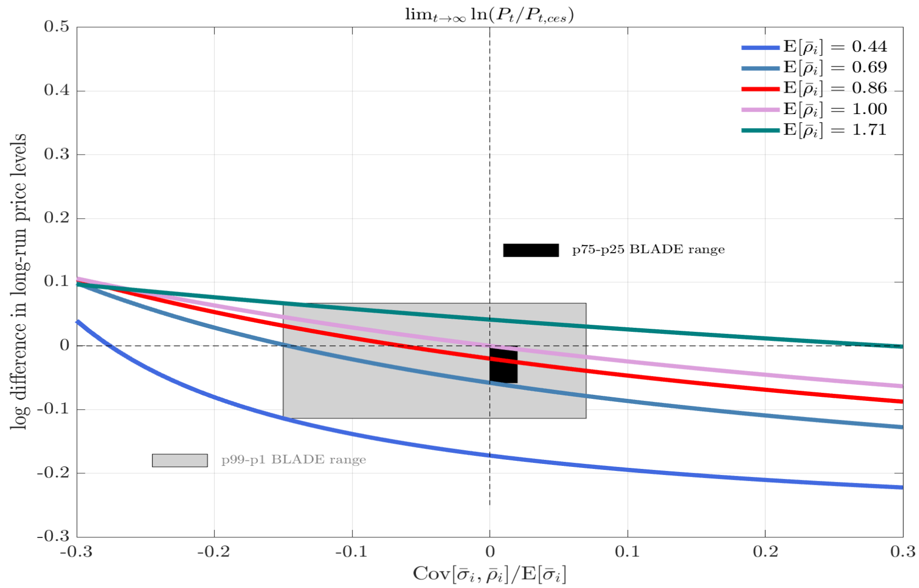
$$\frac{\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]}{\mathbb{E}_\omega[\bar{\sigma}_i]}, \qquad \mathbb{E}_\omega[\bar{\rho}_i]$$

Notice from (27) 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 in Figure 2. Specifically, we plot the long-run difference in price levels as a function of the standardized covariance for different levels of average passthrough, from $\mathbb{E}_\omega[\bar{\rho}_i] = 0.44$ to 1.71, i.e., from the 1st to 99th percentiles of the BLADE 4-digit industry-level estimates from Table 1. To highlight the empirical range of interest, we shade in black the range of outcomes corresponding to the 25th to 75th percentiles and shade in gray the range corresponding to the 1st to 99th percentiles of the 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 $\mathbb{E}_\omega[\bar{\rho}_i] = 1.71$,

Figure 2: Inflation Amplification: Cost Shock



We measure inflation amplification by comparing the long run price level in our model to the price level in an otherwise identical model with CES demand. Here we graph the long-run difference in log price levels as a function of two key moments: the 'standardized covariance' $\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]/\mathbb{E}_\omega[\bar{\sigma}_i]$ and the average passthrough $\mathbb{E}_\omega[\bar{\rho}_i]$. The shaded black area covers the 25th to 75th percentiles of BLADE 4-digit industry-level estimates of these moments and the shaded gray area covers the 1st to 99th percentiles of the BLADE estimates. Even the parameterizations most favorable to inflation amplification, which are relatively rare in the BLADE data, deliver only modest amounts of inflation amplification.

and (ii) a standardized covariance of about -0.15, i.e., on the outer northwest corner of the 1st to 99th percentile range. In terms of the underlying primitives of the model, for a given industry a negative covariance is possible if and only if the superelasticity of demand $\varepsilon/\bar{\sigma}$ for that industry is negative.[14] In turn, if the estimated superelasticity is negative, from (37) we see that the passthrough coefficients will exceed 1. In economic terms, this configuration corresponds to a type of industry where high-markup firms are relatively *small*, since $\mu'(q) < 0$ if the superelasticity $\varepsilon/\bar{\sigma} < 0$. As can be seen from Table 1, this is not a common occurrence.

Moreover, the actual amount of inflation amplification generated by this kind of parameterization is quite modest. Even the parameterization most favorable to inflation amplification only generates a long-run log price level about 0.067 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 1.365 points. So even with this specification most favorable to the inflation amplifying properties of variable markups we

[14] To see this, observe from (36) that the estimated demand elasticities are strictly decreasing in the estimated markups while from (37) the estimated passthrough coefficients are strictly increasing in the estimated markups, leading to a negative covariance if and only if the estimated superelasticity $\hat{b} = \varepsilon/\bar{\sigma} < 0$.

would attribute about $0.067/(1.365+0.067) = 0.0468$, say 5 percent, of the cumulative inflation to the variable markups mechanism, leaving the remaining 95 percent to be attributable to the textbook New Keynesian effects of an adverse cost shock.

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

4.2 Response to demand shocks

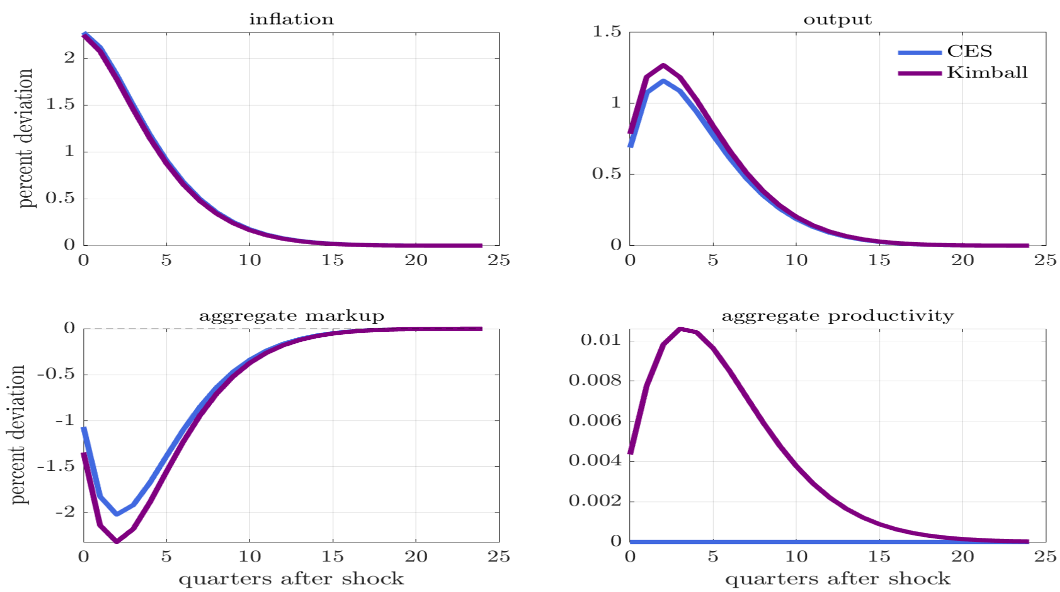
We have conducted a similar set of exercises for the response of the model economy to an exogenous demand shock, modeled as a 1 percent shock to the representative consumer's time discount factor, that leads to rising output and inflation.

Benchmark parameterization. As shown in Figure 3, 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 percent demand shock is an order of magnitude larger than in response to a 1 percent 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 has a dampening effect on inflation relative to the textbook CES version of the model.[15] As with a cost shock, the variable markups version of the model does lead to a rise in aggregate TFP, but these effects are again quite small, on the order of 0.01 percent.

Sensitivity to passthrough conditions. The sensitivity of the inflation amplification in response to demand shocks is similar to the response to cost shocks. As shown in Figure 4, the specification that gives the greatest amount of inflation amplification again features an average passthrough coefficient of $\mathbb{E}_\omega[\bar{\rho}_i] = 1.71$, and a standardized covariance of about -0.15, i.e., again on the outer northwest corner of the 1st to 99th 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 there is about a 2.19 point extra increase in the log price level for demand shocks, as opposed to a 0.067 point extra increase for cost shocks. However, once again this is a relatively modest share of the cumulative inflation response.

[15] By contrast, Aruoba, Oue, Saffie and Willis (2025) find that variable markups can be a source of amplification in a New Keynesian model with idiosyncratic demand shocks and state-dependent pricing, two mechanisms that we abstract from.

Figure 3: Response to Demand Shock: Median BLADE



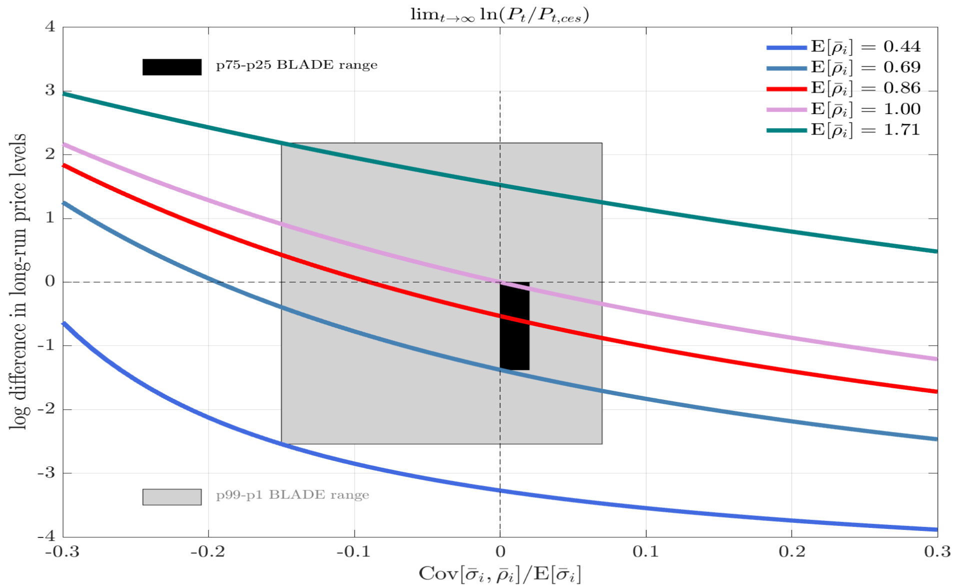
Impulse response functions for our benchmark model with Kimball demand, parameterized to the median BLADE estimates, as given in Table 2 above. These impulse responses are to an exogenous 1 percent shock to the discount factor of the representative consumer, with AR(2) dynamics $[a_1 = 1.4, a_2 = -0.5]$. All variables are measured in percent deviation from the non-deterministic steady state. Also shown are the impulse responses of an otherwise identical model with CES demand. Our benchmark model deliver quantitatively negligible amplification of inflation and only modest amplification of output and markup dynamics.

The textbook CES version of the model generates a long-run increase in the log price level in response to this demand shock of about 11.59 points. So, even with this specification most favorable to the inflation-amplifying properties of markups, we would attribute about $2.19/(11.59 + 2.19) = 0.1589$, say 16 percent, of the cumulative inflation to the variable markups mechanism, leaving the remaining 84 percent 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

Figure 4: Inflation Amplification: Demand Shock



We measure inflation amplification by comparing the long run price level in our model to the price level in an otherwise identical model with CES demand. Here we graph the long-run difference in log price levels as a function of two key moments: the 'standardized covariance' $\mathrm{Cov}_\omega[\bar{\sigma}_i, \bar{\rho}_i]/\mathbb{E}_\omega[\bar{\sigma}_i]$ and the average passthrough $\mathbb{E}_\omega[\bar{\rho}_i]$. The shaded black area covers the 25th to 75th percentiles of BLADE 4-digit industry-level estimates and the shaded gray area covers the 1st to 99th percentiles of the BLADE estimates. Compared with Figure 2 we see that there is generally more inflation amplification in response to demand shocks than in response to cost shocks, but all told the amplification is modest except for outlier industry configurations.

something like 0.05 or 0.06 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.

5 Evidence from Australian Firm-Level Data

To this point, we have used a textbook New Keynesian model augmented with variable markups to ask whether such markup variation, i.e., variation in profit margins, is a quantitatively plausible source of inflation amplification in response to cost or demand shocks. We find that, for our benchmark parameterization calibrated to Australian firm-level data, this model predicts a slight *dampening* of inflation responses to both cost and demand shocks. That said, a potential concern with this analysis is that it makes heavy use of the structure of the model. Moreover, this analysis makes no use of firm-level data on prices.

In this section we address these concerns as follows. First, in Section 5.1 we use newly available firm-level data on prices to directly examine the correlation between firm-level prices and profits. Reassuringly for our structural analysis, these regressions imply almost exactly the same amount of passthrough as we backed out of our structural model. Second, following Bräuning, Fillat and Joaquim (2023), in Section 5.2 we construct estimates of firm-level idiosyncratic variation in costs, aggregate these to the industry level, and examine passthrough of these industry-level cost shocks to industry-level prices. We find evidence that passthrough from cost shocks is lower in more concentrated industries, again consistent with our structural model and inconsistent with variable markups being a substantial source of inflation amplification. Third, following the approach of Conlon, Miller, Otgon and Yao (2023), in Section 5.3, we show that while there is a statistically significant correlation between industry-level markup changes and price changes, that correlation has *not* become stronger during the pandemic period. Finally, as discussed in Section 5.4, we find that this industry-level correlation turns negative during the pandemic period, i.e., industries with higher price increases tended to have lower markup increases or markup decreases, a correlation that is hard to square with markups being an important source of inflation amplification.[16]

In short, these results suggest that variable markups have not been a source of substantial inflation amplification either in general or during the pandemic in particular.

5.1 Firm-level prices and profits

In this section we use newly available data on firm-level prices matched to the BLADE administrative tax data. This price data is webscraped from around 60 retailers on a quarterly basis from 2016–2022.[17] This gives us direct measures of product-level prices, which we aggregate to the firm level, and which can then be compared to firm-level measures of economic activity, but the coverage is much narrower than our primary BLADE sample.

With that caveat in mind, our basic approach is to run quarterly regressions of the form

$$\Delta \ln \pi_{it} = \alpha_t + \beta \Delta \ln p_{it} + \varepsilon_{it} \tag{39}$$

where $\Delta \ln \pi_{it}$ denotes the firm-level change in gross profit margin and $\Delta \ln p_{it}$ denotes the (unweighted) average of the price changes of products that the firm sells in both quarters.[18] We also include a full set of year fixed effects.

We report the regression results in Table 3. The left column reports results for the full sample. The estimated regression coefficient $\hat{\beta} = -0.147$ implies that firms with increasing prices are predicted to have decreasing profits. This is consistent with the incomplete passthrough mechanism in our model, i.e., that when costs go up, firms pass on only part of that increase in higher prices and so profit margins fall. Reassuringly, the point estimate equates to a passthrough coefficient of about 0.85, almost exactly the median passthrough

[16]Whether this correlation is statistically significant or not is quite sensitive to the measure of markups used, the extent of trimming in the sample etc. See Table 8 in Appendix B for a full set of results.

[17]See Fink, Hambur and Majeed (2023) and Section A.2 for more details.

[18]Sales weights are unavailable because the product-level price data is webscraped.

Table 3: Firm-Level Regression of Profit Changes on Price Changes

	full sample	*split sample*
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 percentage change in gross profit margin on average price change for continuing products for a sample of retail firms. Includes year fixed effects, excludes small firms below threshold for expense reporting. Standard errors in parentheses. Left column reports estimates for the full sample 2016–2022. Right column allows regression coefficient to change by year as indicated. See Fink, Hambur and Majeed (2023) and the Section A.2 for more details.

coefficient we backed out of our structural model.[19] In other words, while the sample of firm-level prices used here is narrow, the amount of passthrough we estimate from this data is consistent with the passthrough we backed out of the structural model calibrated to a broad range of industries. The right column of Table 3 allows the regression coefficient to change over time. The first row of the right column reports the coefficient for 2018, which is slightly smaller but much less precisely estimated than for the full sample. The remaining rows show the difference in estimates relative to 2018. For example, the full point estimate for 2022 is $-0.137 + 0.102 = -0.035$. Taken at face-value, this suggests that passthrough has risen over the pandemic period, but the increase in passthrough is statistically insignificant and there is no evidence that passthrough has become more than 1-for-1. The bottom line is that the pattern of firm-level price changes and profit margin changes are not consistent with increasing passthrough being a substantial source of inflation amplification.[20]

[19]The 0.85 passthrough we find for retail firms is however larger than familiar estimates in the literature, such as Amiti, Itskhoki and Konings (2019), who find lower passthrough for large manufacturing firms. Note also that our measure of passthrough in the model is *flexible-price passthrough* and so abstracts from nominal rigidities which may matter for the passthrough estimated from our firm-level quarterly data.

[20]Recall from our structural model that a necessary condition for inflation amplification is that the supere-

5.2 Industry-level passthrough from cost shocks

In the previous section we provided evidence on *firm-level* passthrough using newly available price data for a limited sample of retail firms. In this section we provide complementary evidence on *industry-level* passthrough for a broader range of firms and industries for which we have industry-level price indexes. Specifically, we follow the approach of Bräuning, Fillat and Joaquim (2023) and first construct estimates of firm-level idiosyncratic variation in costs, aggregate these to the industry level, and then examine the passthrough of these industry-level cost shocks to industry-level prices measured in the Producer Price Index (PPI), which covers around about $\frac{1}{3}$ of all industries, with a particular focus in manufacturing.

Industry-level cost shocks. As in Bräuning, Fillat and Joaquim (2023), we construct our industry-level cost shocks using the granular instrumental variable (GIV) approach pioneered by Gabaix and Koijen (2024). We measure firm-level variable costs as total costs less fixed costs (such as depreciation) using administrative tax data. We then regress these firm-level variable costs on a number of controls, including firm sales, firm assets, industry-by-time trends and firm fixed effects.[21] This gives us the residual component of firm-level variable costs, which we interpret as idiosyncratic firm-level cost shocks. We then use lagged sales shares to aggregate these firm-level cost shocks to the industry level. The basic idea behind this approach is that 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 industry-level prices and we can exploit this to construct an instrument. Table 4 gives a sense of the size of the industry-level cost shocks we obtain. By construction the shocks are essentially mean zero, but there is substantial variation, with the standard deviation and interquartile range both being about 4 percent.

Industry-level regressions. We then estimate industry-level regressions of the form

$$\ln \mathrm{PPI}_{j,t+h} = \alpha_j^h + \alpha_t^h + \beta^h \,\mathrm{GIV}_{j,t} + \beta_\mu^h \,\mathrm{GIV}_{j,t} \times \mu_{j,t} + \boldsymbol{\gamma} \cdot \boldsymbol{x}_{j,t} + \varepsilon_{j,t} \tag{40}$$

where $\ln \mathrm{PPI}_{j,t+h}$ denotes the log PPI index for industry j in year $t+h$, $\mathrm{GIV}_{j,t}$ denotes the industry-level cost shock as constructed above, $\mu_{j,t}$ denotes the sales-weighted average markup for industry j, and where α_j^h and α_t^h are industry and time fixed effects and $\boldsymbol{x}_{j,t}$ is a vector of controls including linear industry time trends and the lagged PPI and GIV shock. 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.

lasticity of demand is negative, $\varepsilon/\bar{\sigma} < 0$, so that average passthrough is more than 1-for-1, and that we obtain meaningful amounts of inflation amplification only for parameterizations such that average passthrough is substantially more than 1-for-1.

[21] See the notes to Table 4 for a complete list.

Table 4: Summary of Industry-Level Cost Shocks

number of industries	1,416
mean	0.001
standard deviation	0.041
percentiles	
05	−0.068
25	−0.018
50	0.001
75	0.021
95	0.064

Annual industry-level cost shocks measured by aggregating firm-level residual variable costs to the industry level using lagged sales shares. We measure firm-level variable costs as total costs less fixed costs (such as depreciation). We then regress these firm-level variable costs on a large number of controls — namely: firm fixed effects, industry × time fixed effects, firm × time trend, time × log sales, time × log assets, time × the lag of log sales, and time × the lead of log sales — to obtain our measure of the residual component of firm-level variable costs.

The response of the industry-level price index in year $t+h$ to an industry-level cost shock in year t is given by $\beta^h + \beta^h_\mu \times \mu_{j,t}$. Thus if the interaction coefficient β^h_μ is positive, industries with higher markups, i.e., less competitive industries, have higher passthrough than industries with lower markups. If so, this would be evidence supporting the hypothesis that lack of competition plays a role in amplifying the inflationary consequences of cost shocks. But if β^h_μ is *negative*, industries with higher markups have lower passthrough. And this would be evidence *against* the hypothesis that lack of competition plays a role in amplifying the inflationary consequences of cost shocks. Moreover, a dampening effect of this kind would be in line with the benchmark parameterization of our structural model where passthrough is lower when markups are higher.[22] In this sense, positive β^h_μ would be evidence against the key variable markups mechanism in our structural model.

Figure 5 shows the estimated interaction coefficients β^h_μ, scaled to capture the effect of a one standard deviation GIV cost shock. The point estimates are negative both on impact, $h = 0$, and one year after the shock, $h = 1$, implying that at, these short horizons, industries with higher markups have lower passthrough — in line with the benchmark parameterization of our structural model. The 90 percent confidence intervals around these point estimates are entirely negative. At longer horizons, $h = 2, 3$, the point estimates are positive but statistically insignificant. In short, there is no evidence that industries with higher markups have higher passthrough *at any horizon*. In this sense, these industry-level regressions cast

[22]See equation (33) and observe from Table 1 that we estimate a positive superelasticity of demand, $\varepsilon/\bar{\sigma} > 0$, for around 75 percent of 4-digit industries.

considerable doubt on the hypothesis that lack of competition plays a role in amplifying the inflationary consequences of cost shocks.

Robustness. To assess the robustness of these results we have run two alternative versions of the industry-level regression (40). First, instead of using the industry-level markup on the RHS we have used sales concentration as measured by the industry's Herfindahl-Hirschmann index (HHI). The point estimates are again negative at short horizons, implying that more concentrated industries also have lower passthrough.[23] Second, motivated by concerns about the ability to reliably estimate markup *levels*,[24] instead of using the industry markup $\mu_{j,t}$ on the RHS of (40) we have also used *demeaned* markups.[25] For this specification, we find no statistically significant evidence that industry-level passthrough varies with markups.

Reduced-form vs. structural passthrough. These regressions provides us with an alternative reduced-form estimate of the variation in passthrough *across industries*. This reduced-form estimate is constructed entirely differently from the structural estimate we backed out of the model, which uses the theoretical relationships of the model combined with estimates of the *within-industry* covariation between estimated firm-level markups and observed firm sales shares that are then aggregated to the industry level — an approach which makes no reference to GIV shocks etc.

This raises the basic question of whether these alternative estimates of industry-level passthrough are similar. To assess this, we run analogous regressions of the form

$$\ln \mathrm{PPI}_{j,t+h} = \alpha_j^h + \alpha_t^h + \beta^h \,\mathrm{GIV}_{j,t} + \beta_\rho^h \,\mathrm{GIV}_{j,t} \times \rho_{j,t} + \boldsymbol{\gamma} \cdot \boldsymbol{x}_{j,t} + \varepsilon_{j,t} \tag{41}$$

where $\rho_{j,t}$ denotes the industry-level passthrough coefficient we backed out of the structural model. In this specification the reduced-form passthrough coefficient is $\beta^h + \beta_\rho^h \times \rho_{j,t}$ so that if β_ρ^h is positive there is a positive correlation between the reduced-form passthrough estimates and estimates we backed out of the structural model. Figure 6 reports the key interaction coefficient β_ρ^h at horizons $h = 0, 1, 2, 3$ years. We find that this interaction coefficient is positive at horizons $h = 0, 1$ and statistically insignificant at horizons $h = 2, 3$, suggesting that the industry-level variation we back out of the structural model is at least broadly consistent with direct estimates of the industry-level variation in passthrough, despite the entirely different methods by which these alternative estimates are constructed.

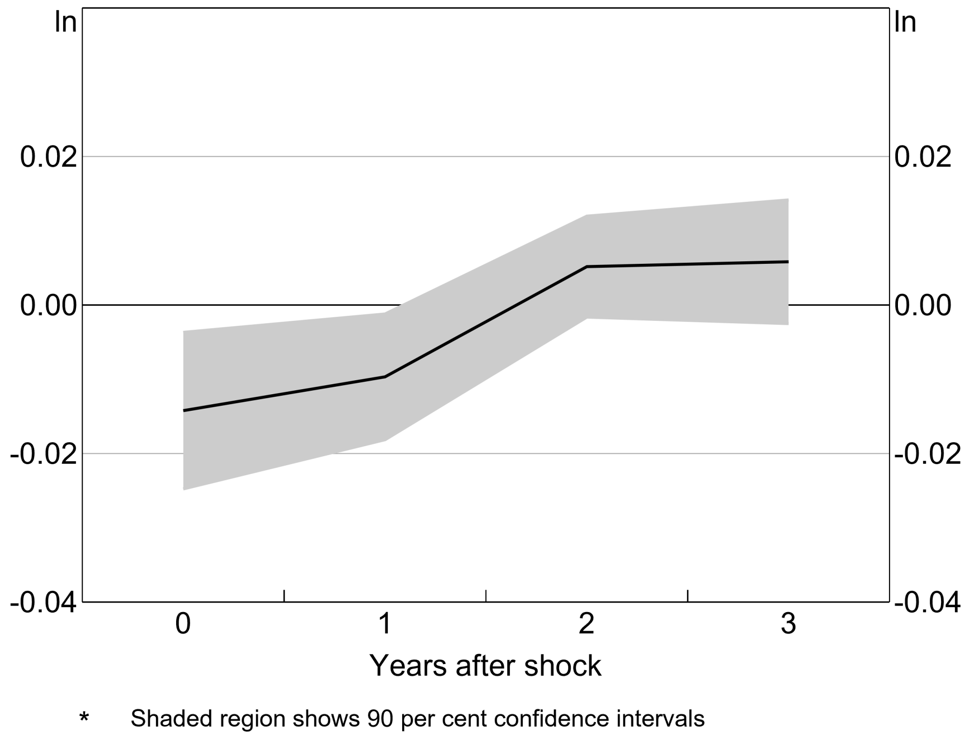
[23] By contrast, Bräuning, Fillat and Joaquim (2023) find in US data that more concentrated industries have higher passthrough. There are many differences between our studies that may explain these different results. Importantly, they use Compustat data for publicly listed US firms while we use administrative data with a more representative sample of Australian firms. In addition, their data is quarterly while ours is annual.

[24] See Bond, Hashemi, Kaplan and Zoch (2021) for a forceful discussion.

[25] More precisely, we allow for a time-invariant industry-specific coefficient for the shock variable $\beta_{h,j}$. In this specification, the coefficient on the markup $\mu_{j,t}$ only captures changes relative to the industry-level average markup over time. Removing the industry-level mean gives similar results.

Figure 5: Industries with Higher Markups have Lower Passthrough

Interaction coefficient β_μ^h at horizons $h = 0, 1, 2, 3$ years.



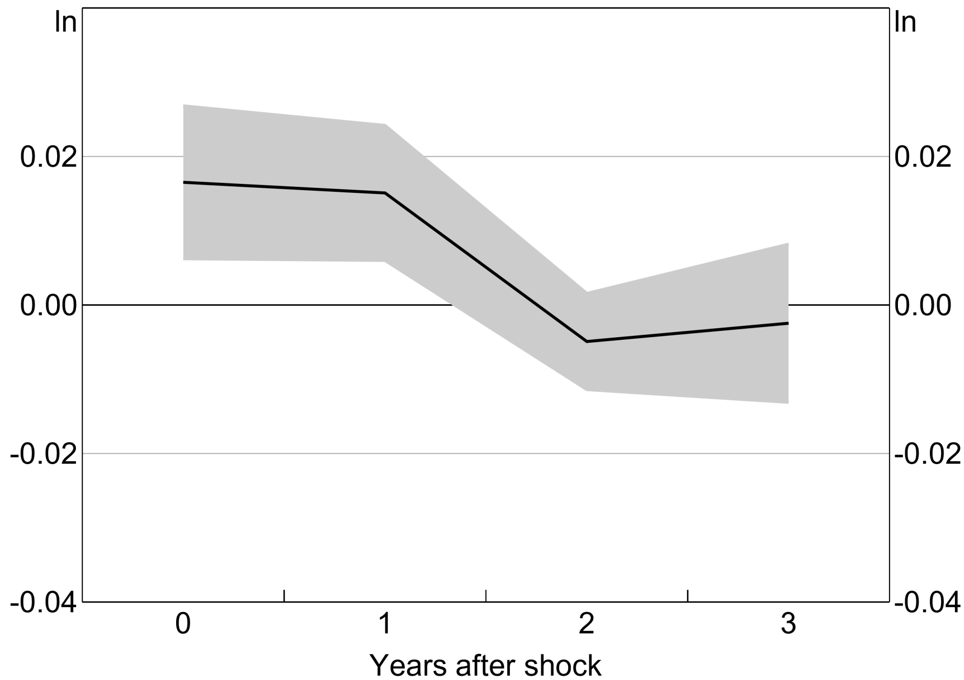
Estimated response of industry-level price index to an industry-level cost shock is $\beta^h + \beta_\mu^h \times \mu_{j,t}$. Here we report the estimated interaction coefficient β_μ^h at horizons $h = 0, 1, 2, 3$ years. The estimated interaction effect is *negative* at horizons $h = 0, 1$ so, on impact, industries with higher markups have lower passthrough, consistent with the benchmark parameterization of our structural model. At longer horizons the interaction effect is statistically insignificant at conventional levels.

All told, these industry-level regressions offer no support to the hypothesis that passthrough is higher in industries where markups are higher, i.e., in industries where competition is weaker. In this sense, these industry-level regressions provide no support for the kinds of parameterizations of our model that would be required for there to be substantial inflationary amplification of costs shocks. If anything, these industry-level regressions provide evidence that passthrough is lower in industries with higher markups. Moreover, these broader industry-level results are qualitatively consistent with our previous firm-level results for the narrower set of retail firms for which we have firm-level price data. And reassuringly, these firm- and industry-level results are both qualitatively and quantitatively consistent with the amount of passthrough we backed out of the structural model.[26]

[26]In particular, as in the structural model, passthrough is lower when markups are higher, and, moreover, firm-level passthrough is estimated to be about 0.85, almost exactly what we back out of the structural model.

Figure 6: Reduced-Form and Structural Passthrough Positively Correlated

Interaction coefficient β_ρ^h at horizons $h = 0, 1, 2, 3$ years.



Reduced-form estimate of industry-level passthrough coefficient is $\beta^h + \beta_\rho^h \times \rho_{j,t}$ where $\rho_{j,t}$ denotes the industry-level passthrough coefficient we backed out of the structural model. Here we report the estimated interaction coefficient β_ρ^h at horizons $h = 0, 1, 2, 3$ years. The estimated interaction effect is *positive* at horizons $h = 0, 1$ so that the reduced-form and structural passthrough estimates are positively correlated.

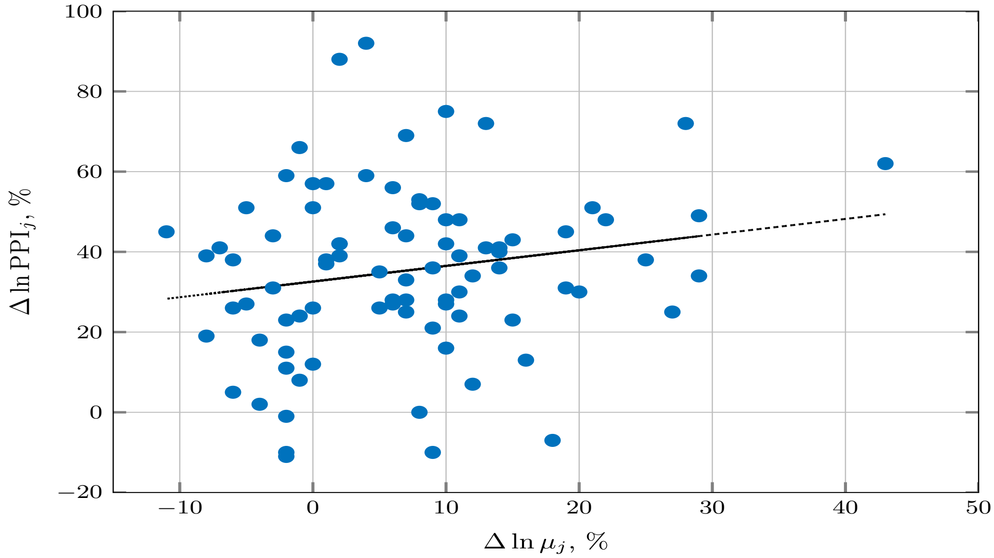
5.3 Industry-level markups and price changes

As one further check on the relationship between markups and inflation in the Australian data, we follow Conlon, Miller, Otgon and Yao (2023) and compare changes over time in industry-level markups and industry-level prices measured by the PPI. One advantage of our data is that we have markup estimates for a much more representative sample of firms using administrative data, whereas they use markups estimated from Compustat, i.e., only for publicly-listed firms. But, as noted above, a disadvantage of our data is that the Australian Bureau of Statistics (ABS) reports PPI data for a narrower set of detailed industries, about $\frac{1}{3}$ of all industries, mostly in manufacturing.

With this caveat in mind, to examine the relationship between industry-level markups and prices we run simple cross-section regressions of the form

$$\Delta \ln \mathrm{PPI}_j = \alpha + \beta \Delta \ln \mu_j + \varepsilon_j \tag{42}$$

Figure 7: Industry-Level Markup Growth and PPI Growth, 2004–2017



Scatterplot of sales-weighted industry-level long-difference markup growth $\Delta \ln \mu_j$ and industry-level long-difference PPI growth $\Delta \ln \mathrm{PPI}_j$ from 2003–04 to 2016–17 for each 4-digit ANZSIC industry j for which we have PPI data. Outliers have been trimmed. Results are statistically significant at the 10 percent level, see Table 8 for further details.

where $\Delta \ln \mathrm{PPI}_j$ denotes the growth in the industry's PPI and $\Delta \ln \mu_j$ denotes the growth in the industry-level sales-weighted average markup from the start to the end of our sample, i.e., our specification is in long-differences.

As a benchmark, Figure 7 shows this relationship over period 2004-2017. There is a statistically significant positive association with an elasticity of around $\beta \approx \frac{1}{3}$ so that in industries where markups rose by 1 percentage point more over the sample, prices tended to increase by $\frac{1}{3}$ percentage points more.[27] This finding contrasts with Conlon, Miller, Otgon and Yao (2023) who find no evidence of such a relationship in US data. There are of course many possible reasons for this, not least of which is that both markups and prices and endogenous and we would expect different reduced-form correlations between prices and markups depending on the underlying configurations of structural shocks in each country. But, in any case, as we discuss below, this statistical relationship has if anything weakened since the onset of the pandemic.

5.4 Was the covid period different?

For our benchmark results we used a set of well-documented and well explored estimates of firm-level markups for Australia from the *pre-covid* period provided by Hambur (2023). Based on these estimates we concluded that passthrough tends to be lower in less competitive industries and hence that markup variation is not a plausible source of substantial inflation

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

amplification. But given the rise in inflation following the covid pandemic, it is natural to ask whether our findings still hold if we use updated estimates of markups that extend to the covid period and post-covid inflation.

In Appendix B we provide a comprehensive set of additional results using updated markup estimates from 2018–19 through 2021–22. Overall, we find that our benchmark results are robust. We continue to find no evidence that passthrough is higher in high-markup industries — which is what would have to be the case if markup variation is a substantial source of inflation amplification. Moreover, we now find that the cross-sectional relationship between industry-level price changes and markup changes has turned *negative*, i.e., that, through the covid period, industries with higher price changes tended to have lower markup increases or markup decreases — again, a correlation which is hard to square with markups being a source of substantial inflation amplification during the pandemic.[28]

These additional results if anything strengthen our main conclusion. But we want to stress nonetheless that these results should be interpreted with caution, for two reasons. First, due to the noisy nature of the firm-level data in this period, we construct these updated markup estimates using production function parameters estimated on our main pre-covid sample up to 2018–19 and then apply these parameters to the materials shares for the additional years through 2021–22. That is, we proceed on the assumption that the parameters of the production function are stable through the pandemic. Second, the key assumption underlying the markup estimation, i.e., that materials are a fully flexible input, may well have been violated during the covid period due to supply disruptions, lockdowns, etc. It is precisely because of our concern with the validity of these assumptions during the covid period that we have chosen not to use this period for quantifying our benchmark model.

5.5 Why variable markups do not amplify inflation

The key challenge to generating substantial inflation amplification is that, in the data, estimated passthrough is typically less than 1-for-1 and is lower in industries where markups are higher. Recall from Table 1 above that the sales-weighted average estimated passthrough coefficient at the 4-digit level is 0.89 and that some 75 percent of 4-digit industries have passthrough less than 1-for-1. To give some sense of the economic significance of the incidence of less than 1-for-1 passthrough, Table 5 summarizes the distribution of our estimates of passthrough coefficients ρ within and across broad 1-digit industries. Only a few broad 1-digit industries have average passthrough that is more than 1-for-1, and even for these few the estimated passthrough coefficients are barely more than one, e.g., $\rho = 1.02$ for agricul-

[28] Again, whether this correlation is statistically significant or not is quite sensitive to the measure of markups used, the extent of trimming in the sample etc. See Table 8 in Appendix B for a full set of results.

ture, 1.05 for construction, and 1.01 for retail trade.[29] And as we have seen, it takes much more extreme parameterizations of the model, e.g., with passthrough $\rho = 1.7$, at the 99th percentile of our 4-digit estimates, to generate meaningful amounts of inflation amplification. Moreover, even within broad 1-digit industries such as construction and retail where average passthrough is more than 1-for-1, a great deal of economic activity is still accounted for by firms with lower passthrough. For example, in construction about $\frac{1}{2}$ of sales are accounted for by firms in industries with sales-weighted average passthrough less than 1-for-1, similarly in retail about $\frac{2}{3}$ of sales are accounted for by firms in industries with passthrough less than 1-for-1. Overall, the share of total sales accounted for by firms in industries with passthrough more than 1-for-1 is some 23 percent. Finally, notice that even at this high level of aggregation, the industries with low passthrough indeed tend to be the industries with high markups — across 1-digit industries the correlation between passthrough and markups is about -0.65, and remains about -0.34 even if we exclude the mining industry, which is a clear outlier. In short, the data clearly suggest that passthrough is typically less than 1-for-1 and is lower in industries where markups are higher.

Viewed through the lens of our model, if most industries have passthrough less than 1-for-1 and most firms within most industries have passthrough less than 1-for-1, then the variable markups mechanism will act to *dampen* not amplify the response to inflationary cost or demand shocks. All told, it is fair to say that any parameterization of the model that is broadly consistent the amount of passthrough estimated in BLADE data will lead to the finding that variable markups cannot generate substantial inflation amplification.

Our findings with Australian micro data add to a growing recent empirical literature that consistently finds that increases in markups did not substantially contribute to the post-pandemic surge in inflation. For example, Leduc, Li and Liu (2024) argue that in US data the rise in markups is confined to a few industries, such as motor vehicles and petroleum and that more broadly markups do not appear to have contributed to the surge in inflation. Similarly, using very detailed product-level US data, Alvarez, MacKay, Cavallo and Mengano (2024) find that retail markups have remained stable, again suggesting that increases in markups did not substantially contribute to the surge in inflation.

[29] Across all of retail trade, we estimate passthrough of $\rho = 1.01$, which contrasts with the estimate of $\rho = 0.85$ we obtained for the limited sample of firms for which we have webscraped product-level prices.

Table 5: Passthrough and Markups Across Broad Industries

	$\varepsilon/\bar{\sigma}$	ρ	share passthrough $\rho > 1$		industry markup μ	
	superelasticity	passthrough	share ind sales	share sub ind	sales-weighted	input-weighted
agriculture	0.00	1.03	0.60	0.43	1.37	1.34
mining	0.16	0.70	0.00	0.13	3.17	2.85
manufacturing	0.18	0.84	0.20	0.21	1.51	1.49
utilities	0.22	0.86	0.28	0.20	1.78	1.74
construction	−0.00	1.03	0.51	0.46	1.30	1.27
wholesale trade	0.23	0.78	0.00	0.03	1.38	1.37
retail trade	0.05	0.99	0.36	0.45	1.20	1.20
accommodation	−0.10	1.18	0.76	0.83	1.34	1.30
transport	0.18	0.79	0.42	0.43	2.11	1.99
rental hire and real estate	0.13	0.83	0.06	0.12	1.84	1.71
professional services	0.13	0.85	0.13	0.19	1.65	1.50
administrative services	0.13	0.85	0.35	0.33	1.91	1.58
arts and recreation	0.12	0.95	0.29	0.18	1.71	1.59
other services	0.05	1.00	0.58	0.44	1.38	1.33

The first two columns reports the sales-weighted averages of 4-digit superelasticity estimates $\varepsilon/\bar{\sigma} = \hat{b}_j$ and firm-level passthrough estimates $\hat{\rho}_i$ aggregated to each broad 1-digit industry. The third column reports the share of sales accounted for by firms in industries with sales-weighted passthrough more than 1-for-1 while the fourth column reports the share of sub-industries with passthrough more than 1-for-1. The fifth and sixth columns report the sales-weighted and input-weighted markups for each broad 1-digit industry. The 4-digit industry-level superelasticities $\varepsilon/\bar{\sigma} = \hat{b}_j$ are estimated as per equation (34) and used to infer firm-level passthrough coefficients $\hat{\rho}_i$ from firm-level markups $\hat{\mu}_i$ and $\hat{b}_j$ as per equations (36)-(37) above.

6 Conclusion

In this paper we ask whether variable profit margins, i.e., variable markups, might play a substantial role in amplifying inflationary cost or demand shocks. We answer this question using two complementary approaches. First, we use a dynamic model calibrated to match key facts on concentration and markups in detailed administrative micro data from Australia's Business Longitudinal Analysis Data Environment (BLADE) 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. This approach has the advantage of a clear *causal* structure, i.e., it commits to a particular theory of why markups and prices may be moving together, to the extent that they do. That said, this commitment to a specific theoretical structure brings with it a host of auxiliary assumptions that may raise some skepticism. Second, we use reduced-form passthrough regressions to assess the extent to which the pattern of firm- and industry-level markup and price changes in the BLADE micro data are consistent with substantial inflation amplification. This approach has the advantage of imposing essentially no theoretical structure but has the disadvantage of having less to say about what causes what.

Neither approach suggests an important role for variable markups in amplifying inflationary dynamics. First, when we calibrate our structural model to match the key facts on concentration and markups in the BLADE micro data we find that the key parameter, the 'superelasticity' of demand, is typically estimated to be positive — reflecting the fact that in most industries, relatively larger firms have larger markups. Viewed through the lens of our model, this positive superelasticity implies that there is incomplete passthrough from changes in costs to changes in prices and hence the variable markup mechanism acts to *dampen* inflation, not to amplify it. Second, our reduced-form firm- and industry-level passthrough regressions, which impose essentially no theoretical structure, independently confirm that passthrough is relatively low and especially so in less competitive industries. We also find that there is no significant evidence that passthrough has risen in the aftermath of the pandemic. In this sense, our reduced-form results confirm our basic finding that there is no evidence that variation in profit margins is a substantial source of inflation amplification.

Our structural model can produce inflation amplification, but only for parameterizations that are fairly extreme outliers in the Australian data. To get even modest amplification we would need to use a negative superelasticity parameter at the lowest 1 percent of what we estimate across narrow 4-digit Australian industries. Put differently, to get substantial inflation amplification the underlying patterns in the data would have to be very different to what we actually observe in Australian industries.

Of course our 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 modeling choices seems like a natural direction for future research. 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 a source of substantial inflation amplification.

Appendix

A Firm-level Data and Approaches

The firm-level data used in this paper come from the ABS's Business Longitudinal Analysis Data Environment (BLADE). This is a longitudinal data set of administrative tax data matched to ABS surveys 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 analyzed.

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 labor 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.
- Labor expense: Labor costs plus superannuation expenses.
- Fixed costs: Rental and leasing expenses, bad debts, interest, royalties, external labor and contractors.
- Intermediate inputs: Total expenses, less labor, depreciation and fixed costs.
- Labor input: Full-time equivalent workers derived from PAYG statements.
- Capital: Book value of non current assets.

All of these metrics apart from labor 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 labor expense is deflated using the output deflator.

A.1 Markup estimates

The firm- and industry-level markup measures used in this paper are taken from Hambur (2023). These are estimated using the production function approach pioneered in De Loecker and Warzynski (2012). The particular implementation of this approach is discussed in Hambur (2023), but below we provide a brief outline.

The production function is estimated using the two-step approach suggested in Ackerberg et al. (2015), where the first step involves regressing gross output on a (fifth-order) polynomial of labour, capital and intermediate inputs – the fitted value of which is taken to be productivity. Wages are included in this polynomial as an auto-correlated firm-specific input prices to aid in identifying the gross output production function, as in De Loecker and Scott (2017), and Amit Gandhi and Rivers (2020). The second step involves combining fitted productivity with assumptions around the flexibility of various inputs to construct moment conditions, which are then estimated via GMM.

Regarding other choices in the estimation procedure, intermediate inputs are taken to be the flexible input in estimating markups, as opposed to labour, given their greater flexibility in the Australian context. The production function is assumed to take on a translog form,, rahter than Cobb-Douglas. This choices has important implications in terms of the identified levels of markups, but the trends look quite similar when a simpler Cobb-Douglas function is used.

The estimates cover an extremely large share of the overall economy. In those sectors considered, the cover on average about 60 percent of the sales in each constituent industry divisions analyzed.

As discussed in a number of papers, the use of industry deflators, and lack of firm-level prices 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). More recent empirical work has also highlights that such approaches can well capture the level, or dispersion in markups, even if not the level (De Ridder et al. (2024)) In this sense, we are confident in our estimates of markup changes over time despite the lack of firm-level prices.

The estimates in Hambur (2023) have also been tested empirically in a number of settings and shown to have relevant information. In particular:

- In sectors where markups have increased, the pace of relation of labour ((Hambur, 2023)) and capital ((Hambur and Andrews, 2023))from low to high productivity firms has slowed. This is consistent with the predictions of standard firm dynamics models if demand becomes more inelastic, as discussed in Decker et al. (2020).

- In sectors where markups have increased, the rate at which firms converge to the global productivity frontier has slowed, consistent with their being less competitive impetus to improve (Dan Adnrews and Wheeler (2022)).

A.2 Price Microdata and Profit Margins

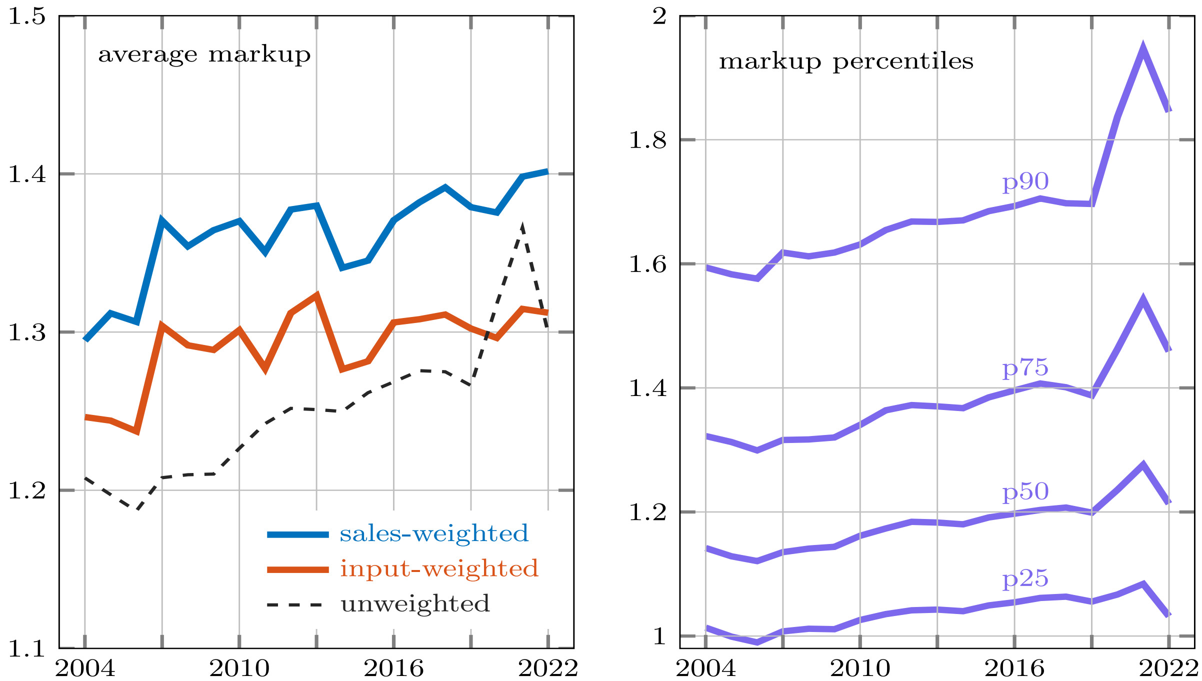
The data used for the analysis of firm-level prices and profit margins come from two sources that have recently been integrated by the ABS.

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.

Figure 8: Markup Estimates



Left panel shows the sales-weighted, input-weighted, and unweighted average markup for our BLADE sample from financial year 2003–04 to 2021–22. Right panel shows key percentiles of the unconditional markup distribution over the same period. There is a clear spike in the upper tail of the markup distribution during the covid period, but this has negligible influence on either the sales- or input-weighted average markup.

B Was the Covid Period Different?

This appendix provides additional results using updated markup estimates through the covid period as discussed in Section 5.4. Overall, we find that our benchmark results are robust.

Updated markup estimates. As shown in Figure 8, we find that markups follow a very similar pattern to that documented in Hambur (2023) up to 2016–17 and continue to increase up to the onset of the covid pandemic. During 2020/21 we find that there is a sharp increase in the upper tail of the markup distribution but that this increase is largely unwound in 2021–22. In any case, these increases in the upper tail of the (unconditional) markup distribution have negligible influence on either the sales- or input-weighted average markup. This suggests that these increases in the upper tail of the (unconditional) markup distribution are driven by increases in the markups of firms that are large within their given industry but in industries that are small relative to the overall economy. Markups in 2021–22 then return to around or just above their pre-covid levels.

Industry-level passthrough from cost shocks. With these updated markup estimates in hand, we next turn to our industry-level estimates of passthrough from cost shocks in the spirit of Bräuning, Fillat and Joaquim (2023). To update this exercise through 2021–22 we update our estimates of the GIV cost shocks as discussed in Section 5.2. As shown in the last column of Table 6 we find that the estimated GIV cost shocks from the covid period are, naturally, more volatile than our benchmark estimates. That said, the increase is perhaps surprisingly modest, with the standard deviation increasing from 0.041 in our benchmark to 0.042 during the covid period. The upper tail of the GIV cost shocks increases more noticeably, from 0.064 at the 95^{th} percentile in our benchmark to 0.067 during the covid period. When we use these updated GIV cost shocks to run our industry-level passthrough regressions, we find, as shown in Table 7, that while the point estimates of the interaction coefficient β_μ^h are now positive, suggesting that through the covid period passthrough was higher in high markup industries, these point estimates are statistically insignificant.[30] Viewed through the lens of our model, this is consistent with markups remaining constant through the pandemic period (i.e., stable profit margins). But, as in our benchmark results, *we continue to find no evidence that passthrough is higher in high-markup industries* — which is what would have to be the case if markup variation is a substantial source of inflation amplification.

Industry-level markups and price changes Finally, we turn to our industry-level correlations of markups and price changes in the spirit of Conlon, Miller, Otgon and Yao (2023). Recall that in our benchmark results we found a mild positive correlation between industry-level changes in markups and changes in prices, as discussed in Section 5.3 above. For our updated results through the covid period we find instead that this correlation turns negative, as reported in Table 8. That is, through the covid period, industries with higher price increases tended to have lower markup increases or markup decreases. Again, this is hard to square with markups being a source of substantial inflation amplification.

This negative correlation over the covid period means that, over the full sample, the correlation between industry-level changes in markups and changes in prices is flatter, as shown in Figure 9. Over this full sample, there is almost no correlation between industry-level changes in markups and changes in prices.

[30] Due to the shorter sample we can only estimate these passthrough regressions over horizons $h = 0, 1$.

Table 6: Summary of Annual Industry-Level Cost Shocks

	benchmark sample	*covid sample*
number of industries	1,416	1,346
mean	0.001	0.0004
standard deviation	0.041	0.042
percentiles		
05	−0.068	−0.067
25	−0.018	−0.016
50	0.001	0.000
75	0.021	0.016
95	0.064	0.067

Annual industry-level cost shocks measured by aggregating firm-level residual variable costs to the industry level using lagged sales shares, as explained in Section 5.2 in the main text. Covid sample is financial years 2018–19 to 2021–22 inclusive.

Table 7: Passthrough Not Higher During Covid

	$h = 0$	$h = 1$
interaction coefficient β_μ^h	0.308	0.487
t-stat	(0.810)	(0.082)
observations	305	305

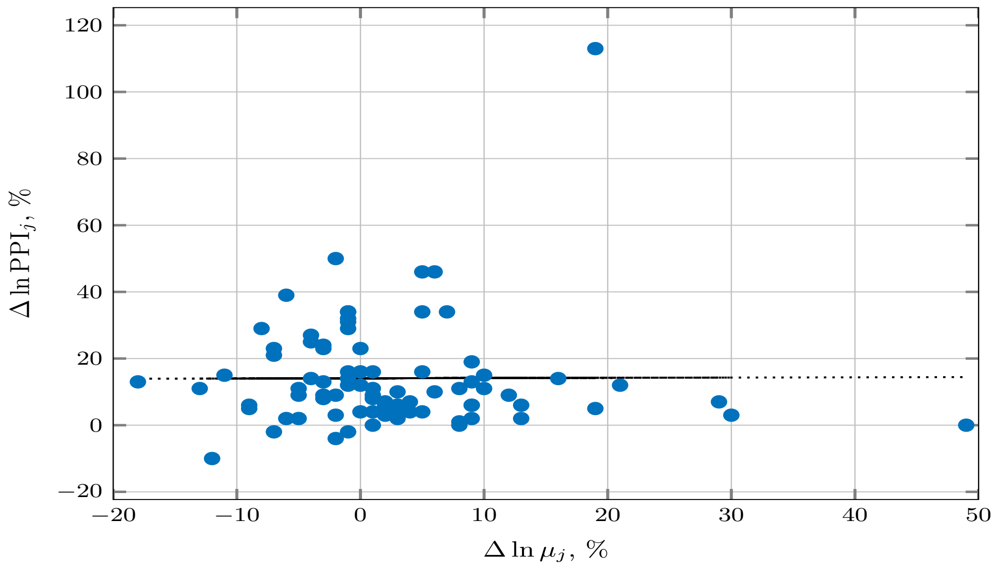
Interaction coefficient β_μ^h at horizons $h = 0, 1$ in industry-level regressions of cost shocks on producer prices, as discussed in Section 5.2 in the main text. For our updated sample covering covid, financial years 2017–18 to 2021–22 inclusive, there is no significant difference in passthrough between high- and low-markup industries.

Table 8: Industry-Level Regressions of Markup Changes on Price Changes

	unweighted	firm-weighted	sales-weighted
benchmark sample 2004–2017, no trimming			
coefficient	0.551***	0.377*	0.320
t-stat	(2.41)	(1.89)	(1.52)
R-squared	0.105	0.067	0.039
observations	109	109	109
benchmark sample 2004–2017, outliers trimmed			
coefficient	0.332**	0.367*	0.377*
t-stat	(1.98)	(1.71)	(1.87)
R-squared	0.024	0.062	0.060
observations	104	104	104
covid sample 2019–2022, no trimming			
coefficient	−0.029	−0.159	−0.075
t-stat	(−0.18)	(−0.95)	(−0.52)
R-squared	0.000	0.009	0.003
observations	106	106	106
covid sample 2019–2022, outliers trimmed			
coefficient	−0.214*	−0.522**	−0.053
t-stat	(−1.69)	(−2.19)	(−0.41)
R-squared	0.020	0.070	0.002
observations	90	90	90

Trimmed specification remove the top and bottom 5 percent of price and markup growth. Unweighted column treats all industries with same weight. Firm- and sales-weighted columns apply larger weight to industries that have more firms, or sales.

Figure 9: Industry-Level Markup Growth and PPI Growth, 2018–2022



Scatterplot of sales-weighted industry-level long-difference markup growth $\Delta \ln \mu_j$ and industry-level long-difference PPI growth $\Delta \ln \mathrm{PPI}_j$ from 2018–19 to 2021–22 for each 4-digit ANZSIC industry j for which we have PPI data. Outliers have been trimmed. Results are statistically significant at the 10 percent level, see Table 8 for further details.

C Data Disclaimer

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 PLIDA 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.

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