Markups and Inflation in Oligopolistic Markets: Evidence from Wholesale Price Data*

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Abstract

How do market power and nominal price rigidity influence inflation dynamics? We formulate a tractable model of oligopolistic competition and sticky prices, and derive closed-form expressions for the pass-through of idiosyncratic and common cost shocks to firms' prices. Using unpublished micro data for Canadian wholesale firms, we estimate that idiosyncratic cost pass-through is incomplete and independent of the sector price stickiness, while common cost pass-through declines with price stickiness. The estimates imply a degree of strategic complementarity that lowers the slope of the New Keynesian Phillips curve by 30% in a one-sector model and by 64% in a multi-sector model.

JEL classification codes: D43, E31, L13, L81.

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1 Introduction

How does market power influence inflation dynamics and the transmission of monetary policy or exchange rate shocks? Standard New Keynesian models are not equipped to answer this question as they assume monopolistic competition among firms. Recent studies generalize the New Keynesian model to competition among a finite number of competing firms (Mongey, 2021; Wang and Werning, 2022). They demonstrate how strategic pricing complementarities among oligopolistic firms can dampen price adjustments and amplify real effects of monetary policy. Although much progress has been made in estimating the degree of strategic complementarities in price setting across firms, empirical studies have relied on frameworks based on models with monopolistic competition (Gopinath and Itskhoki, 2010*a*) or oligopolistic frameworks without nominal price rigidity (Auer and Schoenle, 2016; Amiti, Itskhoki and Konings, 2019). It is therefore an open empirical question how nominal rigidities and market power in oligopolistic markets *jointly* influence inflation dynamics.

In this paper, we answer this question by estimating the effects of nominal price rigidities and market power on pricing decisions of oligopolistically competitive wholesale trade firms. We formulate a tractable model of oligopolistic competition and sticky prices, and derive closed-form expressions for the pass-through of idiosyncratic and common cost shocks to firm markups. We then estimate how pass-through varies with measures of price stickiness and market power across and within sectors using detailed micro data for Canadian wholesale firms. We find strong evidence of the role of both price stickiness and market power in cost pass-through. Pass-through of idiosyncratic shocks is incomplete at 70% and is independent of the degree of sector price stickiness. Common cost pass-through declines with price stickiness: from nearly complete in flexible-price sectors to below 70% in sectors with the stickiest prices. Higher degrees of sector or firm market power lower the pass-through of each type of cost shock. These estimates imply a degree of strategic complementarity that lowers the slope of the New Keynesian Phillips curve (NKPC) by 30% in the one-sector model. Incorporating the observed positive correlation between price rigidity and market power into the multi-sector model lowers the slope by 64%.

While our model builds on recent literature of aggregated models with oligopolistic markets,[1] we make additional assumptions that capture the key features of the pricing behavior of wholesale firms, which enable the derivation of the closed-form pricing condition. Oligopolistic wholesalers (or *distributors*) buy a differentiated input good from suppliers and distribute it to final producers. The distributor's price and cost (i.e., the supplier's price) are sticky as in Calvo (1983), and their adjustments are synchronized, which we show is largely the case in the data. We derive a closed-form expression for the distributor's adjusted price as the sum of two terms: the pass-through of the idiosyncratic cost component and the pass-through of the common cost for all distributors in the sector.

The key prediction of the model is that price stickiness and market power jointly and *differentially* influence pass-through. In an oligopoly with flexible prices, firms adjust their markups in response to idiosyncratic cost changes to prevent their price from deviating too far from the prices of competitors. Since the common cost shock influences all prices equally, there is no incentive to adjust the markup. However, as sector prices become less flexible, common cost pass-through decreases, while idiosyncratic cost pass-through remains unaffected. Intuitively, knowing that after a common cost shock some competitors do not adjust their prices incentivizes the adjusting firm to temper its price changes by absorbing part of the cost shock into its markup. By contrast, idiosyncratic cost pass-through does not depend on the composition of adjusters and non-adjusters among competitors, and therefore it does not depend on price stickiness in the sector. On the flip side, if we hold the degree of price stickiness constant, increases in market power within an oligopoly decrease pass-through of both idiosyncratic and common cost shocks.

We test these predictions using unpublished price micro data from Canadian wholesalers used by Statistics Canada to produce the Wholesale Services Price Index (WSPI). The monthly data track about 14,000 individual products from 1,800 wholesale firms between January 2013 and December 2019. We assign "sectors" according to either the 4-digit North American Industry Classification

[1] As in Wang and Werning (2022), we have Calvo sticky prices under dynamic oligopolistic competition and, like Mongey (2021), we derive expressions for pass-through of both idiosyncratic and common shocks. Under flexible prices, our model nests static models of oligopolistic competition in Atkeson and Burstein (2008), Edmond, Midrigan and Xu (2015), and Amiti, Itskhoki and Konings (2019). Our model contributes to the growing literature that incorporates oligoplistic competition into macro models: Neiman (2011); Burstein, Carvalho and Grassi (2020); Baqaee, Farhi and Sangani (2021); Fujiwara and Matsuyama (2022); Höynck, Li and Zhang (2022); Alvarez, Lippi and Souganidis (2023); Ueda (2023); Ueda and Watanabe (2023).

System (NAICS4) or the 7-digit North American Product Classification System (NAPCS7). The distinguishing feature of the dataset is that for each wholesaler it provides the price at which it buys its products from suppliers ("purchase" price) and the price at which it sells these products to manufacturers or retailers ("selling" price). This allows us to construct accurate measures of nominal price rigidity for wholesalers' prices and costs. The ratio of selling to purchase price—the distributor's product margin—provides a direct measure of price markup, which is a standard measure of market power. We document substantial variation in measures of price stickiness and market power across and within sectors.

We first decompose the purchase price changes faced by wholesalers into common and idiosyncratic cost shocks using the approach in di Giovanni, Levchenko and Méjean (2014). The common cost shocks are derived by regressing monthly changes of log purchase prices on sector-month fixed effects, and the residuals define the idiosyncratic cost component. We then estimate the pass-through of these shocks to wholesalers' adjusted selling prices. Our empirical framework offers several advantages for estimating the joint contribution of price stickiness and market power to firm-product price adjustments: (1) it accounts for the effect of price stickiness on the degree of pass-through at monthly frequency; (2) it incorporates the observed margin as a reliable measure of market power; (3) it distinguishes pass-through of idiosyncratic and common cost shocks; and (4) it exploits variation in price stickiness and market power across and within sectors.

In line with theory, the estimated idiosyncratic cost pass-through is independent of price stickiness at sector and firm levels, and there is only a weak negative relationship at the firm-product level. On average, the pass-through of an idiosyncratic shock is about 70%, implying an underlying degree of strategic complementarity of $\varphi \approx 0.43$. By contrast, the pass-through of the common cost shock decreases with sector price stickiness, as our theory predicts. For a sector with flexible prices, the pass-through is close to 1, consistent with the findings in Amiti, Itskhoki and Konings (2019). As sector price stickiness rises, the pass-through declines quickly: for each additional 10 percentage point fall in price flexibility, the common cost pass-through falls by 10 percentage points for NAICS4 industries and 3 percentage points for NAPCS7 products. These results are primarily driven by sector-level price stickiness, rather than firm or product stickiness. Finally, a higher degree of sector or firm market power reduces the pass-through of both types of cost shocks.

These findings have important implications for inflation dynamics. Under oligopolistic competition, the slope of the NKPC in the one-sector model is reduced by a factor $\frac{1}{1+\varphi}$ relative to the slope under monopolistic competition. At the level of strategic complementarity implied by the estimated idiosyncratic cost pass-through, $\varphi = 0.43$, the slope of NKPC is reduced by 30%. This degree of strategic complementarity is substantial. For example, if markups were to increase by 10 percentage points over the next decade—the decennial rate of increase in market power over the last four decades documented in De Loecker, Eeckhout and Unger (2020)—the NKPC would flatten by an additional 12%.

When market power and nominal price rigidity vary across sectors, there is an additional flattening of the aggregate NKPC. The slope of the NKPC in the multi-sector model that matches heterogeneity in price stickiness and strategic complementarity across NAICSC4 (NAPCS7) sectors is only one-third (one-fourth) of the slope in the standard one-sector model without real rigidities. The additional amplification in the multi-sector model is due to the interaction of heterogeneity in price stickiness and strategic complementarity across firms and sectors (Carvalho, 2006; Nakamura and Steinsson, 2010). Right after a monetary shock, the aggregate price response is mostly driven by price adjustments in flexible-price sectors. As time passes, the distribution of price adjustments shifts toward sticky-price sectors, slowing the aggregate price response. We point out a novel dimension of this interaction mechanism, which stems from the positive correlation between nominal price rigidity and strategic complementarity across sectors that we observe in the data. Since sticky-price sectors tend to be more concentrated, price adjustments after the shock become increasingly smaller, further dampening the aggregate price response. Overall, our empirical estimates imply that the joint variation of price stickiness and market power across sectors more than doubles the propagation of nominal shocks obtained in models with identical sectors.

The contributions of this paper lie at the intersection of theoretical studies of how strategic interactions in oligopolistic markets influence inflation dynamics and empirical studies that aim to estimate the degree of strategic complementarities in the data. We build on insights from the first literature to develop a tractable model of oligopolistic competition in the wholesale sector, which gives testable predictions for how distributors' costs pass through to their prices. Although recent papers (Mongey, 2021; Wang and Werning, 2022) have highlighted some possible mechanisms linking strategic complementarity with the transmission of aggregate shocks, direct empirical evidence on these mechanisms remains scarce. Our paper takes advantage of the unique features of wholesale price data to estimate the combined effects of nominal price rigidity and market power on micro price adjustments, both across firm-products within a sector and across sectors. Our empirical evidence supports conclusions in this literature that models with a reasonable degree of oligopolistic competition provide significant amplification of the effects of nominal rigidities in standard New Keynesian models.[2]

In the context of the empirical literature, our framework generalizes two existing approaches. First, it extends flexible-price approaches to a setting with variation in the degree of nominal price rigidity across sectors. Amiti, Itskhoki and Konings (2019) estimate strategic complementarity under flexible prices where an instrumental variable is needed to generate exogenous movements in competitor prices. We do not use competitors' prices since only some of them adjust in response to shocks. Instead, we leverage our data and use cost measures to estimate the pass-through of cost shocks directly, avoiding the need to address endogeneity of competitors' prices to underlying costs. In a related paper, Gagliardone, Gertler, Lenzu and Tielens (2023) extend and enrich the annual dataset used by Amiti, Itskhoki and Konings (2019). They estimate a high pass-through of marginal cost into prices, showing that the implied NKPC slope is relatively high. We demonstrate, both theoretically and empirically, that the pass-through depends on variation in nominal price rigidity and market power across and within sectors. We show that accounting for heterogeneity in price stickiness and market power substantially lowers the slope of NKPC.

Furthermore, our framework generalizes monopolistically competitive sticky-price approaches to an oligopolistic environment with variation in the degree of market power across sectors. Gopinath and Itskhoki (2010*a*) find that goods with a higher frequency of price adjustments in the US import price micro data tend to have higher long-run exchange rate pass-through. They argue that

[2] Our paper also connects to a broader macro literature that emphasizes the role of the distribution margin in the transmission of domestic or international shocks (see, e.g., Burstein, Neves and Rebelo (2003); Burstein, Eichenbaum and Rebelo (2005); Corsetti and Dedola (2005); Goldberg and Campa (2010); Nakamura and Zerom (2010); Eichenbaum, Jaimovich and Rebelo (2011); Gopinath, Gourinchas, Hsieh and Li (2011); Gopinath and Itskhoki (2011); Goldberg and Hellerstein (2012); Berger, Faust, Rogers and Steverson (2012)). Our paper also relates to Ganapati (2024), which provides an in-depth study of the US wholesale sector using detailed administrative data. Ganapati (2024) documents that the share of manufactured goods distributed by wholesale firms has increased over time, representing roughly half of all goods by 2012, and that the sector exhibits clear patterns of firm heterogeneity and concentration.

monopolistically competitive sticky price models with variable markups and imported intermediate inputs can generate this relationship. Our empirical evidence highlights variation in market power as a key additional factor in the transmission of nominal shocks to the economy.

The paper proceeds as follows. Section 2 outlines the general equilibrium model with sectors of oligopolistically competitive distributors and derives the closed-form solution for optimal pass-through of distributors' supply costs to their adjusted prices. Section 3 summarizes the Canadian wholesale price micro data. Section 4 explains the decomposition of distributor cost changes into idiosyncratic and common components, presents our estimation method, and reports the estimation results. Section 5 distills the implications of the empirical estimates for inflation dynamics. Section 6 concludes.

2 Model with oligopolistic markets and sticky prices

This section outlines the model with oligopolistically competitive heterogeneous distributors. We derive a closed-form solution for optimal price adjustments by distributors that depend on changes in their own costs and costs of competitors. The pass-through of the idiosyncratic component of the firm's cost shock is incomplete due to strategic pricing complementarity arising endogenously under oligopolistic competition. The pass-through of the common component of the firm's cost shock is higher than the idiosyncratic cost pass-through, but it decreases with the degree of price stickiness in the sector. The degree of pass-through of both idiosyncratic and common cost shocks is decreasing in market power. We estimate these relationships in Section 4 using Canadian wholesale trade price micro data introduced in Section 3. In this section, we summarize the key assumptions and features of the model. We relegate the remaining details to Appendix B.

2.1 Model outline

Households. There are infinitely many identical households who derive utility from consuming a basket of J final goods c_{jt}, $j = 1, ..., J$, and dis-utility from working l_t hours, at wage W_t. We assume unit elasticity of substitution between sectors in aggregate consumption $c_t = \prod_j c_{jt}^{\alpha_j}$, with $\sum_j \alpha_j = 1$. Households with discount factor β hold cash M_t, government bonds B_t returning risk-free rate R_t, and obtain dividends Π_t.

Each household maximizes their lifetime utility

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\ln c_t - l_t \right),$$

subject to the sequence of budget constraints

$$M_t + B_t \leq W_t l_t + R_{t-1} B_{t-1} + M_{t-1} - \sum_{j=1}^{J} P_{jt-1} c_{jt-1} + \Pi_t,$$

cash-in-advance constraints for consumption spending $\sum_{j=1}^{J} P_{jt} c_{jt} \leq M_t$, and the lower-bound constraints on the risk-free rate $R_t \geq 1$.

The optimal consumption spending shares are constant: $\frac{P_{jt} c_{jt}}{P_t c_t} = \alpha_j$, where P_t denotes the price of the bundle c_t. Assuming that the risk-free rate constraint is never binding, we obtain two standard first-order conditions. Total consumption is characterized by the Euler equation:

$$1 = \beta R_t \mathbb{E}_t \left[\frac{P_t c_t}{P_{t+1} c_{t+1}} \right],$$

and the optimal labour supply satisfies

$$W_t = P_t c_t = M_t. \tag{1}$$

Sector output and prices. The production sector consists of producers who supply differentiated inputs to oligopolistically competitive distributors, which are then aggregated into sector outputs. As is standard in the literature, assumptions of log-linear utility and the Cobb-Douglas consumption aggregator lead to constant sector expenditure shares and one-to-one transmission of monetary policy change to the wage and total expenditure as in (1). This allows us to analyze price dynamics in a sector independently from prices in other sectors.

The output in sector j, c_{jt}, is aggregated over goods supplied by a finite number N_j of distributors using a constant elasticity of substitution (CES) technology:

$$c_{jt} = \left[\sum_{i=1}^{N_j} (c_{ijt})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}},$$

where θ is the within-sector elasticity of substitution, c_{ijt} is the demand for distributor i's output from the consumer's optimization problem,

$$c_{ijt} = \alpha_j \left(\frac{P_{ijt}}{P_{jt}} \right)^{-\theta} \frac{P_t}{P_{jt}} c_t,$$

and P_{jt} is the price index for sector j:

$$P_{jt} \equiv \sum_{i=1}^{N_j} \left(P_{ijt} \frac{c_{ijt}}{c_{jt}} \right) = \left[\sum_{i=1}^{N_j} (P_{ijt})^{1-\theta} \right]^{\frac{1}{1-\theta}}.$$

Distributors. Distributor i in sector j purchases input good y_{ijt} from the producer of good i at price Q_{ijt}, which it takes as given. The distributor uses linear technology to produce c_{ijt} units of the good:

$$c_{ijt} = y_{ijt}.$$

The distributor's marginal cost is equal to the producer's price, Q_{ijt}.

Distributors' prices are sticky, where each period only a fraction $1 - \lambda_j$ of firms are able to change their prices, assigned according to a Poisson process as in Calvo (1983). Similarly to Mongey (2021), we assume that in period t an adjusting firm observes marginal cost realizations for all firms, but it does not observe price adjustments of other firms until later in the period. All adjustments are simultaneous, so that no firm can respond to the new price chosen by another firm within the period. Under these assumptions, all adjusting firms have the same information for adjusting their prices and, therefore, they form identical expectations of current and future period variables. Expected values conditional on the information at the beginning of period t are denoted by operator $\mathbb{E}_t$.

For the distributor adjusting its price in period t, the optimal reset price is

$$P_{ijt,t} = \frac{\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda_j)^\tau \vartheta_{ijt+\tau,t} c_{ijt+\tau,t}}{\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda_j)^\tau (\vartheta_{ijt+\tau,t} - 1) c_{ijt+\tau,t}/Q_{ijt+\tau}}, \tag{2}$$

where the second time subscript denotes the period of the last price adjustment; $\mathbb{E}_t\vartheta_{ijt+\tau,t}$ is the expected effective demand elasticity facing this distributor at $t+\tau,\ \tau = 0, 1, \ldots$,

$$\mathbb{E}_t\vartheta_{ijt+\tau,t} = \begin{cases} \mathbb{E}_t\left[\theta(1 - s_{ijt+\tau,t}) + s_{ijt+\tau,t}\right] & \text{(under Bertrand competition)} \\ \mathbb{E}_t\left[\frac{1}{\theta}(1 - s_{ijt+\tau,t}) + s_{ijt+\tau,t}\right]^{-1} & \text{(under Cournot competition)} \end{cases}, \tag{3}$$

where $\mathbb{E}_t s_{ijt+\tau,t}$ is the period-t expected value of the market share of distributor i in period $t+\tau$:

$$\mathbb{E}_t s_{ijt+\tau,t} \equiv \mathbb{E}_t\left[\frac{P_{ijt+\tau}c_{ijt+\tau}}{P_{jt+\tau}c_{jt+\tau}}\right] = \mathbb{E}_t\left[\frac{(P_{ijt+\tau})^{1-\theta}}{\sum_{i=1}^{N_j}(P_{ijt+\tau})^{1-\theta}}\right]. \tag{4}$$

Producers. Varieties are supplied to distributors by producers competing in monopolistically competitive markets. We assume a producer's price, Q_{ijt}, is sticky, changing according to a Poisson process with probability $1 - \lambda_j^p$: when the price adjusts, the producer resets it to the frictionless price Q^*_{ijt}, equal to the constant markup over its marginal cost, otherwise the price remains equal to the last period's price, Q_{ijt-1}.

2.2 Derivation of the closed-form solution for distributor's price changes

There are two challenges in solving (2) in closed form. First, the adjusting firm needs to take into account the effect of its price on the price of its competitors and vice versa. Second, it needs to form expectations about the dynamic path of the sector price.

Strategic pricing complementarity. Under log-linear approximation of (3) and (4), the firm's expected markup $\mathbb{E}_t\mu_{ijt+\tau,t} \equiv \mathbb{E}_t\frac{\vartheta_{ijt+\tau,t}}{\vartheta_{ijt+\tau,t}-1}$ depends on its reset price today and the expected sector price in the future:

$$\mathbb{E}_t\widehat{\mu}_{ijt+\tau,t} = -\varphi_{ij}\left[\widehat{P}_{ijt,t} - \mathbb{E}_t\widehat{P}_{jt+\tau}\right], \tag{5}$$

where hatted variables represent log-linear deviations of corresponding variables from steady state. Equation (5) shows that firms have an incentive to lower their markup as their price is pushed above the sector average price, known as strategic pricing complementarity.[3] It arises endogenously in oligopolistic markets and its strength is summarized by φ_{ij}:

$$\varphi_{ij} \equiv \begin{cases} \frac{s_{ij}}{[\theta(1-s_{ij})+s_{ij}](1-s_{ij})}(\theta-1) & \text{(under Bertrand competition)} \\ \frac{s_{ij}}{1-s_{ij}}(\theta-1) & \text{(under Cournot competition)} \end{cases} \tag{6}$$

In either case, φ_{ij} is increasing in firm i's market share, s_{ij} (i.e., pricing complementarity is stronger with market power). As will become clear in the following discussions in this section and in Section 5, φ_{ij} is a key statistic that governs the micro and macro price dynamics under oligopolistic competition.

Plugging (5) in the log-linearized pricing equation (2) and rearranging yields the reset price as the sum of its expected costs and expected sector prices:

$$\widehat{P}_{ijt,t} = \frac{1-\beta\lambda}{1+\varphi_{ij}} \sum_{\tau=0}^{\infty} (\beta\lambda_j)^{\tau} [\mathbb{E}_t \widehat{Q}_{ijt+\tau,t} + \varphi_{ij} \mathbb{E}_t \widehat{P}_{jt+\tau}]. \tag{7}$$

Expected sector prices. The expected average reset price in period t is $\mathbb{E}_t \widehat{P}_{jt,t} \equiv \mathbb{E}_t \sum_i s_{ij} \widehat{P}_{ijt,t}$, which, after using (7), becomes

$$\mathbb{E}_t \widehat{P}_{jt,t} = \sum_i \left\{ s_{ij} \frac{(1-\beta\lambda_j)}{(1+\varphi_{ij})} \sum_{\tau=0}^{\infty} (\beta\lambda_j)^{\tau} [\mathbb{E}_t \widehat{Q}_{ijt+\tau,t} + \varphi_{ij} \mathbb{E}_t \widehat{P}_{jt+\tau}] \right\}. \tag{8}$$

Under Calvo pricing, the expected sector price can be written as follows:

$$\begin{aligned} \mathbb{E}_t \widehat{P}_{jt+\tau} &= \mathbb{E}_t \sum_i s_{ijt+\tau} \widehat{P}_{ijt+\tau} \\ &= (1-\lambda_j) \mathbb{E}_t \sum_i s_{ijt+\tau} \widehat{P}_{ijt+\tau,t+\tau} + \lambda_j \mathbb{E}_t \sum_i s_{ijt+\tau} \widehat{P}_{ijt+\tau-1} \\ &\approx (1-\lambda_j) \mathbb{E}_t \widehat{P}_{jt+\tau,t+\tau} + \lambda_j \mathbb{E}_t \widehat{P}_{jt+\tau-1}, \end{aligned} \tag{9}$$

[3] See, e.g., Kimball (1995), Atkeson and Burstein (2008), Nakamura and Steinsson (2013).

where the first equality is the definition of sector price, the second equality follows from Calvo pricing, and the third approximate equality follows from the fact that the effects of time variation in market shares s_{ijt} on the sector price P_{jt} are at most second order.[4]

Combining (8) and (9) gives the equation for expected sector inflation $\mathbb{E}_t\widehat{\pi}_{jt} \equiv \mathbb{E}_t(\widehat{P}_{jt} - \widehat{P}_{jt-1})$:

$$\mathbb{E}_t\widehat{\pi}_{jt} = \sum_i s_{ij} \frac{(1-\beta\lambda_j)(1-\lambda_j)}{\lambda_j\,(1+\varphi_{ij})} \mathbb{E}_t(\widehat{Q}_{ijt,t} - \widehat{P}_{jt}) + \beta\mathbb{E}_t\widehat{\pi}_{jt+1}. \tag{10}$$

Given expected cost processes $\{\mathbb{E}_t\widehat{Q}_{ijt+\tau,t}\}_{\tau=0}^{\infty}$, equation (10) fully characterizes the dynamics of expected sector prices $\{\mathbb{E}_t\widehat{P}_{jt+\tau}\}_{\tau=0}^{\infty}$. Note that (10) is the sector NKPC. It holds in expectations because the realized fraction of adjusting prices among finitely many firms varies over time even though the probability of price changes is constant due to Calvo pricing. We follow Wang and Werning (2022) and assume that the number of similar sectors is sufficiently large so that the variation in the sector fraction of adjusting prices does not have a first-order effect on the aggregate price.

Solving the expected sector prices from (10) together with the individual firms' price dynamics from (7) allows us to derive the expression for the distributor's optimal reset price in two steps. Proposition 1 derives the reset price condition assuming that costs $\widehat{Q}_{ijt}$ are flexible, i.e., $\widehat{Q}_{ijt} = \widehat{Q}^*_{ijt}$, and follow an AR(1) process. Proposition 2 then derives the reset price condition assuming that the costs $\widehat{Q}_{ijt}$ are sticky, which will form the basis for our empirical analysis.

Proposition 1 *Assume the producer's price $\widehat{Q}_{ijt}$ is flexible and follows an AR(1) process with serial correlation ρ_j. The distributor's optimal reset price response to idiosyncratic and common*

[4] Intuitively, because market shares add up to 1, the effects of market winners on sector price are approximately offset by the effects of market losers if their average prices are similar. To illustrate, consider a shock δ that changes the market share of firm i by $ds_i(\delta)$ and its price by $dP_i(\delta)$, and assume that firm prices are identical in steady state, $P_i = P$. The first-order effect of δ on the weighted sum of prices is $P\sum_i ds_i(\delta) + \sum_i s_i dP(\delta)$. Since market shares must add up to 1, $\sum_i ds_i(\delta) = 0$, variation in market shares has at most a second-order effect on the weighted mean.

(average) cost changes, up to a first-order approximation, is given by

$$\widehat{P}_{ijt,t} = \underbrace{\frac{1}{1+\varphi_{ij}}\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}}_{PT\ to\ idiosyncratic\ cost\ changes}\left(\widehat{Q}_{ijt}-\widehat{Q}_{jt}\right)+\underbrace{\left[\frac{1}{1+\varphi_{ij}}+\frac{\varphi_{ij}}{1+\varphi_{ij}}\frac{\rho_j-\Lambda_j}{1-\beta\lambda_j\Lambda_j}\varkappa_j\right]\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}}_{PT\ to\ common\ (average)\ cost\ changes}\widehat{Q}_{jt}, \tag{11}$$

where $\widehat{Q}_{jt} \equiv \sum_i s_{ij}\widehat{Q}_{ijt}$ *is the common (or average) cost change in sector* j*,* $\Lambda_j \geq \lambda_j$ *captures market power augmented price stickiness in sector* j*, and* $\varkappa_j = 1$ *when firms are symmetric* ($s_{ij} = s_j$)*:*

$$\Lambda_j \equiv \frac{1}{2}\left[\lambda_j + \frac{1-b_j}{\beta\lambda_j} - \sqrt{\left(\lambda_j + \frac{1-b_j}{\beta\lambda_j}\right)^2 - \frac{4}{\beta}}\right], \tag{12}$$

$$\varkappa_j \equiv \frac{a_j}{1-b_j+\lambda_j\left[\beta(\lambda_j-1)-1\right]}, \tag{13}$$

$$a_j \equiv \left(\sum_i \frac{(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}s_{ij}\widehat{Q}_{ijt}\right)/\widehat{Q}_{jt},$$

$$b_j \equiv \sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}.$$

Proof. *See Appendix B.1.*

Proposition 1 demonstrates that in a dynamic oligopolistic competition model with price stickiness, a firm's current cost and its competitors' current prices are no longer sufficient to characterize the firm's optimal price decision, as is the case in static oligopolistic competition models (Amiti, Itskhoki and Konings, 2019). This is because some of the competitors' current prices are not adjusted, and therefore do not reflect the optimal response to their cost. Rather, the adjusting firm recognizes that even if the competitor's cost shock is not reflected in the competitor's current price, it may influence the competitor's future price when it is adjusted. Proposition 1 shows that in the dynamic setting, the firm's idiosyncratic cost change $\widehat{Q}_{ijt} - \widehat{Q}_{jt}$ and the average cost change $\widehat{Q}_{jt}$ are sufficient to capture the optimal pricing decision.

Although Proposition 1 establishes the case under flexible producer prices, in the data producer prices are sticky and highly synchronized with distributor prices, as we show in Section 3 below.[5] Proposition 2 shows that the distributor's optimal reset price condition can be derived for the

[5]Infrequent adjustment and high synchronization of upstream and downstream prices have been documented for the retail sector in Eichenbaum, Jaimovich and Rebelo (2011) and Goldberg and Hellerstein (2012).

case with sticky costs under the assumption that the *timing* of distributor and producer price adjustments are synchronized.

Proposition 2 *Let the timing of the producer and distributor price adjustments be determined by the identical Poisson process with the parameter $\lambda_j = \lambda_j^p$. The distributor's optimal reset price response to idiosyncratic and common cost shocks is*

$$\widehat{P}_{ijt,t} = \underbrace{\frac{1}{1+\varphi_{ij}}}_{\psi_{ij}} \left(\widehat{Q}^*_{ijt} - \widehat{Q}^*_{jt}\right) + \underbrace{\left[\frac{1}{1+\varphi_{ij}} + \frac{\varphi_{ij}}{1+\varphi_{ij}} \left(\frac{\rho_j - \Lambda_j}{1-\beta\lambda_j\Lambda_j}\right) \varkappa_j\right]}_{\Psi_{ij}} \widehat{Q}^*_{jt}. \tag{14}$$

where ψ_{ij} (Ψ_{ij}) denotes idiosyncratic (common) cost pass-through.

Proof. *See Appendix B.1.*

With perfectly synchronized price and cost adjustments, the firm's cost is fixed over the duration of the price spell, and therefore, the adjusted price depends on the current cost. This implies that the pass-through of the idiosyncratic shock does not depend on the persistence of the shock ρ_j. The common cost pass-through still depends on ρ_j because the adjusting firm forms expectations of competitors' future price adjustments given competitors' current costs.[6]

Figure 1 illustrates the key properties of the pass-through of these shocks to the distributor's reset price under Proposition 2, for the case with symmetric firms and random walk shocks ($\rho_j = 1$). The idiosyncratic cost pass-through (in solid blue), which we denote by $\psi_j \equiv \frac{1}{1+\varphi_j}$, decreases with the degree of strategic complementarity φ_j for this firm, and it does not depend on the degree of price stickiness in the sector. The common cost pass-through (in dashed red), denoted by $\Psi_j \equiv \frac{1}{1+\varphi_j} + \frac{\varphi_j}{1+\varphi_j}\left(\frac{1-\Lambda_j}{1-\beta\lambda_j\Lambda_j}\right)\varkappa_j$, decreases with both strategic complementarity (albeit at a slower rate than ψ_j) and sector price stickiness.

Two special cases of equation (14) provide further intuition.

[6] At the aggregate level, the assumption of perfectly synchronized price and cost adjustments effectively collapses two layers of nominal rigidity—one at the producer level and the other at the distributor level—into a single layer, making our model more comparable to models with only one layer of nominal rigidity (e.g., Wang and Werning 2022 and Mongey 2021). See Appendix B.3 for more details.

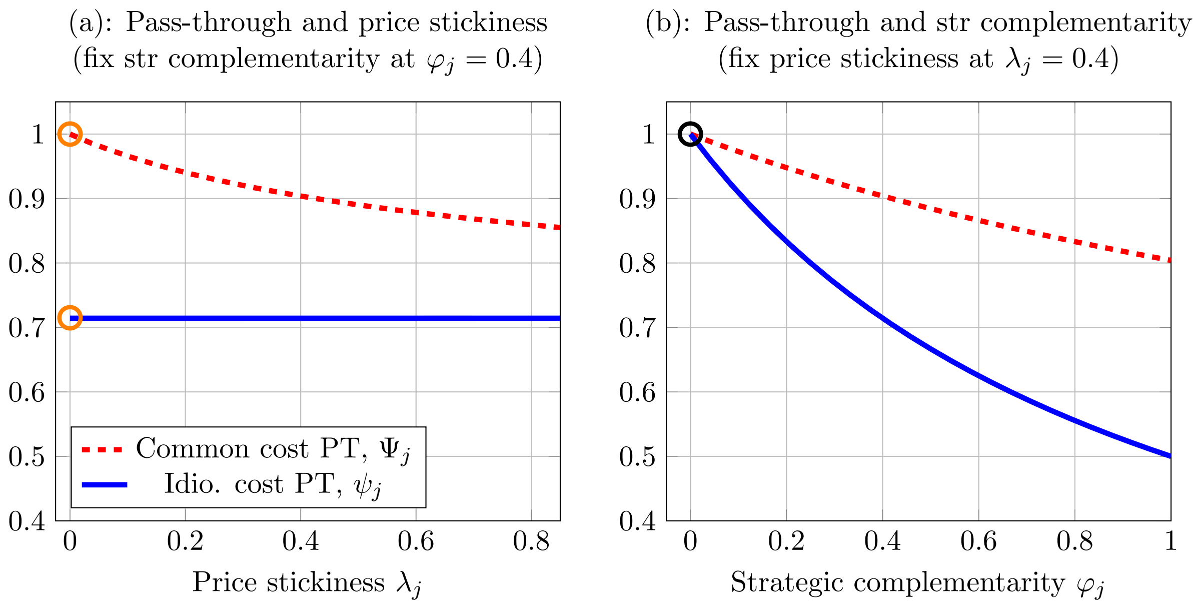

Figure 1: Idiosyncratic and common cost shock pass-through (symmetric firms)

Notes: The figure plots pass-through coefficients given by equation (14) for symmetric firms and random walk shocks ($\rho_j = 1$). Panel (a) demonstrates variation over λ_j for $\varphi_j = 0.4$. Panel (b) shows variation over φ_j for $\lambda_j = 0.4$. The orange circles in Panel (a) indicate special case of flexible prices ($\lambda_j = 0$). The black circle in Panel (b) indicates special case of monopolistic competition.

Special case 1: Flexible prices, $\lambda_j = 0$:

$$\widehat{P}_{ijt,t} = \frac{1}{1+\varphi_{ij}} \left(\widehat{Q}^*_{ijt} - \widehat{Q}^*_{jt} \right) + \left[\frac{1}{1+\varphi_{ij}} + \frac{\varphi_{ij}}{1+\varphi_{ij}} \varkappa_j \right] \widehat{Q}^*_{jt}.$$

Under flexible prices, our model nests static models of oligopolistic competition in Atkeson and Burstein (2008), Edmond, Midrigan and Xu (2015), and Amiti, Itskhoki and Konings (2019) [AIK]. Similarly to AIK, when firms are symmetric ($s_{ij} = s_j$, $\varkappa_j = 1$), the common shock pass-through is complete ($\Psi_{ij} = 1$) and independent of the degree of market concentration in a sector or market power within a sector. Even in asymmetric cases, the common shock pass-through is close to one when cost shocks are small.[7] By contrast, a firm only partially responds to idiosyncratic cost shocks in an effort to prevent its price from deviating too far from competitors' prices, which would affect its market share. Such strategic motives are absent when all competing firms are hit by the common shock, resulting in complete pass-through.

[7] If $\widehat{Q}^*_{ijt} \to 0$, $\varkappa_j \to 1$ for any distribution of market power.

Our framework extends flexible-price cases to a more general setting with variation in the degree of nominal price rigidity across sectors. When prices are sticky, a common shock introduces relative price dispersion between adjusting and non-adjusting firms. Adjusting firms have an incentive to moderate their price responses to the common shock to limit deviation of their price from those of non-adjusting competitors. Given realization of the common shock, a higher degree of price stickiness means a higher number of non-adjusters, and hence a stronger motive for adjusters to mute their price deviation, implying lower common shock pass-through as shown in Figure 1(a). By contrast, the firm's own cost pass-through is not directly influenced by the composition of adjusters and non-adjusters. Hence, idiosyncratic cost pass-through does not depend on the degree of price stickiness.

Special case 2: Monopolistic competition. Taking the limit $s_{ijt} \to 0$ brings strategic complementarity to zero ($\varphi_{ij} \to 0$). The firm has no incentive to vary its markup in response to competitors' prices, and it fully passes through either idiosyncratic or common shocks ($\psi_{ij} \to 1$, $\Psi_{ij} \to 1$) by adjusting its price to changes in its cost: $\widehat{P}_{ijt,t} = \widehat{Q}_{ijt,t} = \widehat{Q}^{*}_{ijt}$.

Under oligopolistic competition, strategic pricing complementarity lowers both idiosyncratic and common shock pass-through (Figure 1(b)). As the degree of market power rises and there are fewer competitors, it becomes more costly for the firm to pass-through its own cost relative to the common cost, since the latter also affects its competitors. Therefore, as market power increases, idiosyncratic cost pass-through decreases faster than common cost pass-through.

Non-CES demand. In the benchmark model, strategic complementarities φ_j arise from oligopolistic competition and the nested CES demand following Atkeson and Burstein (2008). It is well known that models with monopolistic competition and Kimball (1995) demand can also generate strategic complementarities due to extra curvature of the demand curve determined by a superelasticity parameter (Klenow and Willis, 2016). As we discuss in Appendix B.8, an alternative model with Kimball demand can be calibrated (via the superelasticity) to match the total effect of strategic complementarities on aggregate responses in the multi-sector oligopoly model. The caveat is that, in a multi-sector setting with Kimball demand, one would need to assume that the superelasticity varies systematically across sectors to capture heterogeneity in strategic complementarity. Our approach does not need to rely on the variation of preference parameters because sector-specific φ_j are informed by estimated idiosyncratic pass-through coefficients ψ_j.

Feedback versus strategic effects. The equilibrium response of the distributor's reset price (14) reflects two types of strategic interactions, coined by Wang and Werning (2022) as the "feedback" and "strategic" effects. The feedback effect reflects the response to competitors' price adjustments over the adjusting firm's price horizon. The strategic effect reflects the responses of competing firms' future price adjustments to the firm's adjusted price. Our solution accounts for both effects.

As we demonstrate in detail in Appendix B.6, the strategic effect is quantitatively small. Following the approach in Wang and Werning (2022), we construct a counterfactual "naïve" model where a firm resets its price as a function of its competitors' prices in the *same* period, while still forming the correct expectations about future sector price dynamics. By construction, the difference in equilibrium price responses reflects the contributions of strategic effects. Similarly to Wang and Werning (2022), we find the difference to be quantitatively small, less than 1% for realistic calibrations. We also show that the log-linear approximation does not influence these results. In Appendix B.5, we numerically solve a nonlinear duopoly model and compare its equilibrium responses to the theoretical responses under the first-order approximation of our benchmark model. We find that the difference is quantitatively small (less than 4%).

3 Canadian wholesale trade price micro data

This paper uses unpublished survey-based price micro data used by Statistics Canada to construct the monthly WSPI. The survey's target population includes all statistical establishments primarily engaged in wholesaling, classified as NAICS wholesale trade (41).

Survey respondents are required to report product-specific figures for the average monthly purchase price (amount paid for the acquisition of a given product) and the average monthly selling price (amount received for selling the same product), whether the product was imported and, if imported, the product's country of origin. The data also include other price characteristics that could help inform observed price dynamics. These include establishment-level NAICS 5-digit (NAICS5) codes, product-specific NAPCS7 codes, and two variables that indicate the reason for a price change, for the purchase price and selling price, respectively, based on a predetermined list of reasons. Finally, the data also include information on the currency in which prices are reported.

The survey program is longitudinal in design, with the goal of continuously monitoring each product reported by a given establishment over several collection cycles. Respondents are instructed to report up to six products that are representative of their wholesaling activity, chosen based on either the products' contribution to annual sales or frequency of purchases.

The raw micro data used in this paper have not been cleaned prior to receiving the data, and none of the prices in our data are imputed. To the extent that is possible, we exclude outliers and anomalies from the raw micro data. For more information on the dataset and the data cleaning process, see Appendix A.1.

Our cleaned sample of monthly prices covers the period from January 2013 to December 2019. It has roughly 280,000 firm-product observations, including about 1,800 individual firms and 14,000 individual firm-products. The average firm-product variety has roughly 40 monthly observations, nearly all of which are consecutive. In terms of country of origin, the split across observations is 44% domestic, 32% US, and 25% other origins.

The dataset includes three sets of establishment-level weights that can be applied in regression analysis or summary statistics. The first is a "revenue weight," derived from establishment revenue data based on the Statistics Canada Business Register (BR) and industry gross margins based on the Annual Wholesale Trade Survey micro data.[8] The second is a "design weight," equal to the inverse of the firm's selection probability. This weight can be interpreted as the number of times that each sampled firm should be replicated to represent the entire population. Finally, a "sampling revenue weight" is equal to the product of the revenue weight and the design weight. It represents the relative importance of the establishment in the industry and is used to construct an index that is representative of the aggregate. When a wholesaler distributes multiple products, we divide the firm's weight equally across products. The sample and the weights are typically updated every 5 years. Unless otherwise noted, the weighted statistics or regressions in the paper use the sampling revenue weight to capture the economic importance of firms in the population.

[8]The BR is Statistics Canada's central repository of information on businesses and institutions operating in Canada. The sampling unit for the WSPI survey is the "establishment" level, and revenue weights are associated one-to-one with individual establishments.

3.1 Key features of the data

WSPI price micro data offer several key advantages for analyzing the interaction between nominal rigidities and market power. The literature has stressed that variable markups and strategic complementarities play only a limited role at the retail level, but an important role at the wholesale level (Nakamura and Zerom, 2010; Eichenbaum, Jaimovich and Rebelo, 2011; Gopinath, Gourinchas, Hsieh and Li, 2011; Gopinath and Itskhoki, 2011; Goldberg and Hellerstein, 2012). For each wholesaler, the dataset provides the price at which it buys its products from suppliers (purchase price) and the price at which it sells these products (selling price). Sectors are identified by an industry classification (NAICS4, 25 industries) or product classification (NAPCS7, 166 products). We use the selling price for the wholesaler product i in sector j in month t to represent the distributor's output price P_{ijt} in the model, and we use the purchase price to represent the producer's price Q_{ijt} in the model. Since the data contain both purchase and selling prices, they provide accurate measures of nominal rigidity and markups at a firm-product level.

Nominal rigidity. We follow the literature by measuring nominal rigidity as the fraction of adjusting prices in a given month (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008). The average (mean) monthly fraction of selling price changes is defined as

$$Fr_j^P \equiv \frac{\sum_{i \in I_j} \sum_{t \in T_{ij}} \omega_{ij}^D \mathbb{1}\left[P_{ijt} \neq P_{ijt-1}\right]}{\sum_{i \in I_j} \sum_{t \in T_{ij}} \omega_{ij}^D}, \tag{15}$$

where I_j denotes the set of firm-products in industry j; T_{ij} denotes the set of months that firm-product i in industry j is surveyed; ω_{ij}^D represents the design weight of the firm (the inverse of the probability of being selected for the survey); and $\mathbb{1}\left[P_{ijt} \neq P_{ijt-1}\right]$ is an indicator of a selling price change for product-firm i. The fraction of adjusting purchase prices Fr_j^Q is constructed similarly. We refer to $\lambda_j^P \equiv 1 - Fr_j^P$ ($\lambda_j^Q \equiv 1 - Fr_j^Q$) as selling (purchase) *price stickiness* in sector j.

The average monthly fraction of price changes is roughly 0.55 for selling prices and 0.50 for purchase prices. Figure 2 depicts the average fractions for each 3-digit NAICS industry (NAICS3). The monthly fraction of price changes varies significantly across industries: from 0.33 in the "Motor vehicle and motor vehicle parts and accessories merchant wholesalers" industry to 0.97 in the "Petroleum and petroleum products merchant wholesalers" industry.

Nominal price rigidity across sectors and products is highly correlated for selling and purchase prices. Figure 3 provides the corresponding scatter plots for NAICS4 and NAPCS7 classifications. In both cases, the fitted slopes are 0.88 and highly significant with $R^2 = 0.95$.

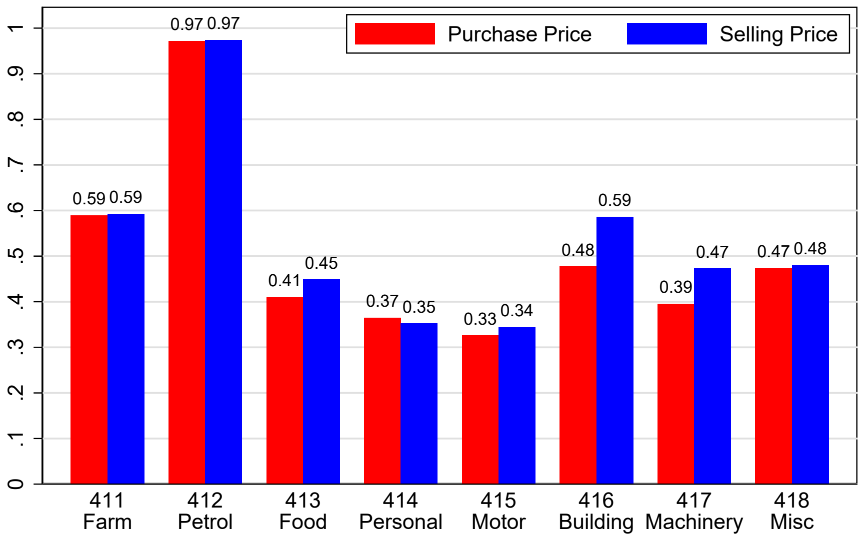

Figure 2: Average fraction of price changes by 3-digit NAICS wholesale industry

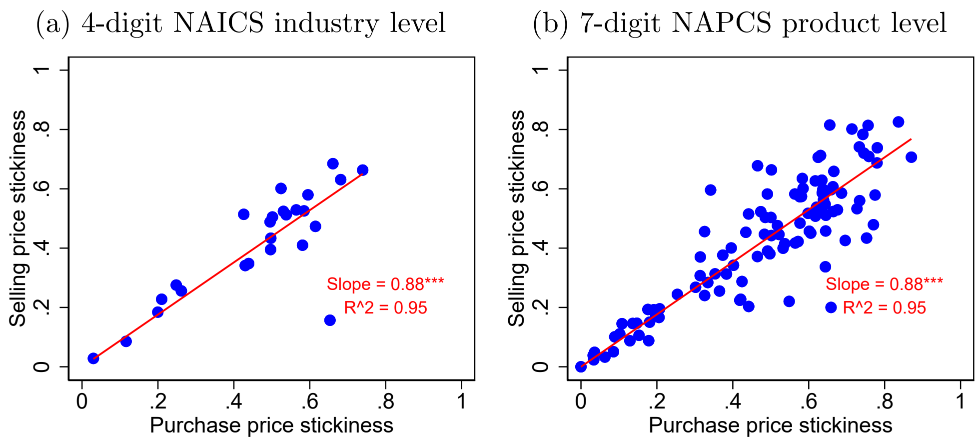

Figure 3: Selling and purchase price synchronization at the industry and product levels

Notes: Purchase (selling) price stickiness is given by λ_j^P (λ_j^Q), where j represents a sector according to NAICS4 industry classification (Panel (a)) or NAPCS7 product classification (Panel (b)).

This evidence suggests that selling price adjustments are highly synchronized with purchase price adjustments. Table 1 provides the firm-product-level (unweighted) frequency of the change of the selling price conditional on the change in the purchase price in the same month. Indeed, purchase and selling price changes are highly synchronized at the firm-product level. When a purchase price adjusts, there is a selling price change 86% of the time. And when the purchase price is unchanged from the previous month, the selling price is unchanged 75% of the time. The derivation of the closed-form solution (14) in Section 2 relies on the assumption of perfect synchronization between purchase and selling price changes, which, as we show here, is largely borne out in the data.

Table 1: Synchronization at the firm-product level

		Selling price change	
		Yes	No
Purchase price change	Yes	0.86	0.14
	No	0.25	0.75

Notes: Table provides unweighted means of an indicator of a selling price change/no change conditional on a purchase price change/no change in the same month.

Markups. Define the margin as the ratio of the firm-product selling price to the firm-product purchase price. Figure 4 provides the mean and standard deviation of (log) margins in our data for each NAICS3 wholesale sector. There is substantial variation in both the level and dispersion of product margins across sectors. The mean margin varies from 0.08 in the "Petroleum and petroleum products merchant wholesalers" industry to 0.53 in the "Personal and household goods" industry, and margin dispersion tends to be higher in industries with higher margin levels. The variation in dispersion presented in the figure indicates that firms have different degrees of market power within industries.

Since the firms represented in the data are wholesalers, they do not transform purchased goods before selling them to other firms. Therefore, the firm-product margin can be used as a reliable proxy for the firm-product markup. In our empirical analysis, we refer to the firm-product margin as *markup* and use it as a measure of the firm's market power.[9]

In practice, a wholesaler may incur other costs, such as wage payments to its staff, the cost of managing inventories, or the cost of maintaining its distribution facilities. We offer three arguments for why measurement issues do not significantly undermine our markup proxy. First, since wholesale

[9] A similar assumption is used in studies using retail price micro data, e.g., Eichenbaum, Jaimovich and Rebelo (2011), Gopinath, Gourinchas, Hsieh and Li (2011), and Anderson, Rebelo and Wong (2018).

firms do not transform the goods that they sell, nearly all of their direct costs come from costs of purchased goods rather than from labour or inventory costs.[10] Other indirect costs, such as the cost of maintaining distribution facilities, should be less variable over short horizons and are unlikely to contribute to the month-to-month marginal cost dynamics. Second, our empirical analysis uses firm-product fixed effects to control for variation in unobserved cost components across firms and products. Third, measurement error should render empirical estimates of idiosyncratic and common shock pass-through rates to be similar; however, our evidence strongly rejects their equality. All in all, we consider the firm-product margin as a reasonable markup proxy for the goals of this study (see Appendix A.6 for further discussion).

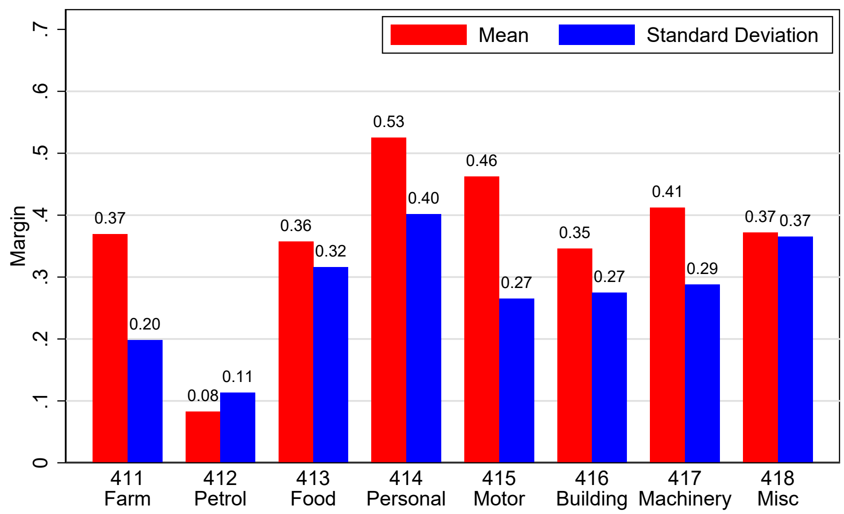

Figure 4: Average product margin by 3-digit NAICS wholesale industry

Notes: Margin is the log of the ratio of the selling and purchase price in the same month. Mean (standard deviation) is design-weighted mean (standard deviation) across all observations in the sector.

4 Estimation of price responses

In this section, we decompose the purchase price changes faced by wholesalers into common and idiosyncratic cost shocks and estimate the firms' pass-through of these two shocks, conditioning on a

[10]For example, Canadian industry statistics indicate that 96% of the wholesale industry's Cost of Goods Sold (COGS) is accounted for by "Purchases, materials and sub-contracts" and only 4% of COGS is accounted for by "Wages and benefits". By comparison, for the manufacturing sector this breakdown is 74% accounted for by "Purchases, materials and sub-contracts" and 26% accounted for by "Wages and benefits". See https://ised-isde.canada.ca/app/ixb/cis/search-recherche.

selling price change. We find strong support for our theoretical predictions: in oligopolistic markets, the pass-through of idiosyncratic shocks is incomplete and independent of the price stickiness of the industry, while the pass-through of common cost shocks decreases with the sector's price stickiness. Moreover, the pass-through of both idiosyncratic and common shocks is decreasing in market power.

In our baseline analysis, we define a sector as an industry at the NAICS4 level. As a robustness check, we define a sector at the product level using NAPCS7 product classification. In the data, each establishment may report multiple products. We treat each product as a separate entity and use i to label firm-product pairs.

4.1 Estimation strategy

In Section 2, we derived the closed-form relationship (14) between the distributor's selling price at the time of adjustment and idiosyncratic and common components of its purchase price at that time. Using wholesale price micro data, we estimate equation (14) in two steps. First, we decompose purchase price changes in a sector into idiosyncratic and common components using the fixed-effect approach in di Giovanni, Levchenko and Méjean (2014). We then estimate the selling price response to these two cost shock measures, conditioning on a selling price change.

In the first step, we decompose the monthly changes of log purchase prices, $\Delta \ln(Q_{ijt}) = \ln(Q_{ijt}) - \ln(Q_{ijt-1})$, into common and idiosyncratic components by estimating an unweighted fixed-effect OLS regression

$$\Delta \ln(Q_{ijt}) = \epsilon_{jt} + \epsilon_{ijt}, \tag{16}$$

where ϵ_{jt} are the sector-month fixed effects and ϵ_{ijt} is the residual. Estimated $\widehat{\epsilon}_{jt}$ captures the average change in the purchase prices of all firm-product pairs in sector j in month t, referred to as the "common cost shock"; and $\widehat{\epsilon}_{ijt}$ captures the idiosyncratic change in the purchase price of firm-product i in sector j at month t, referred to as the "idiosyncratic cost shock."[11]

In the second step, we estimate the pass-through of these shocks to wholesalers' selling price

[11] Since $\Delta \ln(Q_{ijt}) = 0$ for purchase prices that do not adjust in period t, the empirical shocks $\widehat{\epsilon}_{jt}$ and $\widehat{\epsilon}_{ijt}$ are approximations of the theoretical shocks in (14). In Appendix B.7, we use model simulated data to show that estimation using empirical shocks $\widehat{\epsilon}_{jt}$ and $\widehat{\epsilon}_{ijt}$ yields accurate estimates of the theoretical pass-through coefficients.

conditional on adjustment ($\Delta \ln(P_{ijt}) \neq 0$):

$$\Delta \ln(P_{ijt}) = \underbrace{\left(\Psi_0 + \Psi_1\lambda_j + \Psi_2\lambda_{fj} + \Psi_3\lambda_{ij} + \Psi_4 D_j + \Psi_5 D_{ij}\right)}_{\text{common cost pass-through}} \cdot \widehat{\epsilon}_{jt} + \underbrace{\left(\psi_0 + \psi_1\lambda_j + \psi_2\lambda_{fj} + \psi_3\lambda_{ij} + \psi_4 D_j + \psi_5 D_{ij}\right)}_{\text{idiosyncratic cost pass-through}} \cdot \widehat{\epsilon}_{ijt} + FE_{ij} + \nu_{ijt}, \tag{17}$$

where FE_{ij} are firm-product fixed effects that absorb time-invariant heterogeneity in price adjustments across firm-products, and ν_{ijt} is the residual term.

In (17), we allow the pass-through rates to vary with price stickiness across sectors and across firms and products within a sector. We implement these covariates via interactions of the shocks $\widehat{\epsilon}_{jt}$ and $\widehat{\epsilon}_{ijt}$ with three measures of price stickiness and two measures of market power. Price stickiness λ_j, λ_{fj}, λ_{ij} is equal to 1 minus the average monthly fraction of adjusting prices at the sector, firm, or product level, respectively. We use the distributor's markup to proxy for its market power.[12] Dummy D_j identifies the top quartile of the markup distribution across sectors, and dummy D_{ij} defines the top quartile of the markup distribution across firms within sector j.[13] We estimate (17) with a panel fixed-effects regression using all observations with non-zero selling price changes.

Specification (17) offers several advantages in estimating the joint contribution of price stickiness and market power to firm-product price adjustments. First, it incorporates the effect of price stickiness on the degree of cost pass-through at monthly frequency. This feature of our analysis is enabled by detailed micro data for monthly prices and markups of heterogeneous distributors in concentrated markets. As a special case, (17) nests the pass-through under flexible prices, which allows us to cross-validate our results with those in Amiti, Itskhoki and Konings (2019), who used micro data at annual frequency at which most prices are flexible.

Second, it incorporates reliable measures of market power. The margin in the WSPI price micro data provides a direct measure of price markup, which is a standard measure of market power.

[12] According to most imperfect competition models, price markup is a suitable proxy for market power. This is the case in our model, where market power, summarized by strategic complementarity φ_{ij}, is linear in steady-state price markup $\mu_{ij} \equiv \frac{\vartheta_{ij}}{\vartheta_{ij}-1} = \frac{\theta}{\theta-1}\frac{1}{1-s_{ij}}$ for any given θ: $\varphi_{ij} = \left(\frac{\theta-1}{\theta}\mu_{ij} - 1\right)(\theta - 1)$. For empirical analysis, we prefer markup as the measure of market power to an alternative standard measure based on the firm's share of the sector's sales revenue because we do not observe the entire population of firms in each sector; on the other hand, markups in our dataset are observed at the product level and monthly frequency.

[13] See Appendix A.3 for more details on the construction of these variables.

In addition, since in the data we observe distributor costs directly and these costs are plausibly exogenous to distributors' prices, we can estimate the theoretical relationship (11) directly by a panel regression using (17). Studies using observed competitor prices for pass-through estimation face an additional challenge of addressing endogeneity of competitors' prices to underlying costs.[14]

Third, it distinguishes the pass-through of idiosyncratic and common cost shocks. Our model demonstrates how price stickiness and market power jointly and *differentially* influence the pass-through of these shocks. Our empirical analysis bears out these relationships in the data and provides numeric estimates that we use in Section 5 to derive quantitative implications for inflation dynamics.

Fourth, it distinguishes price stickiness and market power for different levels of aggregation. Macro theories in Mongey (2021), Wang and Werning (2022), and our model equation (14) demonstrate that the combined effects of nominal price rigidity and market power on micro price adjustments vary across firm-products within a sector and across sectors. Detailed coverage of the population of firm-products and sectors in our wholesale price data enables us to conduct adequate empirical analysis of these effects.

4.2 Estimation results by sector

We first estimate (17) separately for each of the NAICS4 industries and NAPCS7 products, i.e., we exploit variation within but not across sectors. Figure 5 provides scatter plots of the estimated pass-through coefficients against price stickiness and the average markup of the NAICS4 sector (NAPCS7 results are in Appendix A.4). The plots include the fitted line to summarize the relationship.

The results visualize a negative relationship of both common and idiosyncratic shock pass-through with sector price stickiness and market power for either industry or product classification. Together, price stickiness and average markup account for 53% (34%) of the variance in the common cost pass-through across NAICS4 (NAPCS7) sectors, and for 82% (65%) of the variance in the

[14] For example, Amiti, Itskhoki and Konings (2019) use proxies of competitors' costs as an instrument for competitors' prices. We discuss the differences and equivalence between our estimation approach and AIK in Appendix B.9.

idiosyncratic cost pass-through.[15]

The estimates for the common cost pass-through are in line with the model (Figure 1), which predict that pass-through declines with price stickiness and market power across sectors.

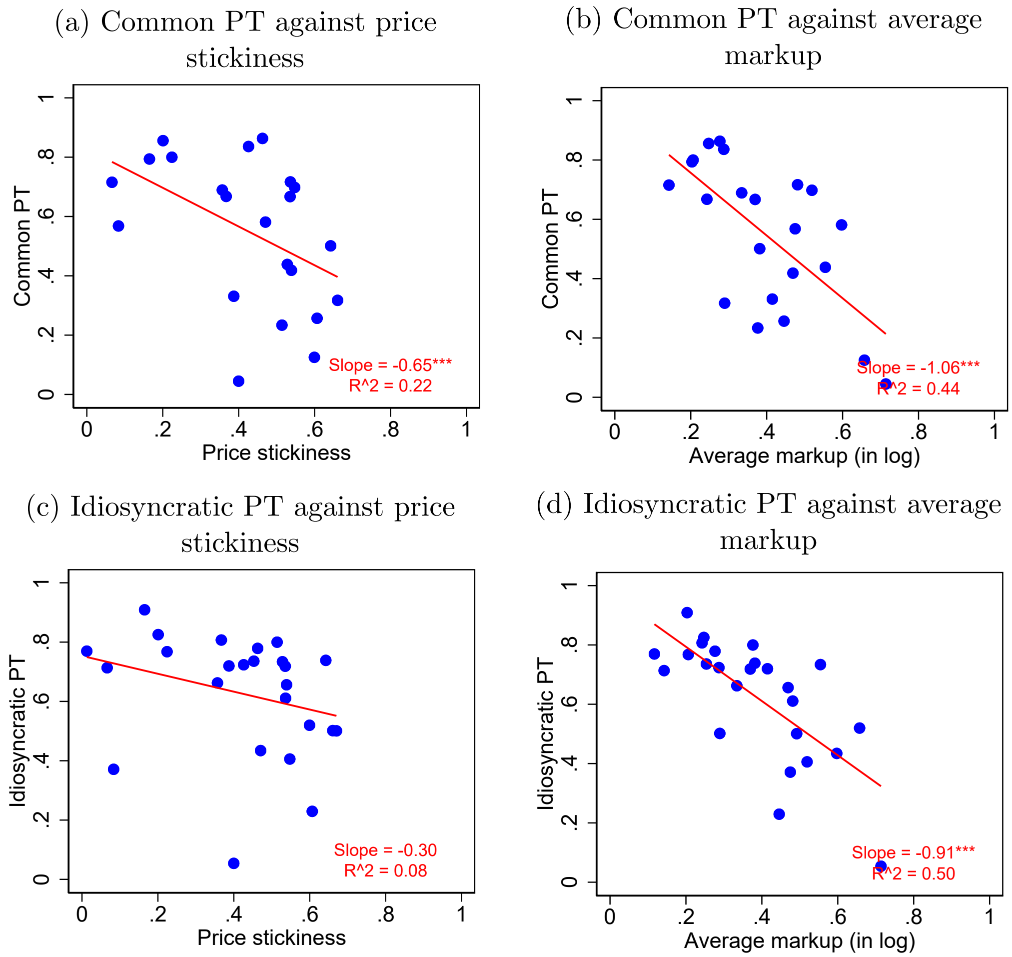

Figure 5: Estimates at the 4-digit NAICS wholesale industry level

Note: The figures plot the estimated selling price pass-through to common and idiosyncratic cost shocks against the average price stickiness and markup measured at the NAICS4 industry level. Specifically, we estimate $\Delta \ln(P_{ijt}) = \Psi_j \epsilon_{jt}^{Est} + \psi_j \epsilon_{ijt}^{Est} + FE_{ij} + \nu_{ijt}$ separately for each industry. For this graphical presentation, we have included only the industries with estimated pass-through rates in the range of $[-0.1, 1.1]$. The red line in each figure represents the fitted line obtained by regressing the estimated coefficients (Ψ_j^{Est}, ψ_j^{Est}) on the price stickiness λ_j or the average markup μ_j. The slope and the R^2 of the fitted line are reported in the bottom right corner of each figure.

Estimates for idiosyncratic cost pass-through are less clearly aligned with the model. Although pass-through significantly decreases with the average markup, the slope is not steeper than the

[15]The contribution of each variable is calculated as $|Cov(x_j, y_j)/Var(y_j)|$, where $y_j \in \{\Psi_j, \psi_j\}$ and $x_j \in \{\lambda_j, \mu_j\}$. Appendix A.5 provides detailed results.

slope of the common cost pass-through, as predicted by the model. Although price stickiness has a weaker influence on the idiosyncratic cost pass-through than the common cost pass-through, it is only for NAICS4 sectors that the slope is not statistically different from zero, and it is negative and significant for NAPCS7 sectors.

However, the negative relationship between idiosyncratic cost pass-through and price stickiness can be explained by the correlation between price stickiness and market power *across* sectors. In Appendix A.3, we document that sectors with high average markup tend to have stickier prices, with a slope of roughly 2/3: increasing a sector's average log markup from 0.2 to 0.6 corresponds to an increase in monthly price stickiness from 0.30 to 0.57, raising the average price duration by roughly one month. To the extent that higher price stickiness reflects higher market power (as opposed to higher price stickiness *given* market power), the slope in panel (c) of Figure 5 would be flatter if we controlled for the negative effect of market power on the pass-through.

4.3 Estimation results for all sectors

To incorporate cross-sector correlation, we now estimate (17) for observations in all sectors. We focus on NAICS4 estimates to summarize the main results and briefly summarize the NAPCS7 results (see Appendix A.4 for details). Table 2 provides estimated pass-through coefficients that capture variation in price stickiness and market power both across and within NAICS4 sectors.

To set the background, column (1) in Table 2 provides the estimated average pass-through coefficients across all wholesale firms in our sample. The average idiosyncratic pass-through of 0.65 is below the average common cost pass-through of 0.82. The theory predicts that both sticky prices and market power imply lower common cost pass-through. In particular, since the common cost pass-through should be 1 under flexible prices, the fact that the common cost pass-through is below 1 suggests an independent effect of price stickiness. As we demonstrated in Section 2, the model with market power and flexible prices predicts full pass-through of the common cost shock. Amiti, Itskhoki and Konings (2019)'s estimates imply that the average pass-through of a common shock is close to complete in their annual micro data, i.e., when prices are close to flexible. Our results validate the theoretical prediction that at higher frequencies the average common cost pass-through is incomplete due to infrequent price adjustments under oligopolistic competition.

Table 2: Pass-through estimates, 4-digit NAICS wholesale industries

	(1)	(2)	(3)	(4)	(5)	(6)
Common cost	0.82***	1.01***†	1.00***†	1.00***†	1.08***†	1.05***†
	(0.089)	(0.107)	(0.107)	(0.107)	(0.11)	(0.054)
Idio. cost	0.65***	0.72***	0.72***	0.72***	0.75***	0.88***
	(0.028)	(0.066)	(0.066)	(0.066)	(0.056)	(0.037)
Common cost × Sector stickiness		-1.16***	-1.02***	-1.00***	-0.96**	-0.70**
		(0.31)	(0.304)	(0.3)	(0.338)	(0.251)
Idio. cost × Sector stickiness		-0.18	-0.13	-0.13	0.03	-0.04
		(0.148)	(0.156)	(0.154)	(0.132)	(0.097)
Common cost × Firm stickiness			-0.20			
			(0.284)			
Idio. cost × Firm stickiness			-0.15			
			(0.082)			
Common cost × Firm-product stickiness				-0.20		
				(0.256)		
Idio. cost × Firm-product stickiness				-0.18*		
				(0.078)		
Common cost × High-markup industry					-0.29**	-0.29**
					(0.106)	(0.095)
Idio. cost × High-markup industry					-0.25***	-0.24***
					(0.046)	(0.042)
Common cost × High-markup firm						-0.05
						(0.186)
Idio. cost × High-markup firm						-0.33***
						(0.041)
Observations	136,085	136,085	136,085	136,085	136,085	136,085
Firm-product fixed effects	✓	✓	✓	✓	✓	✓
R^2	0.49	0.49	0.49	0.49	0.5	0.52

Notes: This table presents estimates for pass-through of common shocks and idiosyncratic shocks, interacted with indicators of sector/firm/firm-product stickiness and high sector/firm markups. The dependent variable is the firm-product selling price. Estimates are based on monthly price data, are weighted using sampling revenue weights, and are conditional on selling price adjustment (cases where the selling price is unchanged between periods are excluded). Common costs are identified via a first-stage regression of the firm-product purchase price on a sector-time fixed effect, where sector is defined as the firm's NAICS4 industry. Idiosyncratic shocks are defined as the residual of this first-stage regression. Standard errors are clustered at the firm level. ***, **, or * indicate the coefficient is statistically different from zero at the 1, 5, or 10 percent significance levels respectively, whereas † indicates the coefficient is not statistically different from one at the 1 percent significance level.

In the remaining regressions, reported in columns (2) through (6), we incorporate the interaction of common and idiosyncratic shocks with price stickiness across sectors. Furthermore, regressions reported in columns (3) and (4) include interactions with firm and firm-product price stickiness, and (5) and (6) add interactions with dummies for high-markup sectors and high-markup firms.

In line with the theory, the estimated idiosyncratic cost pass-through is independent of price stickiness at the sector and firm levels, and there is only a weak negative relationship at the firm-product level. On average, the pass-through of an idiosyncratic shock is about 70%, implying the underlying degree of strategic complementarity of $\varphi \approx 0.43$ in our model with *ex ante* identical sectors.

In contrast to idiosyncratic cost pass-through, the pass-through of the common cost shock decreases with sector price stickiness, as our theory predicts. For a sector with flexible prices, the pass-through is close to 1 (and not statistically different from 1), consistent with the findings in Amiti, Itskhoki and Konings (2019). As sector price stickiness rises, the pass-through declines quickly: for each additional 10 percentage point fall in price flexibility, the common cost pass-through falls by 10 percentage points for NAICS4 industries (and by 3 percentage points for NAPCS7 products). Our theory attributes this relationship to strategic pricing complementarity among firms in the sector. Intuitively, knowing its competitors' prices cannot accommodate the common shock (due to sticky prices), a firm uses its price change opportunity to adjust its markup, leading to an incomplete pass-through of the shock. The interaction terms with the common cost shock in columns (2), (3), and (4) confirm that this result is mostly driven by sector-level price stickiness rather than by firm or firm-product price stickiness.

For a given degree of sector price stickiness, both common and idiosyncratic pass-through decrease with market power of the sector (column 5 in Table 2), in line with the theory in Figure 1(b). Incorporating differences in market power within sectors (column 6) further lowers pass-through, especially for idiosyncratic shocks. When market power measures are included, the estimated effect of sector price stickiness on the common cost pass-through is somewhat more muted, reflecting the idea that some of the variation in price stickiness may be due to differences in market power across sectors and firms, as we discussed in Section 4.2.

All in all, the empirical results using NAICS4 classification corroborate all six predictions of the model for reset price pass-through: unit common cost pass-through and below-unit idiosyncratic cost pass-through under flexible prices; declining common cost pass-through and flat idiosyncratic cost pass-through for stickier sectors; declining pass-throughs with market power (and a steeper decline for idiosyncratic cost pass-through).

The estimation results are generally similar when sectors are defined according to the NAPCS7 product classification. Differences in the magnitude and significance of some estimates could reflect differences in the measurement of price stickiness and market power. In particular, since there is a smaller number of firm-products surveyed within each 7-digit NAPCS product classification than in the 4-digit NAICS industry classification, the measure of sector price stickiness may be less accurate due to noise stemming from adjustments of individual firms or products.

5 Implications for aggregate dynamics

In this section, we discuss the aggregate implications of our micro estimates and quantify the importance of firms' market power and its heterogeneity across sectors in amplifying the real effects of monetary policy. We start by characterizing sector and aggregate price and output dynamics in response to a 1% unanticipated permanent shock to the money supply in the benchmark setting.

Proposition 3 *The sector and aggregate responses to a 1% unanticipated permanent monetary shock at $t = 0$ (i.e., $\widehat{M}_\tau = 1 \; \forall \tau \geq 0$) are characterized as follows:*

(i) The sector price, inflation and output responses are given by

$$\widehat{P}_{j\tau} = 1 - \Lambda_j^{\tau+1}, \quad \widehat{\pi}_{j\tau} = (1 - \Lambda_j)\Lambda_j^{\tau} \quad \textit{and} \quad \widehat{c}_{j\tau} = 1 - \widehat{P}_{j\tau} = \Lambda_j^{\tau+1} \qquad \forall \tau \geq 0, \tag{18}$$

where $\Lambda_j \geq \lambda_j$ is the market power augmented price stickiness defined in (12).

(ii) The aggregate price response is given by

$$\widehat{P}_\tau = \sum_j \alpha_j \widehat{P}_{j\tau} = (1 - \lambda)\widehat{P}_{\tau,\tau} + \lambda \widehat{P}_{\tau-1} - Cov_j \left[\lambda_j, \frac{1 - \Lambda_j}{1 - \lambda_j} \Lambda_j^{\tau}\right] \qquad \forall \tau \geq 0, \tag{19}$$

where $\lambda \equiv \sum_j \alpha_j \lambda_j \equiv E_j(\lambda_j)$ is the average price stickiness in the economy and $\widehat{P}_{\tau,\tau} \equiv \sum_j \alpha_j \widehat{P}_{j\tau,\tau}$

is the average reset price.

(iii) The cumulative output response is given by

$$\sum_j \alpha_j \sum_{\tau=0}^{\infty} \widehat{c}_{j\tau} = E_j\left[\frac{\lambda_j}{1-\lambda_j}\right] E_j\left[\frac{\Lambda_j(1-\lambda_j)}{\lambda_j(1-\Lambda_j)}\right] + Cov_j\left[\frac{\lambda_j}{1-\lambda_j}, \frac{\Lambda_j(1-\lambda_j)}{\lambda_j(1-\Lambda_j)}\right]. \tag{20}$$

Proof. *See Appendix B.4.*

There are two key takeaways from Proposition 3. First, market power amplifies the sluggishness in sector price adjustments in response to a monetary shock and leads to a larger real impact in each sector. Since Λ_j is an increasing function of market power φ_j, the sectors with higher market power increase their prices at a slower rate, as shown in (18).

Second, sector heterogeneity plays a role in further amplifying aggregate responses. Expression (19) shows that the aggregate price response can be decomposed as the average of adjusted and non-adjusted prices weighted by the average price stickiness, $(1-\lambda)\widehat{P}_{t+\tau,t+\tau} + \lambda\widehat{P}_{t+\tau-1}$, and an additional covariance term. In a standard Calvo model ($\varphi_j = 0$), the covariance term simplifies to $Cov_j\left[\lambda_j, \lambda_j^{\tau}\right] \geq 0$. As noted by Carvalho (2006), most price adjustments after the monetary shock are made by firms in more flexible sectors. As time passes, a larger proportion of prices that have yet to adjust are from stickier sectors, slowing the aggregate price adjustment. The covariance term captures this effect.

With market power ($\varphi_j \neq 0$), there are two additional effects. First, even when market power is homogeneous across sectors ($\varphi_j = \varphi$), $\Lambda_j > \lambda_j$ implies a larger covariance term. Strategic complementarities reduce the size of price adjustments, amplifying the effect of heterogeneity in price stickiness. A similar effect was emphasized by Carvalho (2006) in a model with monopolistic firms and real rigidities. Second, when sectors have different market powers, the heterogeneity in market power may amplify or attenuate the real effects of monetary shocks depending on the correlation between market power φ_j and price stickiness λ_j. Intuitively, when market power is positively correlated with price stickiness, sticky sectors not only make slower price adjustments (due to a high λ_j) but also smaller price adjustments (due to a high φ_j) than flexible sectors.

Expression (20) provides a decomposition of the cumulative output response. The term $E_j\left[\frac{\lambda_j}{1-\lambda_j}\right]$ gives the cumulative output response in a standard heterogeneous sector monopolistically competitive Calvo model. The multiplier $E_j\left[\frac{\Lambda_j(1-\lambda_j)}{\lambda_j(1-\Lambda_j)}\right]$ summarizes the amplification effect of firms' market power on the aggregate output response. Lastly, $Cov_j\left[\frac{\lambda_j}{1-\lambda_j}, \frac{\Lambda_j(1-\lambda_j)}{\lambda_j(1-\Lambda_j)}\right]$ is a term analogous to the covariance term in (19), highlighting the importance of the correlation between firms' market power and price stickiness across sectors. We note that Wang and Werning (2022) derived an expression similar to (20) in their continuous-time model. A contribution of our paper is to empirically quantify the relative importance of these channels.

5.1 Role of market power in homogeneous sector models

To unpack the mechanisms influencing inflation dynamics, we discuss aggregate dynamics in different versions of the model, where we separately shut down the effects of strategic complementarity and sector heterogeneity in price stickiness and strategic complementarity. To facilitate this exercise, it is useful to first consider impacts in a homogenous sector version of the model, which yields the following corrollary.

Corollary 1 *With symmetric firms and homogeneous sectors (i.e., $\varphi_{ij}=\varphi$, $\lambda_j=\lambda$), the NKPC is given by*

$$\widehat{\pi}_t = \frac{(1-\beta\lambda)(1-\lambda)}{(1+\varphi)\,\lambda}\widehat{mc}_t + \beta\mathbb{E}_t\widehat{\pi}_{t+1}, \tag{21}$$

where $\widehat{mc}_t$ is the real marginal cost. With market power ($\varphi\neq 0$), the slope of NKPC is reduced by a factor of $1/(1+\varphi)$. In response to a permanent monetary shock, the sector price, inflation and output dynamics are given by

$$\widehat{P}_\tau = 1-\Lambda^{\tau+1}, \quad \widehat{\pi}_\tau = (1-\Lambda)\Lambda^\tau \quad \textit{and} \quad \widehat{c}_\tau = \Lambda^{\tau+1} \quad \forall\tau\geq 0, \tag{22}$$

where

$$\Lambda \equiv \frac{1}{2}\left[\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)} - \sqrt{\left(\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)}\right)^2 - \frac{4}{\beta}}\right]. \tag{23}$$

With market power ($\varphi\neq 0$), the cumulative output response is amplified by $\frac{\Lambda(1-\lambda)}{\lambda(1-\Lambda)}$ relative to an alternative model with the same level of price stickiness but no market power.

Proof. *See Appendix B.3.*

Under oligopolistic competition, the slope of the NKPC in the homogeneous sector model is reduced by a factor of $\frac{1}{1+\varphi}$ relative to the slope under monopolistic competition. At the level of strategic complementarity implied by the idiosyncratic cost pass-through estimated in Section 4, $\varphi^{Data} = 0.43$, the slope of NKPC is reduced by 30%, implying a 28% larger cumulative output response. This effect of strategic complementarity is substantial. For example, if markups were to increase by 10 percentage points over the next decade—the decennial rate of increase in market power over the last four decades documented in De Loecker, Eeckhout and Unger (2020)—the NKPC would flatten by an additional 12%.[16] Our empirical evidence supports conclusions in Mongey (2021) and Wang and Werning (2022) that models with a reasonable degree of oligopolistic competition provide significant amplification of the effects of nominal rigidities in standard New Keynesian models.

5.2 Role of sector heterogeneity

How does sector heterogeneity affect this amplification effect? In this subsection, we quantify the importance of the channels highlighted in Proposition 3 using a multi-sector oligopolistic competition model that is calibrated to match the sector price stickiness λ_j and market power φ_j estimated in Section 4.2.[17] To dissect the underlying channels, we compare the aggregate dynamics in our benchmark model with three counterfactual alternative models that shut down one of the channels at a time.

Panel (a) of Figure 6 compares output impulse responses to an unanticipated 1% permanent monetary shock in four different models. The gray line shows the baseline output response to a monetary shock in the standard one-sector monopolistic competition Calvo model, where aggregate dynamics are given by (22) with $\Lambda = \lambda = 0.42$ calibrated to match the average price stickiness in the data. The black line shows the response from an alternative monopolistic competition Calvo model with sector heterogeneity in price stickiness, calibrated to match the average price stickiness in each 4-digit NAICS industry. Both models have the same aggregate price stickiness, and the difference

[16] Our estimated $\varphi^{Data} = 0.43$ and mean log markup $\ln(\mu^{Data}) = 0.34$ suggest an elasticity of substitution $\theta = 4.8$. A 10 percentage point increase in the markup level implies $\ln(\mu^{new}) = 0.41$. Assuming the same elasticity of substitution, this implies $\varphi^{new} = 0.73$ and thus $1/(1 + \varphi^{new}) = 0.58$.

[17] Specifically, we calibrate the sector market power using the estimated pass-through to idiosyncratic cost shocks in each sector, i.e., $\varphi_j^{Est} = 1 - 1/\psi_j^{Est}$ and use Propositions 2 and 3 to calculate Λ_j and the aggregate dynamics.

in output responses reflects the role of sector heterogeneity in price stickiness, as discussed by Carvalho (2006). The red line shows the output response allowing for homogeneous market power (with $\varphi = 0.43$) and heterogeneous price stickiness. Finally, the blue line shows the response in our benchmark model calibrated to match the heterogeneity in both φ_j and λ_j found in the data.

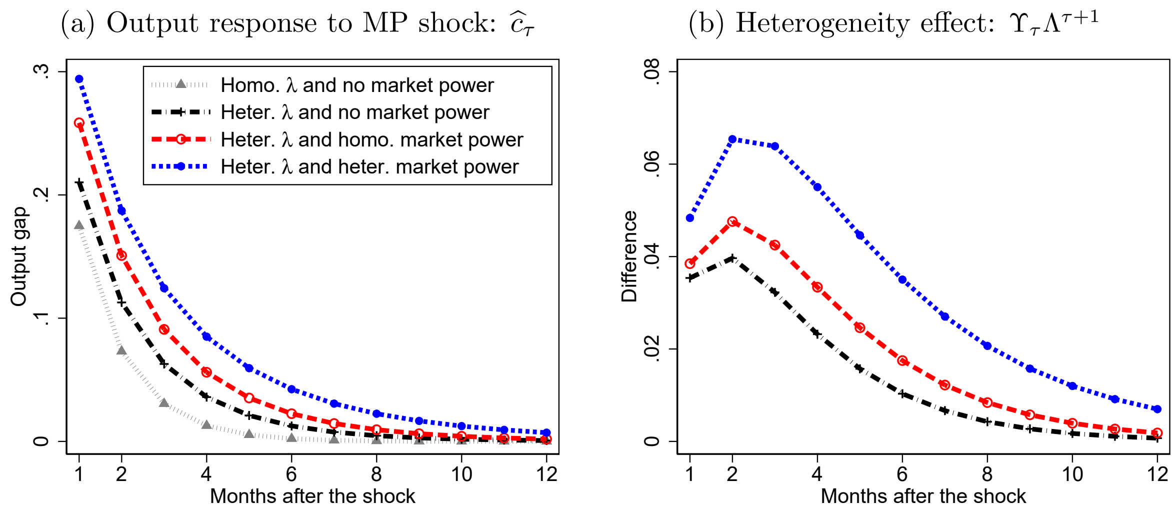

Figure 6: Amplification of monetary non-neutrality due to sector heterogeneity

Notes: The figure provides responses to an unanticipated permanent 1% increase in the money supply. Panel (a) reports output impulse responses. Panel (b) reports the difference between the aggregate output response and the response in an alternative homogeneous sector model with the same aggregate Λ. Models are based on weighted estimates from NAICS4 industries.

The difference in output responses combines the effects of strategic pricing complementarity and heterogeneity in market power and price stickiness. To distinguish the heterogeneity effect, we rewrite the output response into two terms using the relationships (18) and (19) in Proposition 3:

$$\widehat{c}_\tau = 1 - \widehat{P}_\tau = \Lambda^{\tau+1} + \underbrace{\Upsilon_\tau \Lambda^{\tau+1}}_{\text{heterogeneity effect} \geq 0}, \tag{24}$$

where $\Lambda \equiv \sum_j \alpha_j \Lambda_j$, and $\Upsilon_\tau \equiv \sum_j \alpha_j \Lambda_j^{\tau+1}/\Lambda^{\tau+1} - 1 \geq 0$ represents the additional output amplification due to sector heterogeneity (in price stickiness, market power, or both).[18] For comparison, we calibrate an alternative homogeneous sector model with the same Λ so that the difference in output responses in the two models can be attributed to sector heterogeneity.

[18] Note that $\Upsilon_\tau \geq 0$ by Jensen's inequality.

Panel (b) of Figure 6 shows the additional output response due to sector heterogeneity. Comparing the red and black lines, we see that allowing for homogeneous market power leads to a small additional amplification of the output response through sector heterogeneity in price stickiness. Comparison of the blue and red lines shows that heterogeneity in market power significantly amplifies the output response. This amplification is driven by the positive correlation between price stickiness and market power observed in the wholesale price data.[19] In a counterfactual model in which the market power is heterogeneous but randomly assigned (i.e., it is uncorrelated with price stickiness), the output response is similar to the red line with homogeneous market power.

Summary. Table 3 summarizes the key quantitative takeaways for the models we discussed in this section. For each version of the model, Table 3 reports three statistics: (1) the cumulative output response to an unanticipated permanent 1% increase in money supply, (2) the price stickiness multiplier required to match the output response, and (3) the implied slope of the NKPC. Column (1) provides the statistics for the baseline model—the standard one-sector Calvo model with monopopolistic competition ("MC(1)"). The statistics for other versions of the model are expressed as ratios to the corresponding baseline statistics. Panels (a) and (b) of Table 3 report statistics based on NAICS4 and NAPCS7 estimates, respectively (we will focus on Panel (a)).

Relative to the MC(1) baseline, the output response is amplified by 1.24 in the model with heterogeneity in price stickiness (column 3), by 1.57 when there is homogeneous strategic complementarity and heterogeneity in price stickiness (column 4), and by 1.96 when both strategic complementarity and price stickiness vary across sectors (column 5). We can approximate these effects using a standard one-sector Calvo model in which nominal price stickiness λ is increased by a factor of 1.13, 1.27, and 1.40, respectively.[20]

In sum, our empirical estimates imply a substantial degree of strategic pricing complementarity

[19] More precisely, the amplification or attenuation effect depends on the correlation between the relevant market power component in Λ_j, i.e., $\varphi_j/(1+\varphi_j)$, and the price stickiness λ_j across sectors. In the wholesale price data, this correlation is positive at about 0.3 (Figure B3).

[20] At the aggregate level, a calibrated one-sector Calvo model with Kimball demand can match both the average price stickiness and the *total* real impact of a monetary shock in the models in Table 3. For example, assuming $\theta = 4.8$ (as in our benchmark model), the cumulative output response in the homogeneous sector oligopolistic competition model in column 2 of Table 3 can be matched in the one-sector Calvo model with Kimball demand by setting the Kimball demand superelasticity to 1.63, while matching the cumulative output response in our benchmark model in column 5 requires a superelasticity of 6.76. See Appendix B.8 for more details.

Table 3: Statistics in a multi-sector oligopoly model with sticky prices

Statistic	Baseline MC(1) $(\lambda, \varphi = 0)$	× Relative to Baseline OC(1) (λ, φ)	MC(J) $(\lambda_j, \varphi = 0)$	OC(J) (λ_j, φ)	OC(J) (λ_j, φ_j)
	(1)	(2)	(3)	(4)	(5)
(a) NAICS4 sectors					
Output Response	0.72	1.28	1.24	1.57	1.96
Price Stickiness	0.42	1.15	1.13	1.27	1.40
Slope of NKPC	0.81	0.70	0.73	0.52	0.36
(b) NAPCS7 products					
Output Response	0.82	1.27	1.47	1.84	2.38
Price Stickiness	0.45	1.13	1.21	1.33	1.47
Slope of NKPC	0.67	0.70	0.56	0.40	0.26

Notes: The table provides model statistics based on weighted estimates from NAICS4 industries (Panel a) and NAPCS7 products (Panel b). The first row of each panel reports the cumulative response of aggregate output (in %) to an unanticipated permanent 1% increase in the money supply. The second row of each panel reports price stickiness λ in a standard monopolistically competitive model in column (1) that implies the output response in the alternative version of the model. The third row of each panel reports the implied slope of NKPC. Column (1) gives the statistics for the standard one-sector Calvo model with monopolistic competition ("MC(1)"), where price stickiness is equal to the weighted mean price stickiness in the data. Statistics for models in columns (2)–(5) are expressed relative to statistics for MC(1). Column (2) reports the results for an oligopolistically competitive model with homogeneous sectors ("OC(1)"), where λ is set to the weighted mean price stickiness in the data and $\varphi = 0.43$. Column (3) reports statistics for an MC model with heterogeneous sectors ("MC(J)"), where the price stickiness in each sector is calibrated to match the data. Column (4) reports statistics for an OC model with heterogeneity in price stickiness and homogeneous market power, where $\varphi = 0.43$. Column (5) reports statistics for an OC model with heterogeneity in both price stickiness and market power, calibrated to match the estimates in Section 4.2.

in oligopolistic markets. The slope of NKPC in the multi-sector model that matches the heterogeneity in price stickiness and strategic complementarity observed in the data is only one-third of the slope in the standard one-sector model without real rigidities. Of the 64% difference in slope (column 5), 30 percentage points are due to the average effect of oligopolistic competition without sector heterogeneity (column 2), an additional 18 percentage points are due to heterogeneity in price stickiness (column 4), and the remaining 16 percentage points capture the positive correlation of price stickiness and market power across sectors.

6 Conclusions

Using unique data from Canadian wholesalers, we present evidence that firm-product price adjustments depend on the degree of market power and price stickiness within and across sectors. The estimated pass-through of idiosyncratic and common cost components to wholesale prices are in line with predictions of a model with oligopolistic distributors and sticky prices. Through the lens of our model, our estimates suggest that strategic pricing complementarity in the wholesale industry is substantial, e.g., reducing the slope of the NKPC by 30% in a one-sector model and by 64% in a multi-sector model.

The main takeaway is that, in oligopolistic markets, inflation dynamics and transmission of monetary policy or exchange rate shocks depend on the joint distribution of market power and price stickiness in the economy. Future research could explore how this joint distribution evolves over time. For example, if markups were to rise faster in more concentrated sectors, the NKPC would flatten more than if markups were to grow equally across sectors, because more concentrated sectors tend to have stickier prices. Future work should also study how market power influences the transmission of monetary policy in the wake of large inflation swings, such as those observed in the aftermath of the 2020–2022 COVID-19 pandemic. To account for the variation in price flexibility during such events (Montag and Villar, 2023; Cavallo and Kryvtsov, 2024), one needs to incorporate *endogenous* price flexibility in oligopolistic models with sector heterogeneity. Finally, future analyses could focus on how other sources of strategic pricing complementarities—due to non-CES preferences (Kimball, 1995), intermediate inputs (Basu, 1995), firm-specific production factors (Altig, Christiano, Eichenbaum and Lindé, 2011), or "real flexibilities" (Dotsey and King, 2006)—influence inflation dynamics in oligopolistic environments.

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A Data Appendix

A.1 Data cleaning process

Our empirical analysis relies on two raw micro datasets. The first is the monthly WSPI micro data file. This includes information on monthly wholesale purchase prices and selling prices for individual firm-products. It also includes other information we use in our analysis and to inform the cleaning process. The second dataset is the weights file, which is developed to be merged with the WSPI for the purpose of providing a representative sample to construct the WSPI. We discuss more details about both these files below.

The raw micro data has not been cleaned prior to our receiving the data, and none of the prices in our data are imputed. Prior to constructing the WSPI, Statistics Canada conducts various error detection tests and excludes some outliers and anomalies in the data. More generally, Statistics Canada dedicates resources to ensuring any reported price changes in the survey are not contaminated by structural changes to the product definition, including product reclassifications or changes in units. The survey's data collection strategy is designed to ensure that targeted response rates are met every cycle, and the survey receives about a 75% response rate. Following this, an imputation process is undertaken to achieve 100% coverage for the published price index.

The survey is stratified by NAICS5 codes. The largest establishments in a given NAICS industry are selected as "take-all" (100% probability), with remaining establishments selected with probabilities that are proportional to their revenue. To construct the index, individual respondents are assigned weights based on establishment revenues and industry gross margins to arrive at a representative sample of wholesale sector prices. New survey participants are introduced to the survey through telephone calls, where respondents are guided through a process of selecting representative products. The data are updated (and revised) quarterly, where respondents are asked to answer the survey based on information from the preceding three months. The sample of respondents for the price file is updated roughly every five years. The weights file is updated, along with the sample update, roughly every five years. The sample used for this analysis was last updated in May 2023.

The price file includes several variables that correspond in some fashion to firm/establishment/firm-product identifiers: (1) the "PID" is intended to uniquely identify each firm-product in the data. It is assigned by the Producer Price Division (PPD) based on the Generic Processing System (GPS) and serves as our primary unit of analysis in the paper; (2) the "PPDID" is assigned by the PPD and is intended to correspond one-to-one with the establishment level from Statistics Canada's Business Register (BR); the PPDID is the sampling unit for the WSPI survey; (3) the "Operating Entity Number" is also intended to correspond one-to-one with the establishment level and is taken directly from the value reported in the BR; and (4) the "Enterprise Number" is intended to correspond one-to-one with the enterprise level and is taken directly from the value reported in the BR.[21] Also included are classification codes for the NAICS5 industry that the reporting firm is associated with and the NAPCS7 product code that the firm-product is associated with.

The price file also includes information on the country of origin of the product, the currency that product prices are reported in, and several flags that help to ascertain the quality of the data. There are two variables that provide information on the country of origin of the product. One is an "imported" binary variable that takes the value of 1 if imported and 0 if not imported. The second is an "origin" variable that takes different values that each correspond to a specific country of origin. In terms of currency, there are separate "currency of purchase price" and "currency of selling price" variables included in the data. In terms of flags, there is a "product change" flag that identifies cases where the product name appears to change, a "non comparable" flag that identifies where the series appears to have changed in a significant way that suggests a break in the series, and an "exclude" flag that identifies outlier observations based on the patterns observed in that particular firm-product over the periods around that observation. The "non comparable" and "exclude" flags also have associated variables that provide the reason for these flags based on a defined set of possible reasons. All these flags are introduced by analysts in the PPD and not entered by the survey respondents.

The price file sample that we use begins in January 2013. The data are currently available up to 2024, but we drop all observations past December 2019 to exclude the COVID-19 pandemic period.

[21] An "enterprise" (also referred to as a "firm") is defined as an institutional unit that directs and controls the allocation of resources relating to business operations and for which financial statements are maintained. An "establishment" (also referred to as a "plant") is below the enterprise in the statistical hierarchy and is defined as the most homogeneous unit of production for which the business maintains accounting records.

The weights file includes two sub-files: one for the 2013 reference period (released in the second quarter of 2016) and one for the 2020 reference period (released in the third quarter of 2022). Each weight in a given file is intended to correspond uniquely to a single PPDID in the corresponding WSPI file. However, there are cases where a single PPDID is reported in both sampling periods, so that one PPDID has a weight reported in each weight file. In these cases, we use the weight from the older weight sample. In some cases the weight is missing in one weight sample but is available in the other. In these cases, we use the weight that is available. These files includes several weights that we use. The first is a "revenue weight," derived from establishment revenue data based on Statistics Canada's BR and industry gross margins based on the Annual Wholesale Trade Survey micro data.[22] The second is a "design weight," equal to the inverse of the firm's selection probability, induced by the sample design. This weight can be interpreted as the number of times that each sampled establishment should be replicated to represent the entire population. Finally, a "sampling revenue weight" is equal to the product of the revenue weight and the design weight and represents the relative importance of the establishment in the industry. It is used to construct an index that is representative of the aggregate.

Once the WSPI file is merged with the weights file, we initially apply a few small cleaning procedures. In terms of hierarchical structure, a single enterprise might nest several establishments, but a single establishment should not nest several enterprises. So we drop cases where multiple Enterprise Numbers are associated with a single Operating Entity Number or PPDID. The PPDID and the Operating Entity Number are supposed to map one-to-one with one another, so we also drop cases where this mapping is not one-to-one. Once that procedure is applied, we are left with roughly 420,000 observations.

From there, we identify cases where the "imported" variable is 0 but the "origin" variable indicates a foreign origin. We assume the "origin" variable is correct and re-code the "imported" variable to 1. Also, in cases where the "imported" variable is missing, we assume the good is not imported and re-code the variable to 0. We drop observations where the currency of the reported selling or purchase price is in a currency other than Canadian dollars, US dollars, or euros.[23] In

[22]The revenue weight corresponds one-to-one with the wholesale establishment level.

[23]Note that this only affects a small number of observations.

cases where the currency reported is either US dollars or euros, we apply the bilateral monthly exchange rate and convert the price into Canadian dollars. We also drop cases where the firm-product margin is less than 1, indicating that the selling price is lower than the purchase price, and drop observations where the selling price or purchase price changes by more than 100% between consecutive months. We drop cases where a single PID is reported for only one period in the data.

For cases where the "product change" flag is 1, we reclassify the product so that a new PID is assigned. We drop observations where there is an "exclude" flag and cases where there is a "non comparable" but not a "product change" flag (since these are reclassified as new products). We also drop observations where the selling price or purchase price is either missing or zero, and where the establishment revenue weight is either missing or non-positive.

After all of these changes, we are left with roughly 280,000 observations in the cleaned sample.[24]

A.2 Additional descriptions of the data

The breakdown of the average number of products per firm across periods in our cleaned sample is reported in Table A1. We produce this by constructing a new variable equal to the number of PIDs associated with each PPDID per period, and then tabulating the share of this variable in the total sample that falls under 1, 2, 3, 4, and 5+.

Table A1: Number of products per firm in cleaned WSPI sample

	1	2	3	4	5+
Share of firms	9%	15%	67%	3%	6%

Our sample covers 90 months, from January 2013 to December 2019. Table A2 reports the number of observations per firm-product, calculated by creating a new variable that is equal to the number of observations per PID in the sample and then classifying each PID according to which bin this number falls into (e.g., 1–20, 20–40, etc.). As depicted in the table, 75% of products include more than 20 observation months. This feature of the data is attractive in that most of our analysis will rely on product-level cross-time variation, and so a long sample period at the product level is desirable.

[24] Most of the roughly 140,000 observations that are dropped are removed due to missing prices.

Table A2: Number of observation months per firm-product in cleaned WSPI sample

	1–20	21–40	41–60	61–80	80–100
Share of observations	25%	24%	26%	20%	6%

Survey respondents are asked what currency the purchase price and selling price are reported in. Table A3 reports the share of observations in the cleaned dataset that are reported in Canadian dollars and US dollars. Roughly 96% (97%) of respondents report purchase (selling) prices in Canadian dollars, and nearly all the rest report in US dollars. In cases where the currency reported is either US dollars or euros, we apply the bilateral monthly exchange rate and convert the price into Canadian dollars.

Table A3: Currency of prices reported in cleaned WSPI sample, shares

	Purchase prices	Selling prices
Canadian dollar	0.96	0.97
US dollar	0.04	0.03

In terms of the origin of the products reported in the data, we can group products into three different types: domestic goods, goods imported from the US, and goods imported from non-US countries. In the aggregate sample, 44% of goods originate from the domestic economy, 32% originate from the US, and the remaining 25% (rounded) originate from other countries (non-US). This breakdown, however, is different from industry to industry. Figure A1 reports the breakdown separately for each NAICS3 industry, where the heterogeneity is clear. For example, the domestic economy is the top source of goods in most industries, but the US is the most common origin for goods in the "Machinery, equipment and supplies" industry, and non-US foreign economies are the most common origin for goods in the "Personal and household goods" industry. This heterogeneity provides one foundation for heterogeneity in exposure to shocks across industries. For example, industries that are more reliant on imported goods would be more exposed to exchange rate shocks and foreign common shocks.

Figure A2 reports the average size of purchase and selling price changes in the sample for each NAICS3 industry. The cross-industry heterogeneity in this figure is fairly similar to the pattern

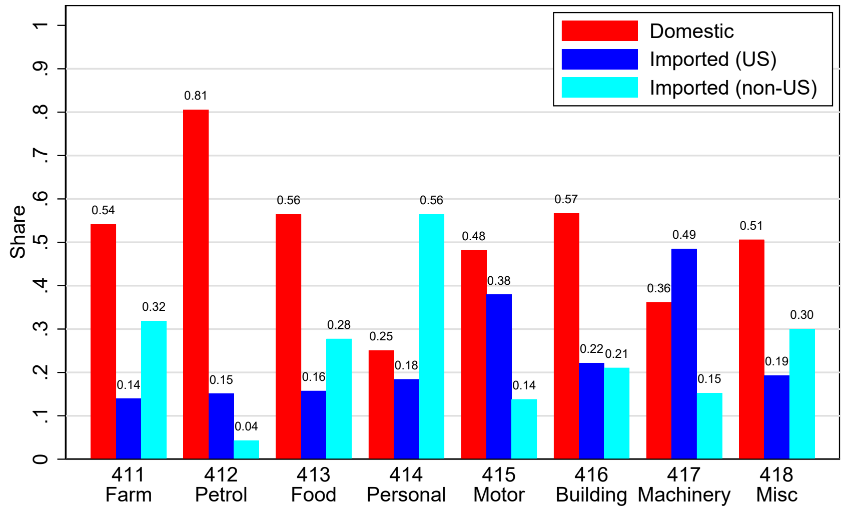


Figure A1: Origin of products by 3-digit NAICS wholesale industry

Notes: Reports the design-weighted mean of product origins across all observations in the sector.

observed in Figure 2, which reports the average fraction of price changes across industries. The average size of price change is equal to the average fraction of price changes times the size of the price change conditional on adjustment, so the positive correlation here indicates that the fraction of price adjustments plays a large role in determining average price changes.

Figure A3 reports a histogram for the (log) markup across firm-products in our cleaned sample. The important thing to note is that the distribution is far from uniform, indicating a high degree of heterogeneity.

Figure A4 reports scatter plots for the correlation between selling and purchase price stickiness across industries and products for NAICS4 and NAPCS7 classifications. The figure is very similar to Figure 3 except, in this case, prices within each industry or product group are weighted by sampling revenue.

Our analysis relies on firm and product classifications according to NAICS4 industry codes and NAPCS7 product codes. The firms surveyed for the WSPI are each classified to a single NAICS code under the 2-digit "wholesale trade" industry (NAICS 41). The complete list of 25 NAICS4 codes under NAICS 41 (i.e., the set of codes assigned to the firms in the WSPI survey) is reported in Table A4. Each firm-product is assigned to a single NAPCS7 product code under the 3-digit

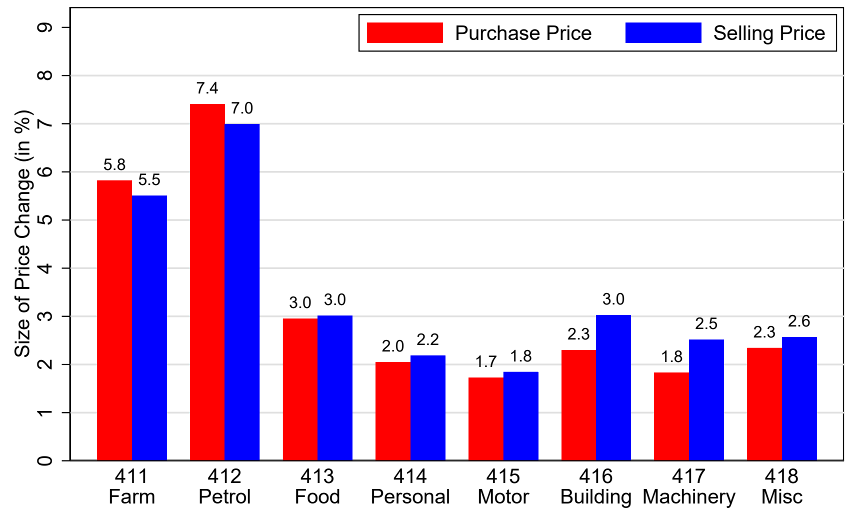


Figure A2: Average size of price changes by 3-digit NAICS wholesale industry

Notes: Reports the design-weighted mean size of price changes across all observations in the sector.

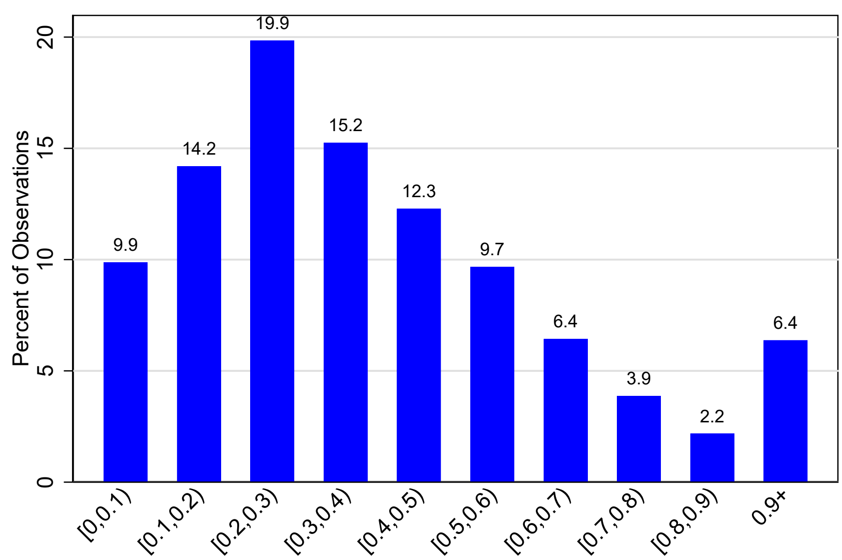


Figure A3: Histogram of markup across firm-products, pooled sample

Notes: Reports the design-weighted distribution of markups across firm-products in the sample.

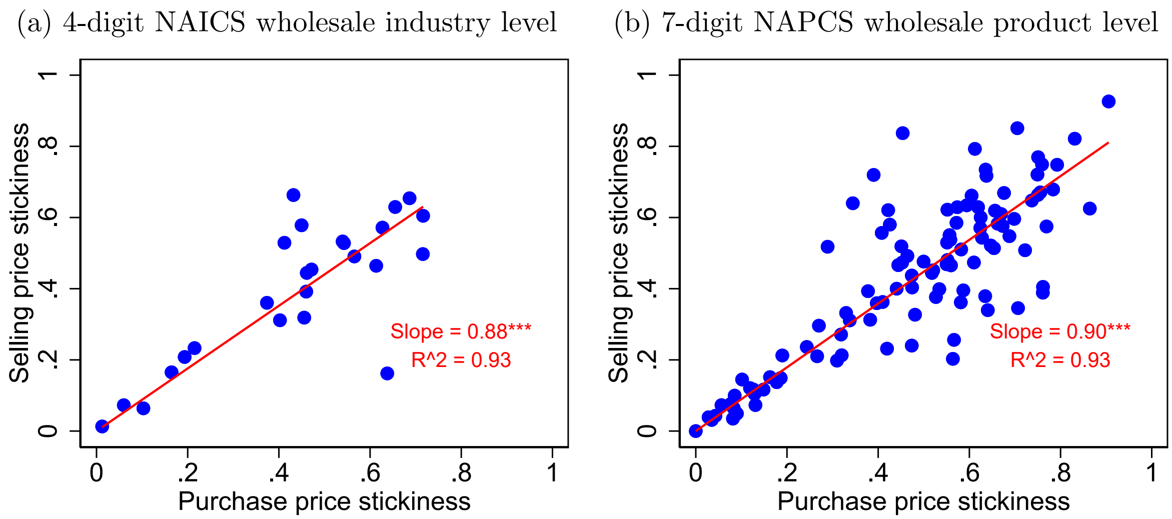


Figure A4: Selling and purchase price synchronization at the industry and product levels (weighted)

product group "Wholesale services (except commissions)" (NAPCS 551). Our cleaned dataset includes 166 NAPCS7 codes under NAPCS 551 (i.e., the set of codes assigned to the products in the WSPI survey). See this link for the complete list of NAPCS product codes.

Table A4: 4-digit NAICS wholesale industries

NAICS	Industry Description
4111	Farm product merchant wholesalers
4121	Petroleum and petroleum products merchant wholesalers
4131	Food merchant wholesalers
4132	Beverage merchant wholesalers
4133	Cigarette and tobacco product merchant wholesalers
4134	Cannabis merchant wholesalers
4141	Textile, clothing and footwear merchant wholesalers
4142	Home entertainment equipment and household appliance merchant wholesalers
4143	Home furnishings merchant wholesalers
4144	Personal goods merchant wholesalers
4145	Pharmaceuticals, toiletries, cosmetics and sundries merchant wholesalers
4151	Motor vehicle merchant wholesalers
4152	New motor vehicle parts and accessories merchant wholesalers
4153	Used motor vehicle parts and accessories merchant wholesalers
4161	Electrical, plumbing, heating and air-conditioning equipment and supplies merchant wholesalers
4162	Metal service centres
4163	Lumber, millwork, hardware and other building supplies merchant wholesalers
4171	Farm, lawn and garden machinery and equipment merchant wholesalers
4172	Construction, forestry, mining, and industrial machinery, equipment and supplies merchant wholesalers
4173	Computer and communications equipment and supplies merchant wholesalers
4179	Other machinery, equipment and supplies merchant wholesalers
4181	Recyclable material merchant wholesalers
4182	Paper, paper product and disposable plastic product merchant wholesalers
4183	Agricultural supplies merchant wholesalers
4184	Chemical (except agricultural) and allied product merchant wholesalers
4189	Other miscellaneous merchant wholesalers

A.3 Measures of price stickiness and market power

Measures of the average degree of price stickiness are constructed as follows:[25]

$$\lambda_j = 1 - \frac{1}{2}\frac{\sum_{i\in I_j}\sum_{t\in T_{ij}} \omega_{ij}^E \left\{\mathbb{1}\left[\Delta\ln(P_{ijt}) \neq 0\right] + \mathbb{1}\left[\Delta\ln(Q_{ijt}) \neq 0\right]\right\}}{\sum_{i\in I_j}\sum_{t\in T_{ij}} \omega_{ij}^E}, \quad \text{(Sector price stickiness)}$$

$$\lambda_{fj} = 1 - \frac{1}{2}\frac{\sum_{i\in I_f}\sum_{t\in T_{ij}} \omega_{ij}^E \left\{\mathbb{1}\left[\Delta\ln(P_{ijt}) \neq 0\right] + \mathbb{1}\left[\Delta\ln(Q_{ijt}) \neq 0\right]\right\}}{\sum_{i\in I_f}\sum_{t\in T_{ij}} \omega_{ij}^E}, \quad \text{(Firm price stickiness)}$$

$$\lambda_{ij} = 1 - \frac{1}{2}\frac{\sum_{t\in T_{ij}} \left\{\mathbb{1}[\Delta\ln(P_{ijt}) \neq 0] + \mathbb{1}\left[\Delta\ln(Q_{ijt}) \neq 0\right]\right\}}{\sum_{t\in T_{ij}} \mathbb{1}}, \quad \text{(Firm-product price stickiness)}$$

where I_j and I_f denote the sets of firm-product observations in industry j and in firm f, respectively; T_{ij} denotes the set of months for which a price change from the previous month is observed for firm-product i in industry j; and ω_{ijt}^E is the economic weight of the firm, calculated as the establishment revenue of the firm divided by the probability of selection. Intuitively, price stickiness is equal to 1 minus the average monthly fraction of adjusting prices at a sector, firm, or product level. As discussed in Section 3, the selling price stickiness is very similar to the purchase purchase stickiness for most sectors and products. We take the average of the two measures to account for the small discrepancy in some industries.

Unlike price stickiness, the market power of a firm is not directly observed in the data. According to most models of imperfect competition, the price markup is a suitable proxy for market power. In our model, market power, summarized by strategic complementarity φ_{ij}, is linear in the steady-state price markup $\mu_{ij} \equiv \frac{\vartheta_{ij}}{\vartheta_{ij}-1} = \frac{\theta}{\theta-1}\frac{1}{1-s_{ij}}$ for any given θ:

$$\varphi_{ij} = \left(\frac{\theta-1}{\theta}\mu_{ij} - 1\right)(\theta - 1)$$

We exploit the distributor's margin as the proxy for the price markup to construct two dummies

[25] As discussed in Section 3, the degree of selling price stickiness is highly correlated with that of purchase price stickiness. Using the purchase price stickiness measures yields similar estimates for our pass-through results.

that capture the variation in market power across and within sectors:

$$D_j = \begin{cases} 1 & \text{if } \mu_j \in \text{upper quartile of } \{\mu_j\} \text{ across all sectors,} \\ 0 & \text{otherwise,} \end{cases},$$

$$D_{ij} = \begin{cases} 1 & \text{if } \mu_{ij} \in \text{upper quartile of } \{\mu_{ij}\} \text{ among all } i \in I_j, \\ 0 & \text{otherwise,} \end{cases},$$

where $\mu_j = \frac{\sum_{i\in I_j}\sum_{t\in T_{ij}} \omega_{ij}^E \mu_{ijt}}{\sum_{i\in I_j}\sum_{t\in T_{ij}} \omega_{ij}^E}$ is the weighted mean margin across all firm-product observations in sector j,[26] and μ_{ij} is the average margin of firm-product i. $D_j = 1$ identifies the top quartile of high-markup sectors, and $D_{ij} = 1$ defines the top quartile of high-markup firms in sector j.

[26] Conditioning on observations with price changes yields similar average sector markups.

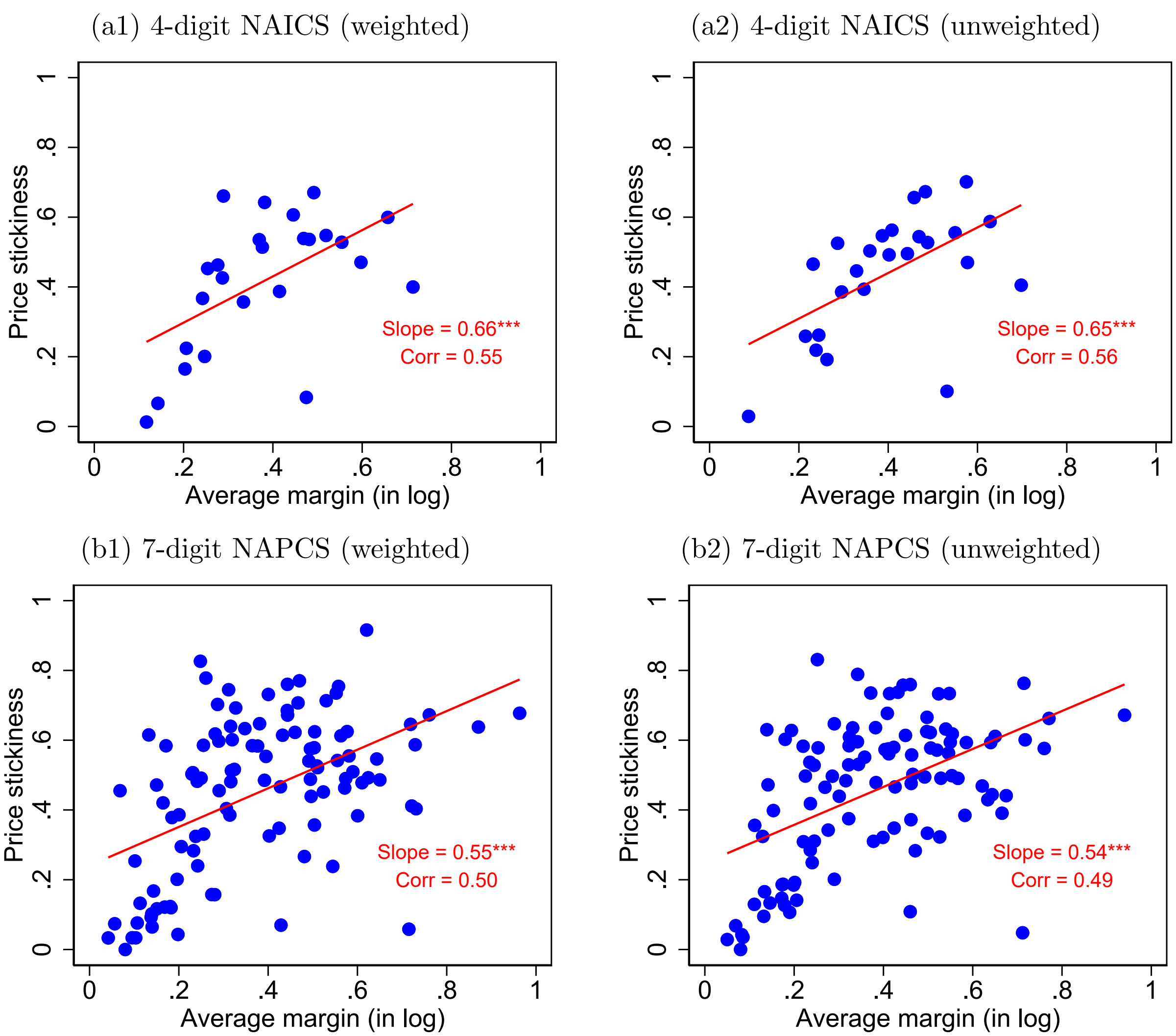


Figure A5: Correlation between price stickiness and average markup

Notes: The figures illustrate the cross-industry correlation between the average price stickiness λ_j and the average markup μ_j, with measures calculated at NAICS4 and NAPCS7 levels, respectively. The weighted measures constructed use the economic weight ω_{ij}^{E}.

A.4 Estimation results using product classification

In the main text, sectors are defined using a 4-digit industry classification (NAICS4). In this section, we present the results using 7-digit product classification (NAPCS7) to define sectors. Figure A6 provides scatter plots of the estimated pass-through coefficients against the price stickiness and the average markup of the sector. The plots include the fitted line to summarize the relationship. Table A5 provides estimated pass-through coefficients capturing variation in price stickiness and market power both across and within sectors.

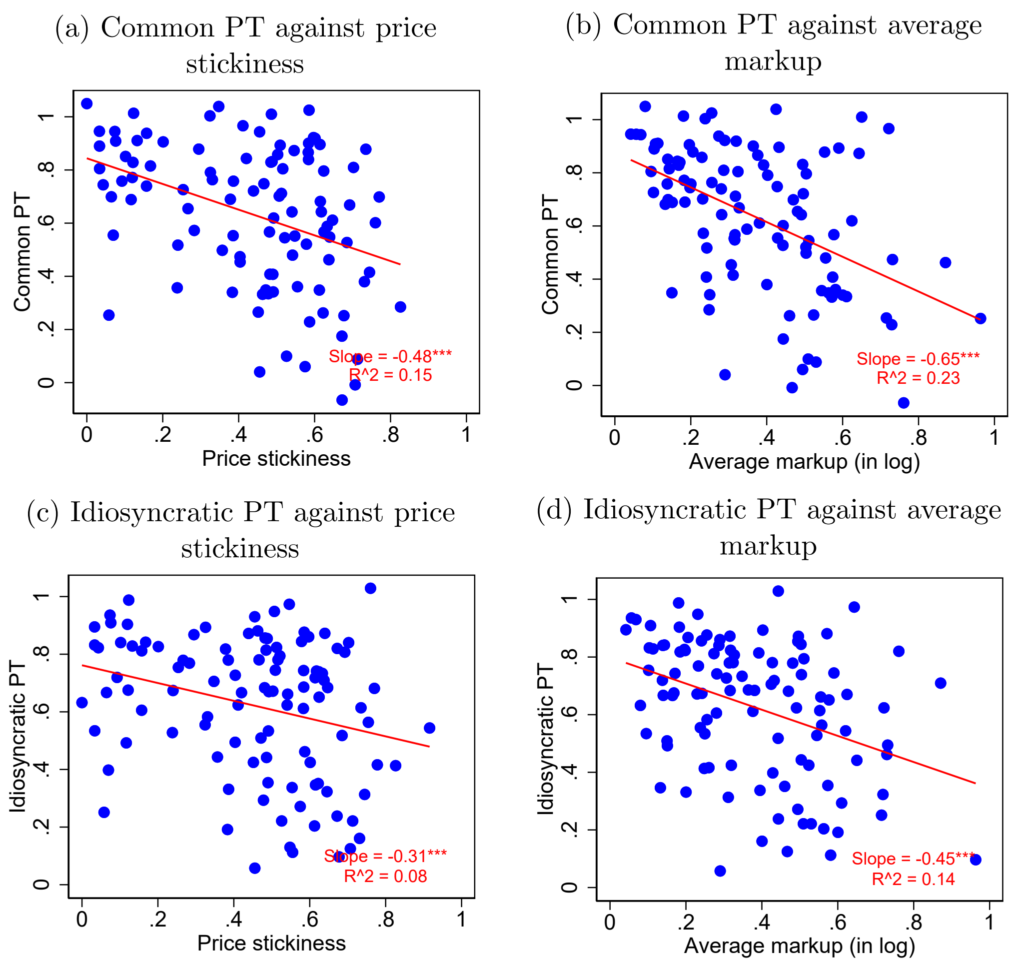


Figure A6: Estimates at the 7-digit NAPCS wholesale product level

Note: The figures plot the estimated selling price pass-through to common and idiosyncratic cost shocks against the average price stickiness and markup measured at the NAPCS7 product level. Specifically, we estimate $\Delta \ln(P_{ijt}) = \Psi_j \epsilon_{jt}^{Est} + \psi_j \epsilon_{ijt}^{Est} + FE_{ij} + \nu_{ijt}$ separately for each product. For this graphical presentation, we have included only the products with estimated pass-through rates in the range of $[-0.1, 1.1]$ and an average markup $\mu_j < 1$. The red line in each figure represents the fitted line obtained by regressing the estimated coefficients (Ψ_j^{Est}, ψ_j^{Est}) on the price stickiness λ_j or the average markup μ_j. The slope and the R^2 of the fitted line are reported in the bottom right corner of each figure.

Table A5: Pass-through estimates, 7-digit NAPCS wholesale products

	(1)	(2)	(3)	(4)	(5)	(6)
Common cost	0.79***	0.86***	0.86***	0.86***	0.89***	0.93***
	(0.038)	(0.063)	(0.063)	(0.063)	(0.044)	(0.032)
Idio. cost	0.69***	0.70***	0.70***	0.70***	0.75***	0.84***
	(0.028)	(0.065)	(0.065)	(0.065)	(0.042)	(0.037)
Common cost × Sector stickiness		-0.32*	-0.30*	-0.26	-0.23	-0.21
		(0.149)	(0.151)	(0.146)	(0.167)	(0.143)
Idio. cost × Sector stickiness		-0.02	0.06	0.04	0.04	0.01
		(0.137)	(0.14)	(0.142)	(0.102)	(0.092)
Common cost × Firm stickiness			-0.03			
			(0.134)			
Idio. cost × Firm stickiness			-0.23**			
			(0.074)			
Common cost × Firm-product stickiness				-0.14		
				(0.131)		
Idio. cost × Firm-product stickiness				-0.22**		
				(0.074)		
Common cost × High-markup industry					-0.22	-0.21
					(0.145)	(0.126)
Idio. cost × High-markup industry					-0.23**	-0.22*
					(0.085)	(0.087)
Common cost × High-markup firm						-0.18*
						(0.08)
Idio. cost × High-markup firm						-0.28***
						(0.034)
Observations	133,620	133,620	133,620	133,620	133,620	133,620
Firm-product fixed effects	✓	✓	✓	✓	✓	✓
R^2	0.54	0.54	0.54	0.54	0.55	0.57

Notes: This table presents estimates for pass-through of common shocks and idiosyncratic shocks, interacted with indicators of sector/firm/firm-product stickiness and high sector/firm markups. The dependent variable is the firm-product selling price. Estimates are based on monthly price data, are weighted using sampling revenue weights, and are conditional on selling price adjustment (cases where the selling price is unchanged between periods are excluded). Common costs are identified via a first-stage regression of the firm-product purchase price on a product-time fixed effect, where product is defined as the firm-product's NAPCS7 product code. Idiosyncratic shocks are defined as the residual of this first-stage regression. Statistical significance, based on robust standard errors clustered at the firm level is reported at the 1, 5, or 10 percent level, which is indicated by ***, **, or *, respectively.

A.5 Supplementary estimation results

Table A6: Variance decomposition of the pass-through rates

	4-digit NAICS		7-digit NAPCS	
	Stickiness λ_j	Markup μ_j	Stickiness λ_j	Markup μ_j
Common PT Φ_j	22.2%	30.4%	16.3%	16.7%
Idiosyncratic PT ϕ_j	26.7%†	55.0%	25.8%	37.4%

Notes: The table shows the contribution of price stickiness and average markup in explaining the cross-industry variance in the pass-through rates, with measures defined at the NAICS4 industry and NAPCS7 product levels, respectively. The contribution of each variable is calculated as $|Cov(x_j, y_j)/Var(y_j)|$, where $y_j \in \{\Psi_j, \psi_j\}$ and $x_j \in \{\lambda_j, \mu_j\}$. † indicates the statistic is not different from zero at the 10% significance level.

Table A7: Variance decomposition of the pass-through rates (unweighted)

	4-digit NAICS		7-digit NAPCS	
	Stickiness λ_j	Markup μ_j	Stickiness λ_j	Markup μ_j
Common PT Φ_j	25.2%	37.9%	17.1%	19.0%
Idiosyncratic PT ϕ_j	19.6%†	57.2%	19.1%	28.5%

Notes: The table shows the contribution of price stickiness and average markup in explaining the cross-industry variance in the pass-through rates, with measures defined at the NAICS4 industry and NAPCS7 product levels, respectively. The contribution of each variable is calculated as $|Cov(x_j, y_j)/Var(y_j)|$, where $y_j \in \{\Psi_j, \psi_j\}$ and $x_j \in \{\lambda_j, \mu_j\}$. † indicates the statistic is not different from zero at the 10% significance level.

Table A8: Pass-through estimates, 4-digit NAICS wholesale industries (unweighted)

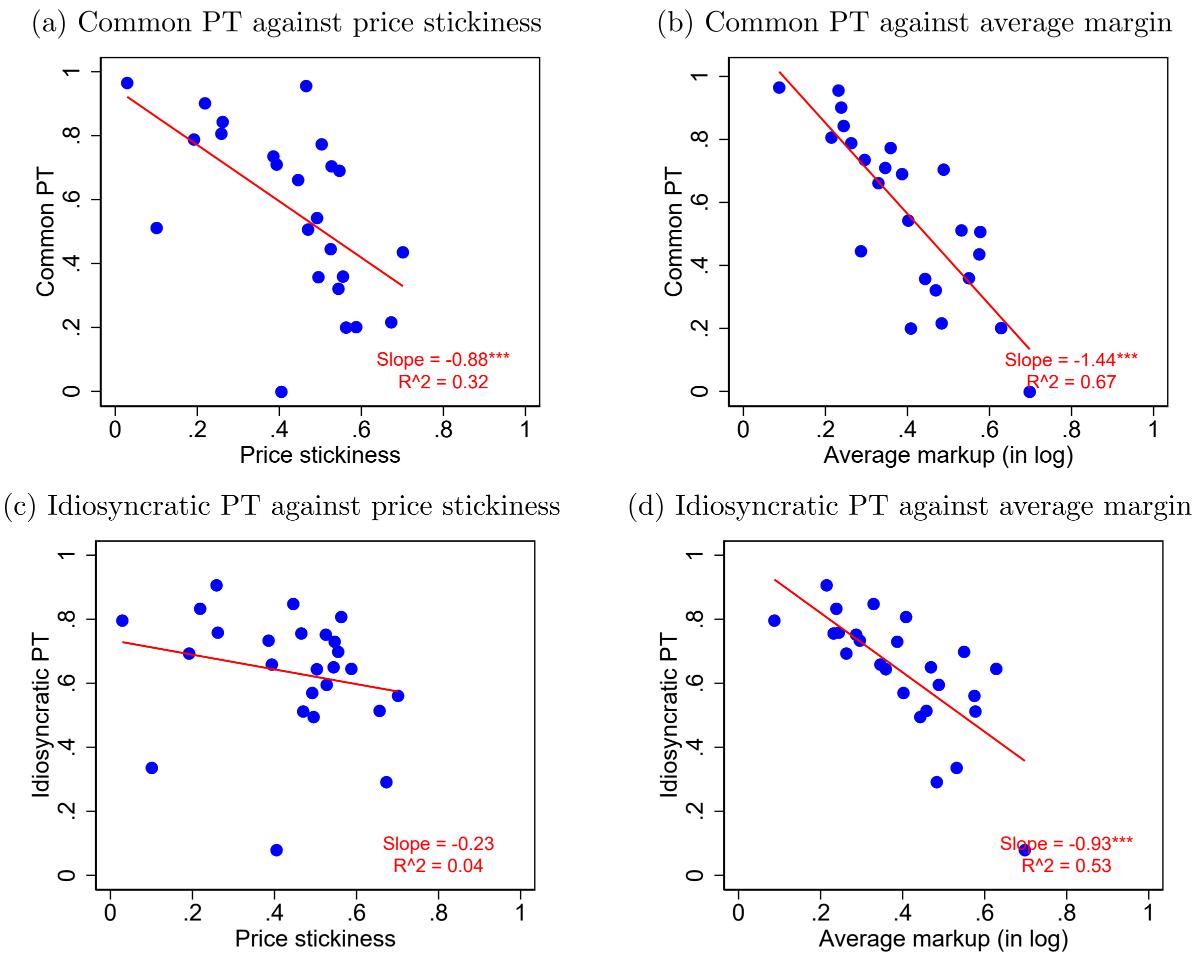
	(1)	(2)	(3)	(4)	(5)	(6)
Common cost	0.76***	0.91***	0.91***	0.91***	0.96***	0.98***
	(0.028)	(0.038)	(0.038)	(0.038)	(0.031)	(0.023)
Idio. cost	0.69***	0.74***	0.74***	0.74***	0.75***	0.87***
	(0.017)	(0.048)	(0.048)	(0.048)	(0.04)	(0.036)
Common cost × Sector stickiness		-0.76***	-0.82***	-0.76***	-0.55***	-0.47***
		(0.119)	(0.135)	(0.126)	(0.11)	(0.098)
Idio. cost × Sector stickiness		-0.10	-0.04	-0.04	-0.03	-0.10
		(0.112)	(0.118)	(0.116)	(0.101)	(0.093)
Common cost × Firm stickiness			0.16			
			(0.16)			
Idio. cost × Firm stickiness			-0.16**			
			(0.058)			
Common cost × Firm-product stickiness				0.05		
				(0.144)		
Idio. cost × Firm-product stickiness				-0.19***		
				(0.056)		
Common cost × High-markup industry					-0.37***	-0.35***
					(0.054)	(0.052)
Idio. cost × High-markup industry					-0.22***	-0.21***
					(0.044)	(0.042)
Common cost × High-markup firm						-0.14**
						(0.053)
Idio. cost × High-markup firm						-0.29***
						(0.037)
Observations	136,085	136,085	136,085	136,085	136,085	136,085
Firm-product fixed effects	✓	✓	✓	✓	✓	✓
R^2	0.48	0.48	0.48	0.48	0.49	0.5

Notes: This table presents estimates for pass-through of common shocks and idiosyncratic shocks, interacted with indicators of sector/firm/firm-product stickiness and high sector/firm markups. The dependent variable is the firm-product selling price. Estimates are based on monthly price data, are not weighted, and are conditional on selling price adjustment (cases where the selling price is unchanged between periods are excluded). Common costs are identified via a first-stage regression of the firm-product purchase price on a sector-time fixed effect, where sector is defined as the firm's NAICS4 industry. Idiosyncratic shocks are defined as the residual of this first-stage regression. Statistical significance, based on robust standard errors clustered at the firm level, is reported at the 1, 5, or 10% level, which is indicated by ***, **, or *, respectively.

Table A9: Pass-through estimates, 7-digit NAPCS wholesale products (unweighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Common cost	0.76***	0.82***	0.82***	0.82***	0.85***	0.90***
	(0.024)	(0.042)	(0.042)	(0.043)	(0.033)	(0.024)
Idio. cost	0.69***	0.68***	0.69***	0.69***	0.69***	0.80***
	(0.018)	(0.039)	(0.0390	(0.038)	(0.033)	(0.027)
Common cost × Sector stickiness		-0.26*	-0.31*	-0.26*	-0.18	-0.13
		(0.103)	(0.124)	(0.118)	(0.096)	(0.079)
Idio. cost × Sector stickiness		0.02	0.09	0.09	0.12	0.09
		(0.084)	(0.089)	(0.088)	(0.076)	(0.068)
Common cost × Firm stickiness			0.12			
			(0.101)			
Idio. cost × Firm stickiness			-0.21***			
			(0.061)			
Common cost × Firm-product stickiness				0.03		
				(0.085)		
Idio. cost × Firm-product stickiness				-0.24***		
				(0.059)		
Common cost × High-markup industry					-0.24*	-0.24**
					(0.096)	(0.085)
Idio. cost × High-markup industry					-0.22***	-0.23***
					(0.049)	(0.048)
Common cost × High-markup firm						-0.23***
						(0.036)
Idio. cost × High-markup firm						-0.31***
						(0.03)
Observations	133,620	133,620	133,620	133,620	133,620	133,620
Firm-product fixed effects	✓	✓	✓	✓	✓	✓
R^2	0.48	0.48	0.48	0.48	0.49	0.51

Notes: This table presents estimates for pass-through of common shocks and idiosyncratic shocks, interacted with indicators of sector/firm/firm-product stickiness and high sector/firm markups. The dependent variable is the firm-product selling price. Estimates are based on monthly price data, are bot weighted, and are conditional on selling price adjustment (cases where the selling price is unchanged between periods are excluded). Common costs are identified via a first-stage regression of the firm-product purchase price on a product-time fixed effect, where product is defined as the firm-product's NAPCS7 product code. Idiosyncratic shocks are defined as the residual of this first-stage regression. Statistical significance, based on robust standard errors clustered at the firm level, is reported at the 1, 5, or 10% level, which is indicated by ***, **, or *, respectively.



(a) Common PT against price stickiness

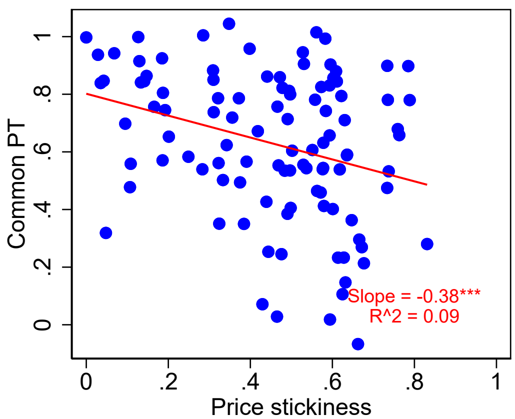
(b) Common PT against average margin

(c) Idiosyncratic PT against price stickiness

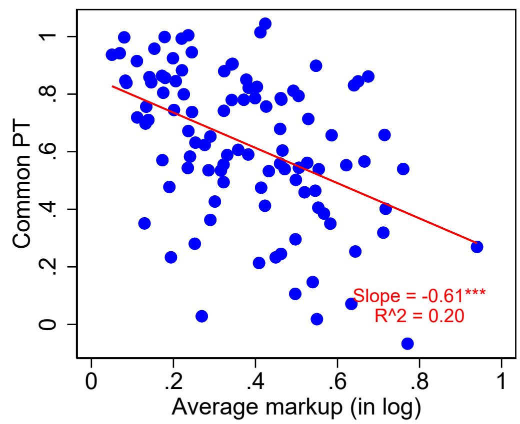
(d) Idiosyncratic PT against average margin

Figure A7: Estimates at the 4-digit NAICS wholesale industry level (unweighted)

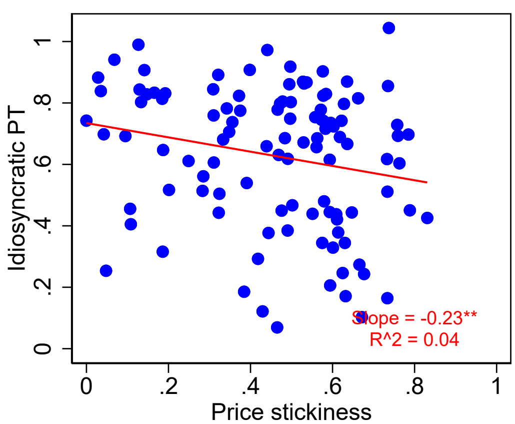
(a) Common PT against price stickiness



(b) Common PT against average margin



(c) Idiosyncratic PT against price stickiness



(d) Idiosyncratic PT against average margin

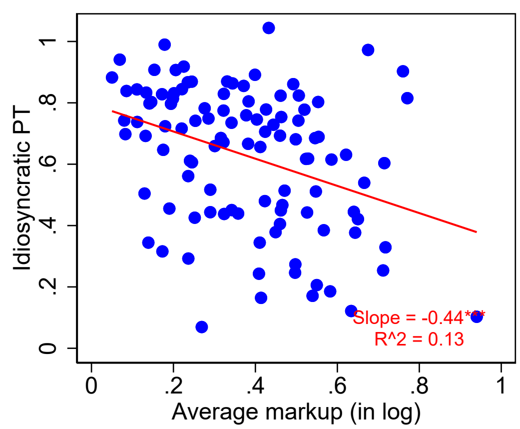


Figure A8: Estimates at the 7-digit NAPCS wholesale product level (unweighted)

A.6 Discussion of approximation of the marginal cost by the purchase price

Our benchmark analysis assumes that the observed purchase price is a good proxy for the true marginal cost of the product sold. In the context of the wholesale industry, we believe this is a reasonable assumption. Nonetheless, in this subsection we discuss the implications when this assumption no longer holds.

Consider a more general setting where the marginal cost of firm-product i in sector j, MC_{ijt}, consists of two components: (1) the observed purchase price Q_{ijt} and (2) the unobserved marginal cost component X_{ijt}:

$$MC_{ijt} = Q_{ijt}^{\gamma} X_{ijt}^{1-\gamma} \quad \text{with} \quad \gamma \in (0, 1].$$

Note that if the unobserved cost component X_{ijt} is highly correlated with the observed component, then the change in the observed purchase price $\widehat{Q}_{ijt}$ remains a good proxy for the change in the marginal cost $\widehat{MC}_{ijt}$. Taking the extreme case where these two variables are perfectly correlated, we have

$$\widehat{MC}_{ijt} = \gamma \widehat{Q}_{ijt} + (1 - \gamma)\widehat{X}_{ijt} = \widehat{Q}_{ijt}.$$

The potential problem arises when the two cost components are not perfectly correlated. In the case where $Corr(\widehat{Q}_{ijt}, \widehat{X}_{ijt}) = a$, we have

$$\widehat{MC}_{ijt} = \gamma \widehat{Q}_{ijt} + (1 - \gamma)\widehat{X}_{ijt} = [\gamma + (1 - \gamma)a]\widehat{Q}_{ijt}. \tag{A.1}$$

If the actual change in marginal cost is smaller than the observed purchase price change (i.e., $\widehat{MC}_{ijt} < \widehat{Q}_{ijt}$ or $\gamma + (1 - \gamma)a < 1$), then the estimated price pass-through to the cost shocks measured by the purchase price changes may be downward biased. For example, one concern is that our estimated pass-through to the common cost shock is incomplete not because of the interaction between price stickiness and market power but simply because the costs are not precisely measured. For example, in the context of a monopolistic competition Calvo model, the estimated reset price pass-through rate using $\widehat{Q}_{ijt}$ as the regressor will be $\gamma + (1 - \gamma)a$, smaller than the theoretical 100% obtained using the true marginal cost $\widehat{MC}_{ijt}$ if $a < 1$.

We note that this hypothesis is rejected by our estimates of the price pass-through to common cost shocks in a flexible price sector. Under the assumptions of our oligopolistic competition Calvo model and the cost process of (A.1), the pass-through to a common purchase price shock in the *flexible price sector* is

$$\Psi = \gamma + (1 - \gamma)a.$$

Our empirical estimate of Ψ^{Est} is very close to 1, which implies that $\gamma + (1 - \gamma)a \approx 1$. In other words, our empirical estimates implicitly suggest that the observed purchase price is a good proxy for the unobserved marginal cost in the wholesale industry.

B Model Appendix

B.1 The closed-form solution of the optimal reset price

In this subsection, we first solve for the firm's optimal reset price in response to both common and idiosyncratic cost shocks, when costs are flexible $\widehat{Q}_{ijt} = \widehat{Q}^*_{ijt}$ to prove Proposition 1. We then show that Proposition 2 can be solved following similar steps.

B.1.1 Proof of Proposition 1

We begin by characterizing how the expected sector price reacts to an arbitrary set of firm-level cost shocks, which follow the same AR(1) process:

$$\widehat{Q}^*_{ijt} = \rho_j \widehat{Q}^*_{ijt-1} + \epsilon_{ijt},$$

where ϵ_{ijt} are ex-ante mean zero shocks that can be correlated across firms. For example, a common (sector) shock occurs when $\epsilon_{ijt} = 1 \; \forall i \in j$, and an idiosyncratic shock occurs when $\epsilon_{ijt} = 1$ and $\epsilon_{kjt} = 0 \; \forall k \neq i \in j$.

We can re-express the sector NKPC (10) as a second-order difference equation in price levels:

$$\mathbb{E}_t \left[\widehat{P}_{jt+\tau} - \lambda_j \widehat{P}_{jt+\tau-1} - \beta\lambda_j (\widehat{P}_{jt+\tau+1} - \lambda_j \widehat{P}_{jt+\tau}) \right] = \mathbb{E}_t \sum_i s_{ij} \frac{(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})} (\widehat{Q}^*_{ijt+\tau} + \varphi_{ij} \widehat{P}_{jt+\tau}). \tag{B.1}$$

For any arbitrary set of realized shocks $\{\epsilon_{ijt}\}$ at t, the expected sector price at $t+\tau$ can be solved as

$$\mathbb{E}_t \widehat{P}_{jt+\tau} = \frac{\rho_j^{\tau+1} - \Lambda_j^{\tau+1}}{\rho_j (1-b_j) + \lambda_j [\beta\rho_j(\lambda_j - \rho_j) - 1]} a_j \widehat{Q}^*_{jt} \quad \forall \tau \geq 0, \tag{B.2}$$

where

$$\Lambda_j \equiv \frac{1}{2}\left[\lambda_j + \frac{1-b_j}{\beta\lambda_j} - \sqrt{\left(\lambda + \frac{1-b_j}{\beta\lambda_j}\right)^2 - \frac{4}{\beta}}\right], \tag{B.3}$$

$$a_j \equiv \left(\sum_i \frac{(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})} s_{ij}\widehat{Q}^*_{ijt}\right)/\widehat{Q}^*_{jt} \quad \text{with} \quad \widehat{Q}^*_{jt} \equiv \sum_i s_{ij}\widehat{Q}^*_{ijt}, \tag{B.4}$$

$$b_j \equiv \sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}. \tag{B.5}$$

Plugging the expected sector prices back into the firm's reset price (7), we have

$$\widehat{P}_{ijt,t} = \frac{1-\beta\lambda_j}{1+\varphi_{ij}}\sum_{\tau=0}^{\infty}(\beta\lambda_j)^{\tau}\left[\rho_j^{\tau}\widehat{Q}_{ijt} + \varphi_{ij}\frac{\rho_j^{\tau+1} - \Lambda_j^{\tau+1}}{\rho_j\,(1-b_{jt}) + \lambda_j\,[\beta\rho_j(\lambda_j-\rho_j)-1]}a_j\widehat{Q}^*_{jt}\right].$$

Solving the geometric series gives

$$\widehat{P}_{ijt,t} = \frac{1}{1+\varphi_{ij}}\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}\widehat{Q}^*_{ijt} + \frac{\varphi_{ijt}}{1+\varphi_{ij}}\frac{\rho_j - \Lambda_{jt}}{1-\beta\lambda_j\Lambda_j}\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}\varkappa_{jt}\widehat{Q}^*_{jt}, \tag{B.6}$$

where

$$\varkappa_j \equiv \frac{a_j}{\rho_j\,(1-b_j) + \lambda\,[\beta\rho_j(\lambda_j-\rho_j)-1]}. \tag{B.7}$$

Note that, under the case of symmetric firms, $\varkappa_j = 1$.

We can rewrite (B.6) as responses to idiosyncratic and common (or average) cost shocks:

$$\widehat{P}_{ijt,t} = \underbrace{\frac{1}{1+\varphi_{ij}}\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}}_{\text{PT to idiosyncratic cost changes}}\left(\widehat{Q}^*_{ijt} - \widehat{Q}^*_{jt}\right) + \underbrace{\left[\frac{1}{1+\varphi_{ij}} + \frac{\varphi_{ij}}{1+\varphi_{ij}}\frac{\rho_j-\Lambda_j}{1-\beta\lambda_j\Lambda_j}\varkappa_j\right]\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}}_{\text{PT to common (or average) cost changes}}\widehat{Q}^*_{jt} \tag{B.8}$$

Due to strategic interactions, the effects of a cost shock on a firm's optimal reset price can be decomposed into two distinct components: (1) the impact of deviations of the firm's cost from the average cost change; and (2) the impact of average cost change. ■

B.1.2 Price and cost synchronization and proof of Proposition 2

When the timing of price adjustment is perfectly synchronized with that of the cost changes, the firm's expected future cost during the periods that its price remains fixed is just its current cost:

$$\mathbb{E}_t[\widehat{Q}_{ijt+\tau,t}] = \widehat{Q}^*_{ijt} \quad \forall \tau \geq 0.$$

In this case, the optimal individual (7) and sector (8) reset prices become

$$\widehat{P}_{ijt,t} = \frac{1}{1+\varphi_{ij}}\widehat{Q}^*_{ijt} + \frac{\varphi_{ij}(1-\beta\lambda_j)}{(1+\varphi_{ij})}\sum_{\tau=0}^{\infty}(\beta\lambda_j)^\tau \mathbb{E}_t\widehat{P}_{jt+\tau} \tag{B.9}$$

$$\mathbb{E}_t\widehat{P}_{jt,t} = \sum_i s_{ij}\frac{1}{1+\varphi_{ij}}\widehat{Q}^*_{ijt} + \sum_i \left\{ s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)}{(1+\varphi_{ij})}\sum_{\tau=0}^{\infty}(\beta\lambda_j)^\tau \mathbb{E}_t\widehat{P}_{jt+\tau} \right\}. \tag{B.10}$$

Using the relationship $\mathbb{E}_t\widehat{P}_{jt+\tau} = (1-\lambda_j)\mathbb{E}_t\widehat{P}_{jt+\tau,t+\tau} + \lambda_j\mathbb{E}_t\widehat{P}_{jt+\tau-1}$, we have

$$\begin{aligned}
&\mathbb{E}_t\left[\widehat{P}_{jt+\tau} - \lambda_j\widehat{P}_{jt+\tau-1} - \beta\lambda_j(\widehat{P}_{jt+\tau+1} - \lambda_j\widehat{P}_{jt+\tau})\right] \\
&= (1-\lambda_j)\mathbb{E}_t\left(\widehat{P}_{jt+\tau,t+\tau} - \beta\lambda_j\widehat{P}_{jt+\tau+1,t+\tau+1}\right) \\
&= \mathbb{E}_t\sum_i s_{ij}\frac{1-\lambda_j}{1+\varphi_{ij}}\left(\widehat{Q}^*_{ijt+\tau} - \beta\lambda_j\widehat{Q}^*_{ijt+\tau+1}\right) + \mathbb{E}_t\sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}\widehat{P}_{jt+\tau} \\
&= \sum_i s_{ij}\frac{(1-\lambda_j)(1-\beta\lambda_j\rho_j)}{1+\varphi_{ij}}\widehat{Q}^*_{ijt+\tau} + \mathbb{E}_t\sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}\widehat{P}_{jt+\tau} \\
&= \sum_i s_{ij}\frac{(1-\lambda_j)(1-\beta\lambda_j\rho_j)}{1+\varphi_{ij}}\rho_j^\tau\widehat{Q}^*_{ijt} + \mathbb{E}_t\sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})}\widehat{P}_{jt+\tau}
\end{aligned}$$

Solving the dynamics gives

$$\mathbb{E}_t\widehat{P}_{jt+\tau} = \frac{\rho_j^{\tau+1} - \Lambda_j^{\tau+1}}{\rho_j\left(1-b_j\right) + \lambda\left[\beta\rho(\lambda_j-\rho_j) - 1\right]}\frac{1-\beta\lambda_j\rho_j}{1-\beta\lambda_j}a_j\widehat{Q}^*_{jt} \quad \forall\tau \geq 0, \tag{B.11}$$

where Λ_j, a_j, and b_j are defined in (B.3), (B.4), (B.5), respectively.

Finally, plugging the expected sector prices back into the firm's reset price (B.9) and solving the geometric series gives

$$\widehat{P}_{ijt,t} = \frac{1}{1+\varphi_{ij}}\widehat{Q}^*_{ijt} + \frac{\varphi_{ij}}{1+\varphi_{ij}}\frac{\rho_j - \Lambda_j}{1-\beta\lambda_j\Lambda_j}\varkappa_j\widehat{Q}^*_{jt}, \tag{B.12}$$

■

B.1.3 Two underlying shock processes

In this subsection, we show that a similar expression to (B.8) can be obtained when there are two underlying shock processes. Specifically, we allow for two different AR(1) processes for the common $\widehat{Q}^C_{jt}$ and idiosyncratic $\widehat{Q}^I_{ijt}$ components of the cost process $\widehat{Q}^*_{ijt}$, and arbitrary serial correlations in the residual terms ϵ_{jt} and ϵ_{ijt} of these two AR(1) processes:

$$\begin{aligned}
\widehat{Q}^*_{ijt} &= \widehat{Q}^I_{ijt} + \widehat{Q}^C_{jt} \\
\widehat{Q}^I_{ijt} &= \rho^I_j \widehat{Q}^I_{ijt-1} + \epsilon_{ijt} \\
\widehat{Q}^C_{jt} &= \rho^C_j \widehat{Q}^C_{jt-1} + \epsilon_{jt}
\end{aligned}$$

Note that, due to the limited number of firms in a sector, the idiosyncratic shocks ϵ_{ijt} may not sum to zero. As a result, we need to keep track of the evolution of both idiosyncratic and aggregate shocks in deriving the expected change in sector prices. Under these conditions, the expression for expected sector price becomes more complicated:

$$\mathbb{E}_t\widehat{P}_{jt+\tau} = \frac{\Lambda_{1,j}\Lambda_{2,j}}{\lambda(\Lambda_{1,j}-\rho^I_j)(\Lambda_{2,j}-\rho^I_j)(\Lambda_{1,j}-\rho^C_j)(\Lambda_{2,j}-\rho^C_j)}K_{jt+\tau} \tag{B.13}$$

with

$$\begin{aligned}
K_{jt+\tau} \equiv\ & -d_j\widehat{Q}^C_{jt}(\rho^I_j)^\tau(\Lambda_{1,j}-\rho^C_j)(\Lambda_{2,j}-\rho^C_j) - a_j\widehat{Q}^I_{jt}(\rho^C_j)^\tau(\Lambda_{1,j}-\rho^I_j)(\Lambda_{2,j}-\rho^I_j) \\
& + \Lambda^\tau_{1,j}\left[\Lambda_{1,j}\Lambda_{2,j}(a_j\widehat{Q}^I_{jt}\rho^I_j + (\Lambda_{1,j}+\Lambda_{2,j})(a_j\widehat{Q}^I_{jt}\rho^C_j + d_j\widehat{Q}^C_{jt}\rho^I_j) + a_j\widehat{Q}^I_{jt}(\rho^C_j)^2 + d_j\widehat{Q}^C_{jt}(\rho^I_j)^2\right]
\end{aligned}$$

where

$$\Lambda_{1,j} \equiv \frac{1}{2}\left[\lambda_j + \frac{1-b_j}{\beta\lambda_j} - \sqrt{\left(\lambda_j + \frac{1-b_j}{\beta\lambda_j}\right)^2 - \frac{4}{\beta}}\right],$$
$$\Lambda_{2,j} \equiv \frac{1}{2}\left[\lambda_j + \frac{1-b_j}{\beta\lambda_j} + \sqrt{\left(\lambda_j + \frac{1-b_j}{\beta\lambda_j}\right)^2 - \frac{4}{\beta}}\right],$$
$$a_j \equiv \left(\sum_i \frac{(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})} s_{ij}\widehat{Q}^I_{ijt}\right)/\widehat{Q}^I_{jt} \quad \text{with} \quad \widehat{Q}^I_{jt} \equiv \sum_i s_{ij}\widehat{Q}^I_{ijt},$$
$$b_j \equiv \sum_i s_{ij}\frac{\varphi_{ij}(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})},$$
$$d_j \equiv \sum_i \frac{(1-\beta\lambda_j)(1-\lambda_j)}{(1+\varphi_{ij})} s_{ijt}.$$

Plugging (B.13) into equation (7), we can solve the optimal reset price as

$$\begin{aligned}\widehat{P}_{ijt,t} = {} & \frac{1-\beta\lambda_j}{(1-\beta\lambda_j\rho^I_j)(1+\varphi_{ij})}(\widehat{Q}^I_{ijt} - \widehat{Q}^I_j) + \left[\frac{1-\beta\lambda_j}{(1-\beta\lambda\rho^I_j)(1+\varphi_{ij})} + \frac{\varphi_{ij}}{1+\varphi_{ij}}H_j(\rho^I_j)a_j\right]\widehat{Q}^I_{jt} \\ & + \left[\frac{1-\beta\lambda_j}{(1-\beta\lambda_j\rho^C_j)(1+\varphi_{ij})} + \frac{\varphi_{ij}}{1+\varphi_{ij}}H_j(\rho^C_j)d_j\right]\widehat{Q}^C_{jt} \end{aligned} \tag{B.14}$$

where

$$H_j(\rho_j) \equiv \frac{\Lambda_{1,j}\Lambda_{2,j}(1-\beta\lambda_j)}{\lambda_j(1-\Lambda_{1,j}\beta\lambda_j)(\Lambda_{2,j}-\rho_j)(1-\beta\lambda_j\rho_j)} = \frac{\rho_j - \Lambda_j}{1-\beta\lambda_j\Lambda_j}\frac{1-\beta\lambda_j}{1-\beta\lambda_j\rho_j}\varkappa_j(\rho_j)/a_j \tag{B.15}$$

Therefore, as in the single shock case, the optimal reset price response to the cost shocks can be decomposed into idiosyncratic (the first term of B.14) and common (the second and third terms of B.14) components. Note that the solution holds for any arbitrary realization of $\{\epsilon_{ijt}\}$, and ϵ_{jt} and does not require the shocks to be independent.

B.2 An example of aggregate price evolution with homogeneous duopoly sectors

In this subsection, we describe a simplified version of the model with homogenous duopoly sectors. We do this to illustrate that, while having firms with market power means that aggregate price dynamics are more complex than in a model with monopolistic competitive firms, these dynamics can still be succinctly represented in a simple Calvo form. Figure B1 illustrates the evolution of sector and aggregate prices in this version of the model. Starting from the steady state at $t = 0$, we characterize the exact price dynamics in the model. As shown in the figure, at $t = 1$ there are four types of sectors based on the price adjustment patterns: (1) sectors where both firms adjust their prices, denoted as $[A, A]$; (2) sectors where only the first firm adjusts its price, denoted as $[A, N]$; (3) sectors where only the second firm adjusts its price, denoted as $[N, A]$; and (4) sectors where neither firm adjusts their prices, denoted as $[N, N]$. The proportions of these sectors are given by $(1 - \lambda)^2$, $(1 - \lambda)\lambda$, $(1 - \lambda)\lambda$, and λ^2, respectively. It is evident that the *realization* of sector prices no longer follows standard Calvo due to the limited number of firms and the discrete realization of the Calvo process in each sector. However, with a large enough number of similar sectors, the evolution of the aggregate price can still be expressed in Calvo form as

$$\widehat{P}_1 = (1-\lambda)\widehat{P}_{1A} + \lambda\widehat{P}_{1N} = (1-\lambda)\left[(1-\lambda)\widehat{P}_{[A,A]} + \lambda\widehat{P}_{[A,N]}\right] + \lambda\left[(1-\lambda)\widehat{P}_{[N,A]} + \lambda\widehat{P}_{[N,N]}\right], \quad \text{(B.16)}$$

with

$$\begin{aligned}
\widehat{P}_{[A,A]} &= s_1\widehat{P}_{A_1|[A,A]} + s_2\widehat{P}_{A_2|[A,A]} \\
\widehat{P}_{[A,N]} &= s_1\widehat{P}_{A_1|[A,N]} + s_2\widehat{P}_0 \\
\widehat{P}_{[N,A]} &= s_1\widehat{P}_0 + s_2\widehat{P}_{A_2|[N,A]} \\
\widehat{P}_{[N,N]} &= \widehat{P}_0
\end{aligned}$$

where s_1 is the (within-sector) market share of firm 1 and s_2 is the (within-sector) market share of firm 2; $\widehat{P}_{A_1|[A,A]}$ is the price change of firm 1 in the sector where both firms adjusted their prices, etc. It is worth noting that, since the firm does not observe its competitor's price in t when making its price decision, we have

$$\widehat{P}_{A_1|[A,A]} = \widehat{P}_{A_1|[A,N]} \equiv \widehat{P}_{A_1|[A,.]} \quad \text{and} \quad \widehat{P}_{A_2|[A,A]} = \widehat{P}_{A_2|[N,A]} \equiv \widehat{P}_{A_2|[.,A]}. \tag{B.17}$$

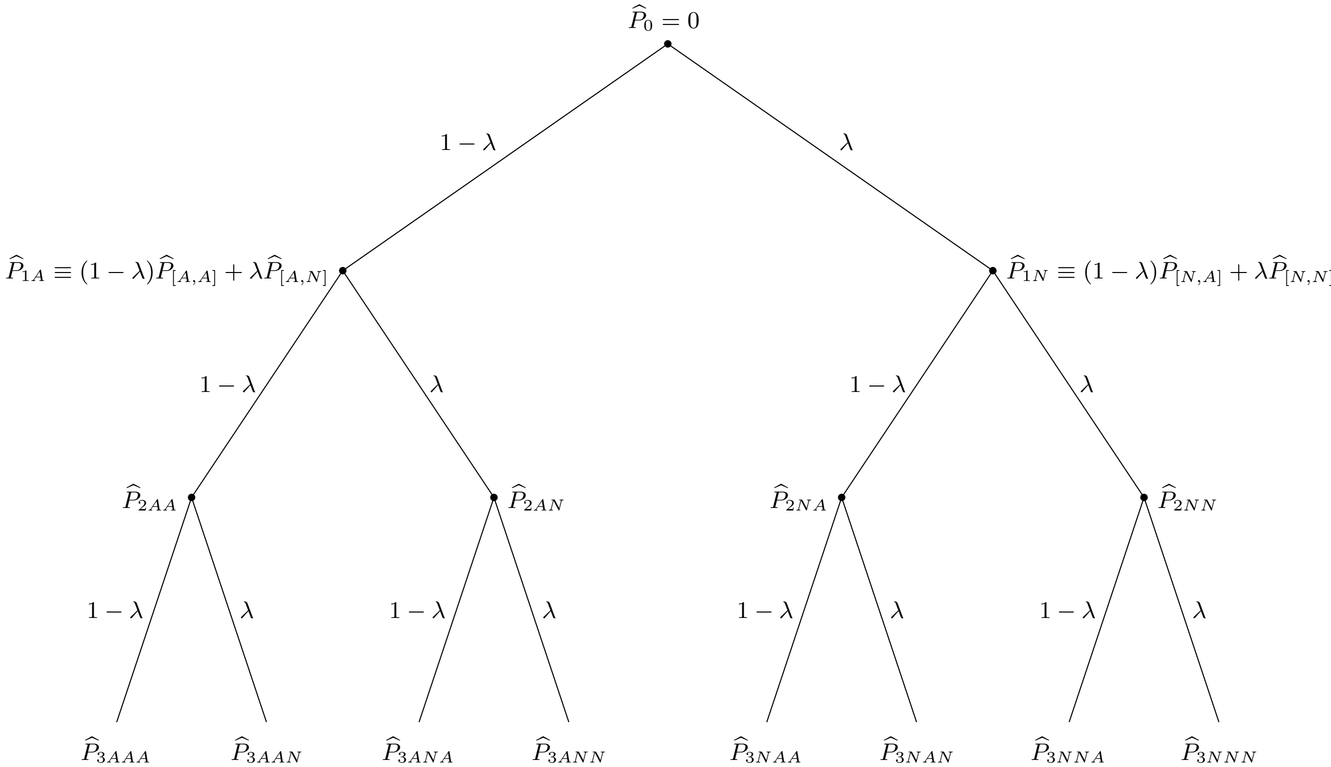


Figure B1: Illustrating the realization of sector and aggregate prices

Notes: This figure illustrates the discrete realization of the sector prices in an economy with ex-ante symmetric firms and homogeneous duopoly sectors.

Define

$$\widehat{P}_{1,1} \equiv s_1 \left(\widehat{P}_{A_1|[A,A]} + \widehat{P}_{A_1|[A,N]}\right) + s_2 \left(\widehat{P}_{A_2|[A,A]} + \widehat{P}_{A_2|[N,A]}\right) = s_1\widehat{P}_{A_1|[A,.]} + s_2\widehat{P}_{A_2|[.,A]}.$$

We can rewrite the aggregate price as

$$\widehat{P}_1 = (1-\lambda)\widehat{P}_{1,1} + \lambda\widehat{P}_0. \tag{B.18}$$

Similarly to expression (B.16), for price adjustments in period 2 we have

$$\widehat{P}_2 = (1-\lambda)^2 \widehat{P}_{2AA} + (1-\lambda)\lambda \widehat{P}_{2AN} + \lambda(1-\lambda)\widehat{P}_{2NA} + \lambda^2 \widehat{P}_{2NN},$$

where

$$\begin{aligned}
\widehat{P}_{2AA} &= (1-\lambda)^2 \widehat{P}_{[AA,AA]} + (1-\lambda)\lambda \widehat{P}_{[AA,AN]} + \lambda(1-\lambda)\widehat{P}_{[AA,NA]} + \lambda^2 \widehat{P}_{[AA,NN]};\\
\widehat{P}_{2AN} &= (1-\lambda)^2 \widehat{P}_{[AN,AA]} + (1-\lambda)\lambda \widehat{P}_{[AN,AN]} + \lambda(1-\lambda)\widehat{P}_{[AN,NA]} + \lambda^2 \widehat{P}_{[AN,NN]};\\
\widehat{P}_{2NA} &= (1-\lambda)^2 \widehat{P}_{[NA,AA]} + (1-\lambda)\lambda \widehat{P}_{[NA,AN]} + \lambda(1-\lambda)\widehat{P}_{[NA,NA]} + \lambda^2 \widehat{P}_{[NA,NN]};\\
\widehat{P}_{2NN} &= (1-\lambda)^2 \widehat{P}_{[NN,AA]} + (1-\lambda)\lambda \widehat{P}_{[NN,AN]} + \lambda(1-\lambda)\widehat{P}_{[NN,NA]} + \lambda^2 \widehat{P}_{[NN,NN]}.
\end{aligned}$$

With some rearrangements, it can be shown that

$$\widehat{P}_2 = (1-\lambda)\widehat{P}_{2,2} + \lambda \widehat{P}_1. \tag{B.19}$$

where

$$\begin{aligned}
\widehat{P}_{2,2} \equiv\; & s_1(1-\lambda)\left[(1-\lambda)\widehat{P}_{A_1|[AA,A.]} + \lambda \widehat{P}_{A_1|[AA,N.]}\right] + s_1\lambda\left[(1-\lambda)\widehat{P}_{A_1|[AN,A.]} + \lambda \widehat{P}_{A_1|[AN,N.]}\right]\\
& + s_1\lambda\left[(1-\lambda)\widehat{P}_{A_1|[NA,A.]} + \lambda \widehat{P}_{A_1|[NA,N.]}\right]\\
& + s_2(1-\lambda)\left[(1-\lambda)\widehat{P}_{A_2|[A.,AA]} + \lambda \widehat{P}_{A_2|[N.,AA]}\right] + s_2\lambda\left[(1-\lambda)\widehat{P}_{A_2|[A.,AN]} + \lambda \widehat{P}_{A_2|[N.,AN]}\right]\\
& + s_2\lambda\left[(1-\lambda)\widehat{P}_{A_2|[A.,NA]} + \lambda \widehat{P}_{A_2|[N.,NA]}\right].
\end{aligned}$$

Further iteration provides expressions for $\widehat{P}_t$ when $t \geq 3$. The key takeaway is as follows: although the exact price dynamics are complex, the aggregate price dynamics can be succinctly represented in simple Calvo forms. As discussed in Section 2, three assumptions are crucial for arriving at this result: (1) the frequency of price adjustment is fixed and independent of the firms' pricing behaviour; (2) there is a sufficiently large number of similar sectors, allowing the law of large numbers to be applicable; and (3) the shocks are small, ensuring that a first-order approximation remains accurate.

B.3 Simplified model with symmetric firms and homogeneous sectors

In this subsection, we prove Corollary 1 and discuss the aggregate price and output dynamics of our model using a simplified version of the model with symmetric firms and homogeneous sectors.

We start by aggregating the sector prices. From (9), we know the expected sector price follows

$$\mathbb{E}_t \widehat{P}_{jt+\tau} \approx (1-\lambda)\mathbb{E}_t \widehat{P}_{jt+\tau,t+\tau} + \lambda \mathbb{E}_t \widehat{P}_{jt+\tau-1}.$$

As illustrated in Appendix B.2, the realization of the sector prices depends on the realization of the Calvo process, and in general,

$$\widehat{P}_{jt+\tau} \neq (1-\lambda)\widehat{P}_{jt+\tau,t+\tau} + \lambda \widehat{P}_{jt+\tau-1}.$$

However, if there is a large number of ex-ante identical sectors, the law of large numbers implies that the aggregate price will still follow a Calvo process:

$$\widehat{P}_{t+\tau} = \frac{1}{J}\sum_j \widehat{P}_{jt+\tau} \approx \frac{1}{J}\sum_j (1-\lambda)\widehat{P}_{jt+\tau,t+\tau} + \frac{1}{J}\lambda \sum_j \widehat{P}_{jt+\tau-1} = (1-\lambda)\widehat{P}_{t+\tau,t+\tau} + \lambda \widehat{P}_{t+\tau-1},$$

where J is the number of ex-ante homogeneous sectors.

Similarly, we can aggregate the sector NKPC (10) and re-express it as a second-order difference equation of aggregate price levels:

$$\widehat{P}_{t+\tau} - \lambda \widehat{P}_{t+\tau-1} - \beta\lambda(\widehat{P}_{t+\tau+1} - \lambda \widehat{P}_{t+\tau}) = \frac{(1-\beta\lambda)(1-\lambda)}{(1+\varphi)}(\mathbb{E}_t \widehat{Q}_{t+\tau} + \varphi \widehat{P}_{t+\tau}) \quad \forall \tau \geq 0. \tag{B.20}$$

Under a permanent monetary supply shock at t (i.e., $\widehat{M}_{t+\tau} = 1 \ \forall \tau \geq 0$), the desired producer price $\widehat{Q}^*_t$ moves one-to-one with the shock:

$$\mathbb{E}_t \widehat{Q}_{t+\tau} = \widehat{Q}^*_{t+\tau} = \widehat{M}_{t+\tau} = 1 \quad \forall \tau \geq 0. \tag{B.21}$$

Substituting (B.21) into (B.20), the aggregate price dynamics can be solved as

$$\widehat{P}_{t+\tau} - \widehat{P}_{t+\tau-1} = (1-\Lambda)\Lambda^{\tau} \quad \text{and} \quad \widehat{P}_{t+\tau} = 1 - \Lambda^{\tau+1}, \tag{B.22}$$

where

$$\Lambda \equiv \frac{1}{2}\left[\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)} - \sqrt{\left(\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)}\right)^2 - \frac{4}{\beta}}\right]. \tag{B.23}$$

Since $P_t C_t = M_t$, the total cumulative change in consumption in response to a permanent monetary supply shock at t can be calculated as

$$\sum_{\tau=0}^{\infty} \widehat{C}_{t+\tau} = \sum_{\tau=0}^{\infty} (1-\widehat{P}_{t+\tau}) = \sum_{\tau=0}^{\infty} \Lambda^{\tau+1} = \frac{\Lambda}{1-\Lambda}.$$

As $\varphi \to 0$, the dynamics of the model converge to a standard Calvo model with $\Lambda \to \lambda$. The output amplification relative to a standard Calvo model is given by $\frac{\Lambda(1-\lambda)}{\lambda(1-\Lambda)}$ and the additional price stickiness relative to a standard Calvo model is given by Λ/λ. Figure B2 illustrates the effect of strategic complementarity on price and output dynamics in this homogeneous sector model. The figure also reports the effect of strategic complementarity on the NKPC slope factor $1/(1+\varphi)$, as described in Corollary 1. ■

B.3.1 Synchronized two-layer models versus standard one-layer models

In our benchmark model, we assume (i) oligopolistic distributors and monopolistically competitive producers and (ii) both producers and distributors face nominal rigidity, with the timing of price adjustments determined by an identical Poisson process. Alternative models in the literature, such as Mongey (2021) and Wang and Werning (2022), have a different market structure, featuring oligopolistically competitive producers that face nominal rigidity but no distributors. Our assumption (ii) is primarily to match the key feature in the data that distributor prices tend to adjust simultaneously with cost adjustments.[27] In what follows, we show that our benchmark model yields the same aggregate dynamics in response to a permanent monetary policy shock as an alternative

[27] Apart from the evidence in Section 3, a similar synchronization pattern has been documented noted in the retail sector by Eichenbaum, Jaimovich and Rebelo (2011) and Goldberg and Hellerstein (2012).

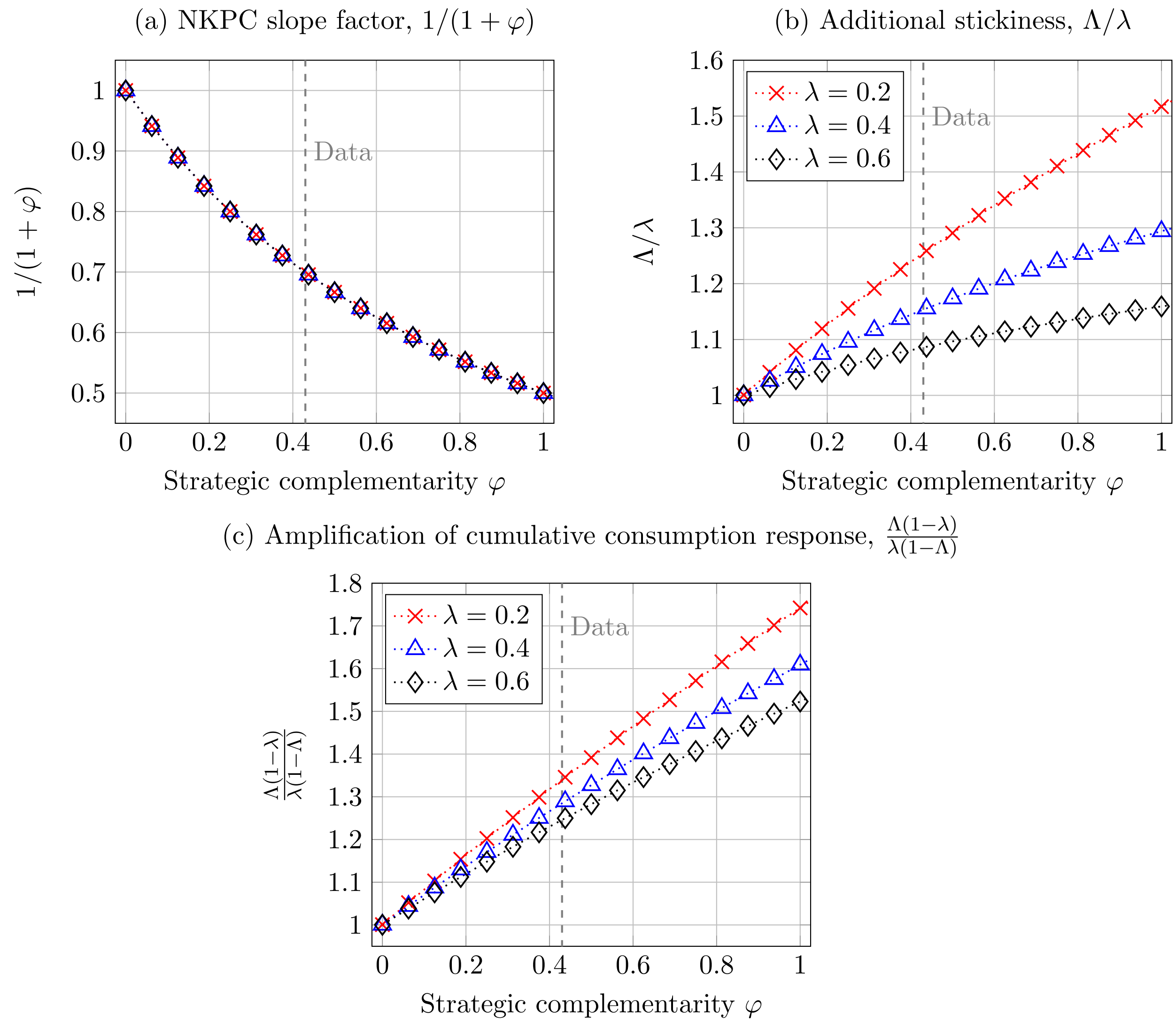


Figure B2: Effect of strategic complementarity on price and output dynamics in the homogeneous sector model (relative to monopolistic competition) one-layer model with oligopolistically competitive sticky price producers.

First, we note that adding an additional layer of *flexible price* monopolistically competitive producers or distributors does not change the aggregate dynamics, as the price pass-through to cost shocks is 100% in this additional layer. For example, adding flexible price monopolistically competitive distributors to the model of Wang and Werning (2022) does not change the aggregate dynamics. Similarly, if the prices of the producers in our benchmark model were fully flexible, the corresponding aggregate price dynamics would be the same as in an alternative model with only oligopolistically competitive sticky price producers and no distributors.

Second, when the additional layer of monopolistically competitive producers or distributors also faces nominal rigidity but the timing of the adjustment is completely *random* and not synchronized with the other layer, the aggregate price sluggishness is amplified, resulting in a larger output response. This is because cost shocks are transmitted more slowly due to the additional layer of nominal rigidity. For example, if we remove the perfect synchronization assumption in our model, the expected change in the distributor's cost becomes

$$\mathbb{E}_t \widehat{Q}_{t+\tau} = [1 - (\lambda^p)^{\tau+1}] \widehat{Q}^*_{t+\tau} = [1 - (\lambda^p)^{\tau+1}] \widehat{M}_{t+\tau} = 1 - (\lambda^p)^{\tau+1} \quad \forall \tau \geq 0,$$

where λ^p is the degree of price stickiness in the monopolistically competitive producer industry.

Finally, when the timing of price adjustments is perfectly synchronized between monopolistically competitive producers and oligopolistic distributors, the aggregate price and output dynamics in response to a permanent monetary policy shock are identical to those in the model with sticky price oligopolistically competitive distributors and flexible price monopolistically competitive producers. This occurs because, when the distributor adjusts its price, its cost is also fully adjusted. More formally, Propositions 1 and 2 show that the pass-through rate to a permanent common cost shock ($\rho = 1$) is the same in both models. Together with (B.21) and Proposition 3, we can infer that the aggregate dynamics in response to a permanent monetary policy shock should be exactly the same in these two models.

In this context, our assumption on the synchronization between the timing of cost and price adjustments not only mirrors the observed data characteristics of wholesalers but also facilitates the comparison of our theoretical results with recent models featuring oligopolistic competitors and no distributors (e.g., Mongey 2021, Wang and Werning 2022).

B.3.2 Multi-country version

The takeaways of the above results carry over in a multi-country version of the model. The key difference in the multi-country version of the model is that a monetary policy or an exchange rate shock can no longer be considered as a "common" shock. For example, a monetary shock may not directly affect the costs of distributors that source their products from abroad, while exchange rate movements may not directly influence the costs of distributors sourcing domestically.

Our theoretical result on sector prices (B.11) suggests that the impact of an unanticipated permanent monetary shock depends on how it affects the average cost index of the industry $\widehat{Q}^*_{jt}$:

$$\mathbb{E}_t \widehat{P}_{jt+\tau} = \frac{\rho^{\tau+1} - \Lambda^{\tau+1}}{\rho(1-b) + \lambda\left[\beta\rho(\lambda-\rho) - 1\right]} a \widehat{Q}^*_{jt} = \left(1 - \Lambda^{\tau+1}\right) \widehat{Q}^*_{jt} \quad \forall \tau \geq 0$$

In a simple setting where the change in marginal cost $\widehat{MC}_{ijt} = \widehat{M}_t = 1$ for domestically-sourced firms and $\widehat{MC}_{ijt} = 0$ for foreign-sourced firms, the change in the average cost index of the industry $\widehat{Q}^*_{jt}$ depends on the total market share of domestically-sourced firms s_{jD}:

$$\widehat{Q}^*_{jt} = s_{jD} \widehat{M}_t = s_{jD}.$$

The aggregate price dynamics can be expressed as a function of the mean market share of domestically-sourced firms $s_D \equiv \sum_j \alpha_j s_{jD}$,

$$\widehat{P}_{t+\tau} = \left(1 - \Lambda^{\tau+1}\right) s_D,$$

and when $\varphi \to 0$, we have $\widehat{P}_{t+\tau} = \left(1 - \lambda^{\tau+1}\right) s_D$ in a standard Calvo model. Therefore, although the magnitude of price change is attenuated by the fact that not all firms are directly affected by the monetary shock, the amplification effect of strategic complementarity relative to Calvo remains the same.

B.4 Model with heterogeneous sectors (and proof of Proposition 3)

In this subsection, we prove Proposition 3 and show how introducing heterogeneous sectors into the model changes the aggregate price and output responses to a monetary shock.

Aggregate price dynamics. Let $\alpha_z = \sum_{j\in z}\alpha_j$ denote the total market share of sectors with market structure z. Assuming a sufficiently large number of sectors of each market structure z, the price index for type z sectors can be expressed as

$$\widehat{P}_{zt+\tau} = \frac{1}{n_z}\sum_{j\in z}\widehat{P}_{jt+\tau} = \frac{1}{n_z}\sum_{j\in z}(1-\lambda_j)\widehat{P}_{jt+\tau,t+\tau} + \frac{1}{n_z}\sum_{j\in z}\lambda_j\widehat{P}_{jt+\tau-1} = (1-\lambda_z)\widehat{P}_{zt+\tau,t+\tau} + \lambda_z\widehat{P}_{zt+\tau-1}$$

where the law of large numbers is applied to derive the second equality. However, due to sector heterogeneity, the aggregate price no longer follows the standard Calvo form:

$$\widehat{P}_t = \sum_z \alpha_z\widehat{P}_{zt} = \sum_z \alpha_z(1-\lambda_z)\widehat{P}_{zt,t} + \sum_z \alpha_z\lambda_z\widehat{P}_{zt-1} \neq (1-\lambda)\widehat{P}_{t,t} + \lambda\widehat{P}_{t-1}, \tag{B.24}$$

where $\lambda \equiv \sum_z \alpha_z\lambda_z$. Note that the last inequality holds because $\widehat{P}_{zt}$ is correlated with λ_z:

$$E[\lambda_z\widehat{P}_{zt}] = E[\lambda_z]E[\widehat{P}_{zt}] + Cov(\lambda_z, \widehat{P}_{zt})$$

where the expectation and covariance are taken over sectors z. To be more concrete, note that (B.24) can be rewritten as

$$\begin{aligned}
\widehat{P}_t =&(1-\lambda)\widehat{P}_{t,t} + \lambda\widehat{P}_{t-1} + Cov(\lambda_z, \widehat{P}_{zt-1}) - Cov(\lambda_z, \widehat{P}_{zt,t}) \\
=&(1-\lambda)\widehat{P}_{t,t} + \lambda\widehat{P}_{t-1} + Cov(\lambda_z, \widehat{P}_{zt-1}) - Cov\left[\lambda_z, \frac{1}{1-\lambda_z}\left(\widehat{P}_{zt} - \lambda_z\widehat{P}_{zt-1}\right)\right] \\
=&(1-\lambda)\widehat{P}_{t,t} + \lambda\widehat{P}_{t-1} - Cov\left[\lambda_z, \frac{1}{1-\lambda_j}\left(\widehat{P}_{zt} - \widehat{P}_{zt-1}\right)\right]
\end{aligned} \tag{B.25}$$

where $\lambda \equiv \sum_z \alpha_z\lambda_z$ and $Cov\left[\lambda_z, \frac{1}{1-\lambda_z}\left(\widehat{P}_{zt} - \widehat{P}_{zt-1}\right)\right]$ represent the additional price stickiness due to sector heterogeneity.

Price and output responses to monetary shock. Under a permanent monetary shock at t, the expected future price of sector j can be solved as

$$\mathbb{E}_t \widehat{P}_{jt+\tau} = 1 - \Lambda_j^{\tau+1} \quad \forall \tau \geq 0,$$

where

$$\Lambda_j \equiv \frac{1}{2}\left[\lambda_j + \frac{1-b_j}{\beta\lambda_j} - \sqrt{\left(\lambda_j + \frac{1-b_j}{\beta\lambda_j}\right)^2 - \frac{4}{\beta}}\right],$$
$$b_j \equiv (1-\beta\lambda_j)(1-\lambda_j)\sum_i s_{ij}\frac{\varphi_{ij}}{(1+\varphi_{ij})}.$$

Summing over similar sectors in each structure type z, we have

$$\widehat{P}_{zt+\tau} \equiv \frac{1}{n_z}\sum_{j\in z}\widehat{P}_{jt+\tau} = 1 - \Lambda_z^{\tau+1} \quad \forall \tau \geq 0, \tag{B.26}$$

Using (B.26), the inflation and output dynamics can be derived as

$$\widehat{\pi}_{zt+\tau} = \widehat{P}_{zt+\tau} - \widehat{P}_{zt+\tau-1} = (1-\Lambda_z)\Lambda_z^{\tau} \quad \text{and} \quad \widehat{c}_{zt+\tau} = 1 - \widehat{P}_{zt+\tau} = \Lambda_z^{\tau+1} \quad \forall \tau \geq 0.$$

Substituting (B.26) into (B.25), we have

$$\widehat{P}_t = (1-\lambda)\widehat{P}_{t,t} + \lambda\widehat{P}_{t-1} - Cov\left[\lambda_z, \frac{1-\Lambda_z}{1-\lambda_j}\Lambda_z^{\tau}\right]. \tag{B.27}$$

Cumulative output response. The cumulative output response in a heterogeneous sector monopolistic competition Calvo model is given by

$$E_z\left[\frac{\lambda_z}{1-\lambda_z}\right]. \tag{B.28}$$

It is well known that the cumulative output response evaluated at the average frequency of price adjustments of the heterogeneous sector economy, $\lambda \equiv E_z[\lambda_z]$, is downward biased. Taking a second-order approximation of the function (B.28), we have

$$E_z\left[\frac{\lambda_z}{1-\lambda_z}\right] \approx \frac{\lambda}{1-\lambda} + \frac{1}{(1-\lambda)^3}\sigma^2_{\lambda_z} \geq \frac{\lambda}{1-\lambda}.$$

But, as shown in Carvalho (2006), the cumulative output response evaluated at the average duration of price adjustment $x_z \equiv 1/(1-\lambda_z)$ gives the correct impact. To see this, note

$$E_z\left[\frac{\lambda_z}{1-\lambda_z}\right] = E_z\left[x_z - 1\right] = x - 1,$$

where $x \equiv E_z[1/(1-\lambda_z)]$. Under monopolistic competition, the cumulative real impact of a monetary shock can be replicated by simply targeting the observed average duration of price adjustments.

With market power, the cumulative output response becomes

$$E_z\left[\frac{\Lambda_z}{1-\Lambda_z}\right].$$

By the same token, the cumulative output response can be obtained by evaluating the average *market power adjusted* duration of price adjustments: $X_z \equiv 1/(1-\Lambda_z)$

$$E_z\left[\frac{\Lambda_z}{1-\Lambda_z}\right] = E_z\left[X_z - 1\right] = X - 1,$$

where $X \equiv E_z[1/(1-\Lambda_z)]$.

Note that, when firms have market power, the conventional average duration of price adjustment x_z is no longer sufficient to capture cumulative output amplification. In this case, accounting for the impact of real rigidity, by targeting the duration implied by Λ_z rather than λ_z, is important. To see this, we can decompose the cumulative output response into two components

$$\begin{aligned} E_z\left[\frac{\Lambda_z}{1-\Lambda_z}\right] &= E_z\left[\frac{\lambda_z}{1-\lambda_z}\frac{\Lambda_z(1-\lambda_z)}{(1-\Lambda_z)\lambda_z}\right] = E_z\left[\frac{\lambda_z}{1-\lambda_z}\right]E_z\left[\frac{\Lambda_z(1-\lambda_z)}{(1-\Lambda_z)\lambda_z}\right] + Cov_z\left[\frac{\lambda_z}{1-\lambda_z}, \frac{\Lambda_z(1-\lambda_z)}{(1-\Lambda_z)\lambda_z}\right] \\ &= (x-1)E_z\left(\frac{X_z-1}{x_z-1}\right) + Cov_z\left(x_z-1, \frac{X_z-1}{x_z-1}\right). \end{aligned}$$

This completes the proof of Proposition 3. ■

Table 3 summarizes the key quantitative impacts in different versions of the model (weighted). Table B1 shows the counterpart statistics, calculated based on the unweighted statistics. Figure B3 shows the correlation between market power and price stickiness across industries and products.

Table B1: Statistics in a multi-sector oligopoly model with sticky prices (based on unweighted moments)

Statistic	**Baseline** MC(1) $(\lambda, \varphi = 0)$	**× Relative to Baseline** OC(1) (λ, φ)	MC(J) $(\lambda_j, \varphi = 0)$	OC(J) (λ_j, φ)	OC(J) (λ_j, φ_j)
	(1)	(2)	(3)	(4)	(5)
(a) NAPCS7 products					
Output Response	0.84	1.27	1.37	1.71	2.11
Price Stickiness	0.46	1.13	1.17	1.29	1.40
Slope of NKPC	0.64	0.70	0.63	0.44	0.31
(b) NAICS4 sectors					
Output Response	0.79	1.28	1.21	1.52	1.81
Price Stickiness	0.44	1.14	1.11	1.24	1.34
Slope of NKPC	0.71	0.70	0.76	0.53	0.41

Notes: The table provides model statistics based on unweighted estimates from NAPCS7 products (Panel (a)) and NAICS4 industries (Panel (b)). The first row of each panel reports the cumulative response of aggregate output (in %) to an unanticipated permanent 1% increase in the money supply. The second row of each panel reports price stickiness λ in a standard monopolistically competitive model in column (1) that implies the output response in the alternative version of the model. The third row of each panel reports the implied slope of the NKPC. Column (1) gives the statistics for the standard one-sector Calvo model with monopolistic competition ("MC(1)"), where price stickiness is equal to the weighted mean price stickiness in the data. Statistics for models in columns (2)–(5) are expressed relative to statistics for MC(1). Column (2) reports the results for an oligopolistically competitive model with homogeneous sectors ("OC(1)"), where λ is set to the weighted mean price stickiness in the data and $\varphi = 0.43$. Column (3) reports statistics for an MC model with heterogeneous sectors ("MC(J)"), where the price stickiness in each sector is calibrated to match the data. Column (4) reports statistics for an OC model with heterogeneity in price stickiness and homogeneous market power, where $\varphi = 0.43$. Column (5) reports statistics for an OC model with heterogeneity in both price stickiness and market power, calibrated to match the estimates in the data.

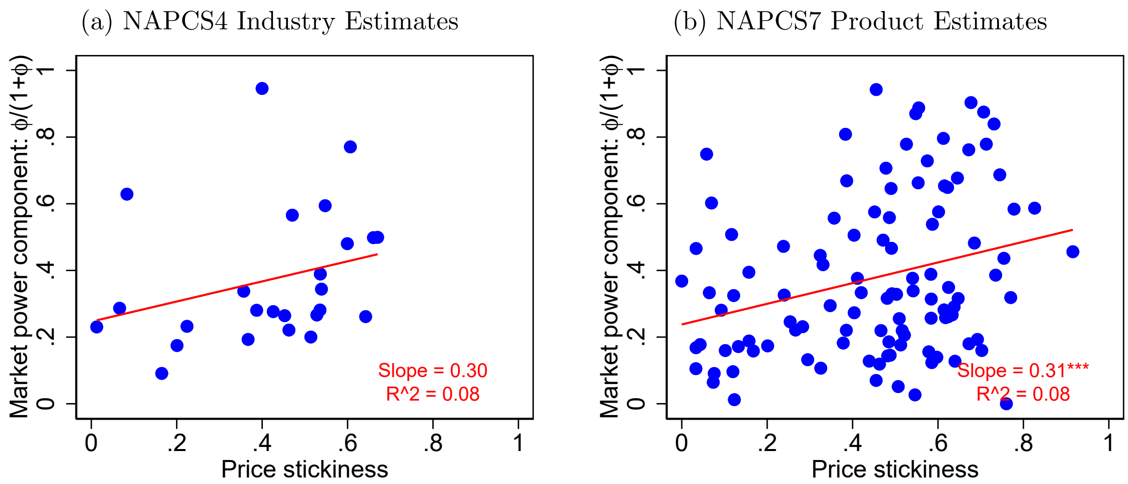


Figure B3: Correlation between market power and price stickiness

B.5 Comparing theoretical vs simulated results

To what extent do our closed-form solutions provide a good approximation for the true theoretical responses? In particular, two concerns may arise: (1) the theoretical responses are derived under the assumption of small shocks, but in practice, the idiosyncratic shocks can be large; and (2) by taking first-order approximations, we might miss important channels revealed in a fully nonlinear dynamic model.

To address these concerns, we fully solve a dynamic oligopolistic Calvo model without taking any approximations and compare the model solutions to our theoretical counterparts. Due to computational constraints, we solve a model with duopoly distributors—a market structure in which strategic interactions among firms are the largest. If we indeed missed any important channels in our approximated model, it would likely be reflected in this setting. We also remove the restriction of perfect synchronization so that our setting is more comparable to Wang and Werning (2022) and Mongey (2021).

Model setting. In the beginning of each period, the firm observes its own and competitors' past prices $\{P_{ij,t-1}, P_{-ij,t-1}\}$, and its own and competitors' current costs $\{Q_{ij,t}, Q_{-ij,t}\}$. These are the four state variables in each sector $S_{j,t} \equiv \{P_{ij,t-1}, P_{-ij,t-1}, Q_{ij,t}, Q_{-ij,t}\}$. Within the period, firms recognize that each firm faces an exogenous probability $1 - \lambda_j$ that it can reset its price. As in

Mongey (2021), we assume that within a period, all moves are simultaneous, meaning that firms do not respond to each other's new prices.[28]

Formally, the problem can be written as

$$V(S_{j,t}) = (1-\lambda_j)V^{adj}(S_{j,t}) + \lambda_j V^{stay}(S_{j,t})$$

with

$$\begin{aligned} V^{adj}(S_{j,t}) = \max_{P^*_{ij,t}} \, &(1-\lambda_j)\left[\pi(P^*_{ij,t}, P_{-ij}(S_{j,t}), Q_{ij,t}) + \beta\mathbb{E}V(P^*_{ij,t}, P_{-ij}(S_{j,t}), Q_{ij,t+1}, Q_{-ij,t+1})\right] \\ &+ \lambda_j\left[\pi(P^*_{ij,t}, P_{-ij,t-1}, Q_{ij,t}) + \beta V(P^*_{ij,t}, P_{-ij,t-1}, Q_{ij,t+1}, Q_{-ij,t+1})\right]; \end{aligned} \tag{B.29}$$

and

$$\begin{aligned} V^{stay}(S_{j,t}) = \, &(1-\lambda_j)\left[\pi(P_{ij,t-1}, P_{-ij}(S_{j,t}), Q_{ij,t}) + \beta\mathbb{E}V(P_{ij,t-1}, P_{-ij}(S_{j,t}), Q_{ij,t+1}, Q_{-ij,t+1})\right] \\ &+ \lambda_j\left[\pi(P_{ij,t-1}, P_{-ij,t-1}, Q_{ij,t}) + \beta\mathbb{E}V(P_{ij,t-1}, P_{-ij,t-1}, Q_{ij,t+1}, Q_{-ij,t+1})\right]; \end{aligned} \tag{B.30}$$

where $P_{-ij}(S_{j,t})$ is the firm's competitor's reset price for state $S_{j,t}$ and the expectation $\mathbb{E}$ is taken over the cost processes $Q_{ij,t+1}, Q_{-ij,t+1}$. The first line of (B.29) and (B.30) gives the profit and expected future value when the firm's competitor has the opportunity to reset its price to $P_{-ij}(S_{j,t})$, whereas the second line gives the corresponding values when its competitor does not have the opportunity to reset its price (and thus stick to $P_{-ij,t-1}$). As in Wang and Werning (2022) and Mongey (2021), we consider symmetric policy solutions. That is, if the two firms' market conditions are swapped, they would have chosen the same strategy as their competitor has chosen, i.e., $P_{-ij}(P_{ij,t-1}, P_{-ij,t-1}, Q_{ij,t}, Q_{-ij,t}) = P_{ij}(P_{-ij,t-1}, P_{ij,t-1}, Q_{-ij,t}, Q_{ij,t})$.

[28] The key difference in the model we set up here and that of Mongey (2021) is that the probability of price adjustment is exogenous in our model. When the probability of price adjustment is endogenous and state dependent (due to a menu cost), obtaining analytical solutions is very hard (if not impossible). A key benefit of relying on a Calvo framework lies in its analytical tractability, where we are able to solve the model for an arbitrary market structure of a sector (rather than restricting the solution to duopoly markets).

Simulation setting. The firm's profit function is given by

$$\pi(P_{i,t}, P_{-ij,t}, Q_{ij,t}) = (P_{i,t} - Q_{ij,t})c_{ij,t}$$

where

$$\begin{aligned} \text{Demand for distributor } i\text{'s good:} \quad & c_{ij,t} \equiv (P_{ij,t}/P_{j,t})^{-\theta} P_{j,t} \\ \text{Sector price index:} \quad & P_{j,t} \equiv \left[(P_{ij,t})^{1-\theta} + (P_{-ij,t})^{1-\theta}\right]^{\frac{1}{1-\theta}} \\ \text{Distributor } i\text{'s cost:} \quad & \ln(Q_{ij,t}) = \rho \ln(Q_{ij,t-1}) + \epsilon_{ij,t} \end{aligned} \tag{B.31}$$

The within-sector elasticity of substitution is set to $\theta = 3$, the household discount factor is set to the standard value $\beta = 0.98^{1/12}$, and the idiosyncratic shock is drawn from a normal distribution $N(0, \sigma_\epsilon^2)$ with $\sigma_\epsilon = 0.25$. We simulate a partial equilibrium model with heterogeneous duopoly firms, incorporating AR(1) cost shocks as described by (B.31).[29] We simulate 10*2 different models, varying the underlying price stickiness λ_j and the persistence of the cost shock ρ. In each model, we simulate 1,000 industries for 100 periods. We estimate our empirical specification on the simulated data from the fully non-linear model.

Figure B4 compares the estimated and theoretical relationships. The dashed lines show the theoretical pass-through coefficients under our first order approximated solution in Proposition 1, evaluated at the mean market share ($s = 0.5$) across simulations periods. The dots represent the pass through estimates from the simulated data. As seen in Figure B4, the estimated coefficients align well with the theoretical predictions.

Remarks. The empirical and theoretical coefficients may not be exactly the same for two reasons. First, our theoretical prediction is evaluated at the average market share of a firm across all periods. With large idiosyncratic shocks, a firm's market share can substantially deviate from this average in some periods. As a result, the estimated coefficient may differ from the theoretical

[29] Note that, under the assumptions of (1) log consumption and linear labor and (2) Cobb-Douglas aggregated consumption across sectors, the price dynamics can be solved separately in each sector (and the aggregate price change can be obtained by aggregating the sector prices). Therefore, verifying our solution in the partial equilibrium model is sufficient for this purpose.

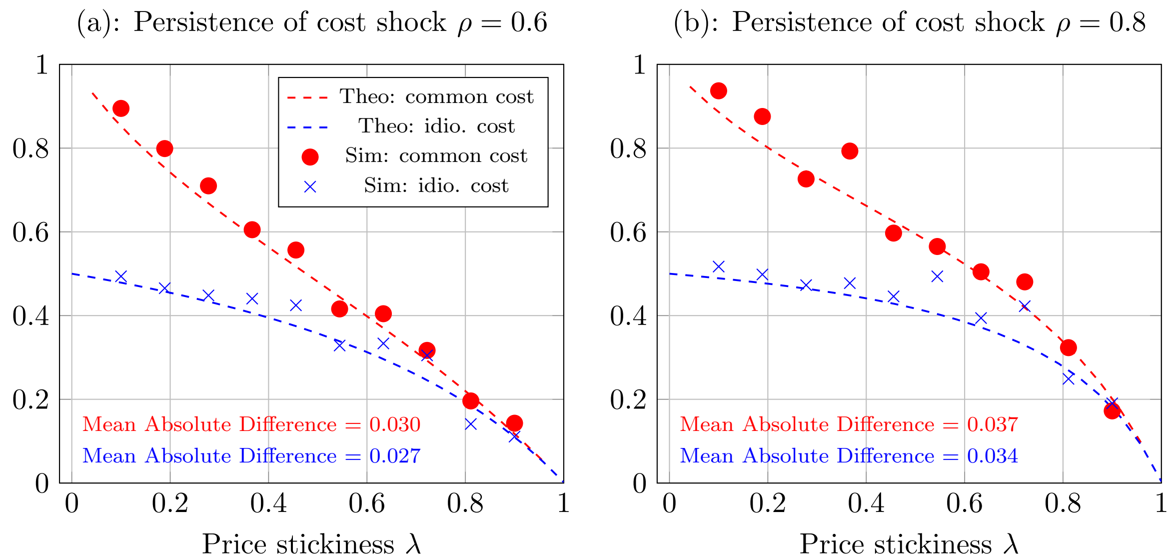


Figure B4: Comparing theoretical vs estimated responses

prediction because the latter is evaluated with the "wrong" parameters. For example, in the full nonlinear model, the competitor's price adjustment may be slightly different when accounting for the fact that the market structure, upon receiving an idiosyncratic shock or a price adjustment in the last period, differs from the steady-state market structure where our theoretical predictions are evaluated.

As seen in Figure B4, this discrepancy does not seem to be significant because the positive biases largely offset the negative biases. This offsetting effect occurs both across firms and over time. Within each period, the presence of a larger-than-average firm simultaneously implies the existence of a smaller-than-average firm. Thus, evaluating the solutions at the average market share results in an upward bias and a downward bias, which largely cancel each other out, thereby having limited impact on the pass-through estimates. Similarly, over time, a firm has an equal probability of receiving positive or negative idiosyncratic cost shocks. Therefore, the periods where the pass-through is higher than the theoretical prediction evaluated at the average (steady-state) market share largely offset the periods where the pass-through is lower than the theoretical prediction evaluated at the average, resulting in a very small overall bias in the estimated pass-through coefficients using our empirical strategy.

Second, the numerical solution is slightly sensitive to the grid points used to solve the model.

For example, alternative numerical settings could bring the fourth red point in panel (b) closer to our theoretical prediction, though this may cause other points to be slightly off. We could achieve a slightly better match between the theoretical and estimated responses by taking the median or mean over several numerical solutions. However, we deliberately choose to show the non-averaged version of responses in Figure B4 to illustrate that fully nonlinear numerical solutions may also suffer from accuracy issues and do not always provide a more informative picture.

B.6 "Feedback" and "strategic" effects

Our theoretical solutions account for both the "feedback" and "strategic" effects defined by Wang and Werning (2022) (WW). Specifically, WW define the feedback effect as those channels that already exist in static models (i.e., channels i and ii mentioned below) and the strategic effect as the additional effect due to the fact that each firm internalizes that, in the words of WW, "its current pricing decision can affect how its rivals will set their prices in the future." In this appendix, we discuss the difference between these two effects through the lens of our discrete time oligoplistic competition Calvo model.

To fix ideas, it is useful to start by thinking about how equilibrium is reached a static version of the model (i.e., where firm optimisation considers only the current period). Consider a two-period problem: the firms start in their steady state in period t, and there are small shocks to the marginal costs of the firms $\{\widehat{M}_{ijt+1}\}_{i=1}^{N_j}$ in $t+1$.

In the static setting, the model can be solved fully non-linearly separately for each period (i.e., t and $t+1$) by solving a fixed point problem that involves a system of first order equations:

$$P_{ijt} = \frac{\vartheta_{ijt}(\{P_{kjt}\}_{k=1}^{N_j})}{\vartheta_{ijt}(\{P_{kjt}\}_{k=1}^{N_j}) - 1} M_{ijt} \quad \forall i = 1, ..., N_j, \tag{B.32}$$

where P_{ijt} in equation (B.32) is the best-response of firm i for the given marginal cost M_{ijt} and competitors' prices $\{P_{kjt}\}_{k \neq i}$. The Nash equilibrium is formed when no firm wants to deviate given the set of prices $(\{P_{kjt}\}_{k=1}^{N_j})$ and the underlying costs $(\{M_{kjt}\}_{k=1}^{N_j})$ in the industry. It is worth noting that this equilibrium accounts for the fact that

(i) a firm's pricing decision affects its competitors pricing decisions, i.e., P_{ijt} appears in the best responses of P_{kjt}; and

(ii) the firm's competitors' pricing decisions affect its price, i.e., P_{ijt} is a function of $\{P_{kjt}\}_{k\neq i}$ as shown in (B.32).

It is worth noting that taking first order approximations does not affect the properties of the solution. Approximating the solution around the market structure at t, we have the following expression for the firm's optimal markup

$$\widehat{\mu}_{ijt+1} \approx -\frac{1}{\vartheta_{ijt}-1}\widehat{\vartheta}_{ijt+1} = -\varphi_{ijt}\left[\widehat{P}_{ijt+1} - \widehat{P}_{jt+1}\right]. \tag{B.33}$$

The log-linearized system of equations in (B.32) is given by

$$\widehat{P}_{ijt+1} = \widehat{M}_{ijt+1} - \varphi_{ijt}\left[\widehat{P}_{ijt+1} - \widehat{P}_{jt+1}\right] = \widehat{M}_{ijt+1} - \varphi_{ijt}\left[\widehat{P}_{ijt+1} - \sum_k s_{kjt}\widehat{P}_{kjt+1}\right] \quad \forall i = 1, ..., N_j. \tag{B.34}$$

We see (B.34) has the same property of (B.32), i.e., it accounts for both (i) and (ii). The only difference is that, with the log-linear approximation, we can solve the system of equations in closed form.

The "Naïve" model in static setting. WW illustrate the difference between the "feedback" effect and the "strategic effect" by specifying a "Naïve" model where only the "feedback" effect is present. To discuss the key assumptions made by WW, we start with the "Naïve" version of the static model described above. To facilitate the comparison of our results with those of WW, we analyze the case of symmetric firms and common cost shocks (i.e., $\widehat{M}_{kjt+1} = \widehat{M}_{ijt+1} = \widehat{M}_{jt+1} = 1$). Under these assumptions, we can rewrite the first order conditions in (B.34) as

$$\widehat{P}_{ijt+1} = \frac{1}{1+\varphi_{jt}} + \frac{\varphi_{jt}}{1+\varphi_{jt}}\widehat{P}_{jt+1} \quad \forall i = 1, ..., N_j. \tag{B.35}$$

The key assumption made by WW is that the deviation of the firm's optimal price from its new steady state price is a linear function of its competitors' deviation from their new steady state prices. Applying this assumption in the static model, and integrating the fact that pass through to a common cost shock is 100%, results in

$$\widehat{P}_{ijt+1} - 1 = b \sum_{k \neq i} \left(\widehat{P}_{kjt+1} - 1 \right) \quad \forall i = 1, ..., N_j, \tag{B.36}$$

where b captures how a firm responds to its competitors' prices.

Summing (B.36) over firms, we have

$$\widehat{P}_{jt+1} - 1 = b(N_j - 1) \left(\widehat{P}_{jt+1} - 1 \right). \tag{B.37}$$

Solving for $\widehat{P}_{jt+1}$ gives $\widehat{P}_{jt+1} = 1$. Substituting back to (B.35), we have $\widehat{P}_{ijt+1} = 1 \; \forall i$.

The solution also implies a response slope of $B \equiv b(N_j - 1) = \varphi_{jt}/(1 + \varphi_{jt})$ as

$$\widehat{P}_{ijt+1} = \frac{1}{1+\varphi_{jt}} + \frac{\varphi_{jt}}{1+\varphi_{jt}} \widehat{P}_{jt+1} = 1 - B + B \frac{1}{N_j - 1} \sum_{k \neq i} \widehat{P}_{kjt+1} = 1 \quad \forall i = 1, ..., N_j. \tag{B.38}$$

In this case, we have the same solution as static Nash because the assumption (B.36) does not impose any additional restriction in the static model.

The "Naïve" model in dynamic setting. Does the restriction in (B.36) make a difference in the dynamic version of the model? We proceed to derive price dynamics in the dynamic "Naïve" set up by WW. Our derivation here follows closely from WW, with the key difference being that our model features discrete time while theirs features continuous time.

As in the static case, we start with the first order conditions of the firms, which now depend on the full trajectory of future sector prices:

$$\begin{aligned} \widehat{P}_{ijt,t} &= (1 - \beta\lambda) \sum_{\tau=0}^{\infty} (\beta\lambda)^{\tau} E_t[\widehat{M}_{t+\tau} - \varphi(\widehat{P}_{ijt,t} - \widehat{P}_{jt+\tau})] \\ &= \frac{1 - \beta\lambda}{1 + \varphi} \sum_{\tau=0}^{\infty} (\beta\lambda)^{\tau} E_t[\widehat{M}_{t+\tau} + \varphi \widehat{P}_{jt+\tau}]. \end{aligned} \tag{B.39}$$

We next analyze the expected change in the sector price following the assumption of WW, where a firm's reset price is a function of its competitors' prices. From Calvo, we have

$$E_t\widehat{P}_{kjt+\tau} = (1-\lambda)E_t\widehat{P}_{kjt+\tau,t+\tau} + \lambda\widehat{P}_{kjt+\tau-1} \tag{B.40}$$

Imposing WW's restriction that a firm's reset price is a linear function of the sum of the deviations of its competitors' prices from their optimal steady state prices:

$$E_t(\widehat{P}_{kjt+\tau,t+\tau} - \widehat{P}_{kjT}) = b\sum_{i\neq k}(E_t\widehat{P}_{ijt+\tau} - \widehat{P}_{ijT}), \tag{B.41}$$

we can rewrite (B.40) as:

$$\begin{aligned} E_t(\widehat{P}_{kjt+\tau} - \widehat{P}_{kjT}) &= (1-\lambda)E_t(\widehat{P}_{kjt+\tau,t+\tau} - \widehat{P}_{kjT}) + \lambda(\widehat{P}_{kjt+\tau-1} - \widehat{P}_{kjT}) \\ &= (1-\lambda)b\sum_{i\neq k}(E_t\widehat{P}_{ijt+\tau} - \widehat{P}_{ijT}) + \lambda(\widehat{P}_{kjt+\tau-1} - \widehat{P}_{kjT}) \\ &= (1-\lambda)b\sum_{i\neq k}(E_t\widehat{P}_{ijt+\tau} - 1) + \lambda(\widehat{P}_{kjt+\tau-1} - 1) \end{aligned} \tag{B.42}$$

where $\widehat{P}_{kjT}$ is the (log) change in the price in the new steady state at T (when all prices are fully adjusted) relative to the price in old steady state before the common cost shock at t. The second line imposes the restriction, with $b \equiv B/(N-1)$ captures how a firm responds to its competitors' prices. The third line uses the fact that the flexible price pass-through of a common cost shock is 100%, i.e., $\widehat{P}_{kjT} = 1$.

To obtain the expected sector price dynamics, we sum over the expected individual price dynamics:

$$\frac{1}{N}\sum_k E_t\widehat{P}_{kjt+\tau} - 1 = (1-\lambda)b\frac{1}{N}\sum_k\sum_{l\neq k}\left(E_t\widehat{P}_{ljt+\tau} - 1\right) + \lambda\left(\frac{1}{N}\sum_k E_t\widehat{P}_{kjt+\tau-1} - 1\right)$$

With the assumption of symmetric firms, $\frac{1}{N}\sum_k E_t\widehat{P}_{kjt+\tau} = E_t\widehat{P}_{jt+\tau}$ and

$$(E_t\widehat{P}_{jt+\tau} - 1) = (1-\lambda)b(N-1)(E_t\widehat{P}_{jt+\tau} - 1) + \lambda(E_t\widehat{P}_{jt+\tau-1} - 1).$$

Rearrange and get

$$E_t\widehat{P}_{jt+\tau} = \frac{(1-\lambda)(1-B)}{1-(1-\lambda)B} + \frac{\lambda}{1-(1-\lambda)B}E_t\widehat{P}_{jt+\tau-1}$$

Solving the dynamics gives

$$E_t\widehat{P}_{jt+\tau} = 1 - \left(\frac{\lambda}{1-(1-\lambda)B}\right)^{\tau+1} \equiv 1-(\Lambda^{\text{Naïve}})^{\tau+1}, \tag{B.43}$$

where (B.43) corresponds to the third equation on page A.31 of WW's Online Appendix.

To complete the solution, we now solve for B. First, we substitute (B.43) into the first order condition (B.39). Solving the dynamics gives

$$\begin{aligned}\widehat{P}_{ijt,t} &= \frac{1}{1+\varphi} + \frac{\varphi}{1+\varphi}\left(1 - \frac{1-\beta\lambda}{1-\beta\lambda\Lambda^{\text{Naïve}}}\Lambda^{\text{Naïve}}\right)\\ &= 1 - \frac{\varphi}{1+\varphi}\frac{1-\beta\lambda}{1-\beta\lambda\Lambda^{\text{Naïve}}}\Lambda^{\text{Naïve}}.\end{aligned} \tag{B.44}$$

Second, we verify the reset price solution under assumption (B.41):

$$\widehat{P}_{ijt,t} - 1 = b\sum_{k\neq i}(E_t\widehat{P}_{kjt}-1) = B(\widehat{P}_{jt}-1) = -B\Lambda^{\text{Naïve}} \tag{B.45}$$

Together, we get a system of two equations to solve for B and $\Lambda^{\text{Naïve}}$:

$$\begin{aligned}\Lambda^{\text{Naïve}} &= \frac{\lambda}{1-(1-\lambda)B}\\ B &= \frac{\varphi}{1+\varphi}\frac{1-\beta\lambda}{1-\beta\lambda\Lambda^{\text{Naïve}}}\end{aligned}$$

Finally, solving B gives

$$B = \frac{1+(2-\lambda)\varphi - \beta\lambda(\varphi+\lambda) - \sqrt{(-1+\beta\lambda^2-2\varphi+\lambda\varphi+\beta\lambda\varphi)^2 - 4(1-\lambda)(1+\varphi)(1-\beta\lambda)\varphi}}{2(1-\lambda)(1+\varphi)}.$$

Special cases. First, without market power (i.e., $\varphi = 0$), we have $B = 0$ and $\Lambda^{\text{Naïve}} = \lambda$. Second, without price stickiness (i.e., $\lambda = 0$), we have $B = \varphi/(1+\varphi)$ and $\Lambda^{\text{Naïve}} = 0$.

Comparison. Recall that, under our benchmark solution, the aggregate price dynamics in a model with homogeneous firms and sectors can be written as

$$\widehat{P}_{t+\tau} - \widehat{P}_{t+\tau-1} = (1-\Lambda)\Lambda^{\tau} \quad \text{and} \quad \widehat{P}_{t+\tau} = 1 - \Lambda^{\tau+1},$$

where

$$\Lambda \equiv \frac{1}{2}\left[\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)} - \sqrt{\left(\frac{1+\lambda\varphi+\beta\lambda(\lambda+\varphi)}{\beta\lambda(1+\varphi)}\right)^2 - \frac{4}{\beta}}\right].$$

In the "Naïve" model, the price dynamics take the same form, with a different adjustment factor $\Lambda^{\text{Naïve}}$:

$$\widehat{P}_{t+\tau} - \widehat{P}_{t+\tau-1} = (1-\Lambda^{\text{Naïve}})(\Lambda^{\text{Naïve}})^{\tau} \quad \text{and} \quad \widehat{P}_{t+\tau} = 1 - (\Lambda^{\text{Naïve}})^{\tau+1}.$$

To compare the aggregate dynamics of the two models, it is sufficient to compare $\Lambda^{\text{Naïve}}$ with Λ. Figure B5 plots the ratio of the two adjustment factors. As in WW, we find the difference is negligible for realistic values of λ and φ.

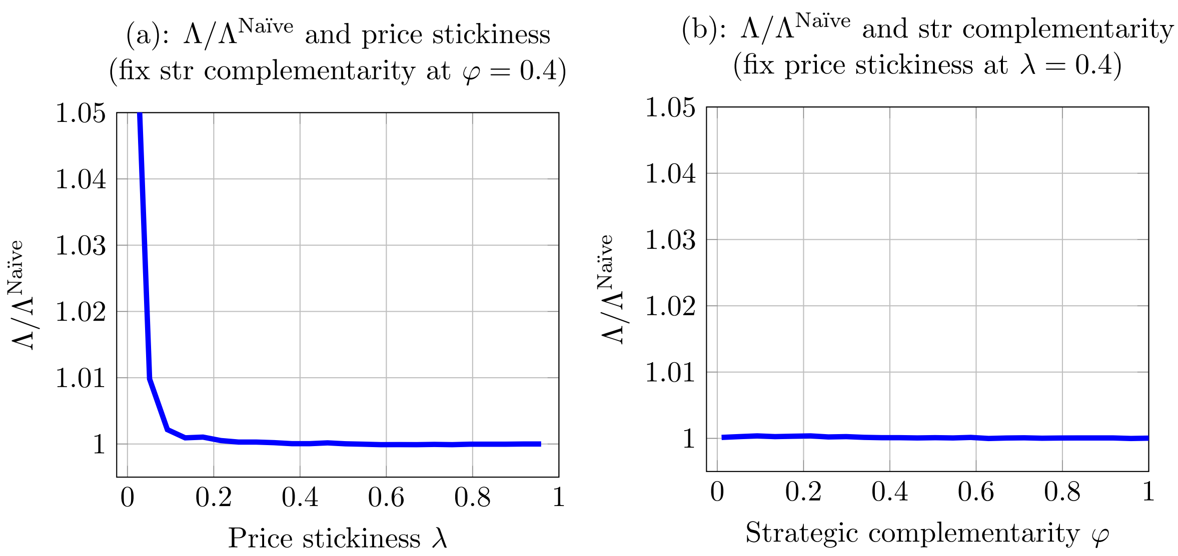


Figure B5: benchmark vs "naïve" dynamics in response to a common cost shock

Discussions. Why does the "strategic effect" not play a big role in the price dynamics of the model? Does this result suggest the firm's reset price has limited impact on its competitors' future reset prices?

To answer these questions, we need to understand the restrictions imposed by (B.41). The key difference between the naïve and the benchmark model lies in how firms take expectations about the their competitors' prices. In the naïve model, the expectation is formed based on assumption (B.41) and equation (B.42). In contrast, in our benchmark model, the expectation is formed based on (B.39). The key restriction imposed by (B.41) is that a firm's reset price in $t+\tau$ only depends on its competitors' prices in $t+\tau$. However, this does not mean that a firm's reset price has no impact on its competitors' future reset prices. To see this, we can iterate expression (B.40) forward to see how firm k's reset price at t influences other firms' reset prices at $t+1$, $t+2$, etc.

At $t+1$:

$$\begin{aligned} E_t\widehat{P}_{kjt+1} &= (1-\lambda)E_t\widehat{P}_{kjt+1,t+1} + \lambda E_t\widehat{P}_{kjt} \\ &= (1-\lambda)E_t\widehat{P}_{kjt+1,t+1} + \lambda\left[(1-\lambda)E_t\widehat{P}_{kjt,t} + \lambda\widehat{P}_{kjt-1}\right]. \end{aligned} \tag{B.46}$$

At $t+2$:

$$\begin{aligned} E_t\widehat{P}_{kjt+2} &= (1-\lambda)E_t\widehat{P}_{kjt+2,t+2} + \lambda E_t\widehat{P}_{kjt+1} \\ &= (1-\lambda)E_t\widehat{P}_{kjt+2,t+2} + \lambda\left\{(1-\lambda)E_t\widehat{P}_{kjt+1,t+1} + \lambda\left[(1-\lambda)E_t\widehat{P}_{kjt,t} + \lambda\widehat{P}_{kjt-1}\right]\right\}. \end{aligned} \tag{B.47}$$

Therefore, even if firm i's reset price at $t+\tau$ only depends on the expected competitors' prices at $t+\tau$, the fact that the expected competitors' prices at $t+\tau$ implicitly depend on their reset prices in earlier periods, i.e., $E_t\widehat{P}_{kjt+\tau}(\widehat{P}_{kjt,t}, \widehat{P}_{kjt+1,t+1}, \ldots, \widehat{P}_{kjt+\tau-1,t+\tau-1})$, makes the optimal reset price of firm i at $t+\tau$, $\widehat{P}_{ijt+\tau,t+\tau}$, an implicit function of $\left\{\widehat{P}_{kjt,t}, \widehat{P}_{kjt+1,t+1}, \ldots, \widehat{P}_{kjt+\tau-1,t+\tau-1}\right\}_{k\neq i}$. Consequently, the restriction (B.41) does not preclude the possibility that a firm may implicitly respond to its competitors' reset prices in the earlier periods.

What the restriction (B.41) imposes is that the firm's reset price at $t+\tau$ responds to its competitors' earlier reset prices in a specific way – the importance of firm k's reset price at t, $\widehat{P}_{kjt,t}$, for firm i's reset price at $t+\tau$, $\widehat{P}_{ijt+\tau,t+\tau}$, is given by $\lambda^\tau(1-\lambda)$, as illustrated by (B.46) and (B.47). Figure B5 shows that when the response factor B is solved to ensure consistent expectations (i.e., (B.44) and (B.45) hold), the restricted "Naïve" solution provides a very good proxy for the true dynamic solutions. This implies that the expected future price index of a competitor, $E_t\widehat{P}_{kjt+\tau}$, provides a good summary of all the prices $(\widehat{P}_{kjt,t}, \widehat{P}_{kjt+1,t+1}, \ldots, \widehat{P}_{kjt+\tau,t+\tau})$ that a firm needs to consider when resetting its price.

B.7 Testing empirical strategy using model simulated data

In this subsection, we test the empirical strategy proposed in Section 4 using simulated data based on our theoretical predictions. Our empirical approach exploits a unique advantage of the wholesale data – the fact that we directly observe the price $\widehat{P}_{ijt}$ and the cost $\widehat{Q}_{ijt}$ for many firms in an industry. This allows us to construct the simple estimation strategy discussed in Section 4. To see this, note that the reset price response in Proposition 2 can be estimated by taking the difference between two price adjustments:

$$\begin{aligned}\widehat{P}_{ijt,t} - \widehat{P}_{ijt-l,t-l} = {} & \frac{1}{1+\varphi_{ij}}\left[\widehat{Q}^*_{ijt} - \widehat{Q}^*_{ijt-l} - (\widehat{Q}^*_{jt} - \widehat{Q}^*_{jt-l})\right] \\ & + \left[\frac{1}{1+\varphi_{ij}} + \frac{\varphi_{ij}}{1+\varphi_{ij}}\left(\frac{\rho-\Lambda_j}{1-\beta\lambda\Lambda_j}\right)\right]\left(\widehat{Q}^*_{jt} - \widehat{Q}^*_{jt-l}\right)\end{aligned} \tag{B.48}$$

where $t-l$ is the period of the last observed price change for firm i in sector j. Note that most components in (B.48) are directly observable in the data: $\widehat{P}_{ijt,t} = \widehat{P}_{ijt}$, $\widehat{P}_{ijt-l,t-l} = \widehat{P}_{ijt-1}$, $\widehat{Q}^*_{ijt} = \widehat{Q}_{ijt}$, and $\widehat{Q}^*_{ijt-l} = \widehat{Q}_{ijt-1}$. A small caveat here is that $\widehat{Q}^*_{jt} - \widehat{Q}^*_{jt-l}$ is not directly measurable as not all firms adjust their their prices (and receive cost shocks) at the same time.[30]

Our empirical approach approximates $\widehat{Q}^*_{ijt} - \widehat{Q}^*_{ijt-l}$ and $\widehat{Q}^*_{jt} - \widehat{Q}^*_{jt-l}$ using a simple fixed effect regression. In what follows, we construct a realistic environment to test whether this empirical

[30]Note that we observe the cost of a firm for all the surveyed periods. This measurement problem only arises when we account for the fact that wholesalers' costs are sticky and may not reflect the optimal price of their suppliers. According to our model, wholesalers may react to *unrealized* price and cost changes of their competitors. To clarify, consider an industry where suppliers' prices (wholesalers' costs) are updated every two months. The timing of the cost adjustment is specific to the wholesaler; say half adjust in even months and the other half adjust in odd months. Further, assume firms adjust their prices at the time they receive the cost shock (i.e., perfect synchronization in the timing of price and cost adjustments). Now, there is a positive common cost shock to the suppliers at t. Half of the wholesale firms will receive a cost increase this month and adjust their prices. However, when resetting their prices, the adjusting firms account for the fact that the underlying cost for non-adjusting firms also increases, and this cost change will be reflected in the next month's price adjustments of the non-adjusting firms. Therefore, the adjusting firms respond to the underlying cost shocks of the non-adjusting competitors even though these cost shocks have not materialized. In this section, we verify the accuracy of our empirical estimation in this more complicated (but model-consistent) scenario where our observed costs do not reflect the optimal price of their suppliers.

strategy can uncover the true theoretical pass-through rates of idiosyncratic and common cost changes.

Simulation setting. We assume the observed purchase price of wholesalers follows the process:

$$Q_{ijt} = \begin{cases} Q^*_{ijt}, & \text{if } \zeta_{ijt} > \lambda_j, \\ Q_{ijt-1}, & \text{otherwise.} \end{cases} \tag{B.49}$$

where ζ_{ijt} is drawn from a standard uniform distribution, and the underlying cost shocks Q^I_{ijt} and Q^C_{jt} follow an AR(1) process:

$$\ln(Q^*_{ijt}) = \ln(Q^I_{ijt}) + \ln(Q^C_{jt}), \tag{B.50}$$

$$\ln(Q^I_{ijt}) = \rho^I \ln(Q^I_{ijt-1}) + \epsilon_{ijt}, \tag{B.51}$$

$$\ln(Q^C_{jt}) = \rho^C \ln(Q^C_{jt-1}) + \epsilon_{jt}, \tag{B.52}$$

with the error terms normally distributed $\epsilon_{ijt} \sim \mathcal{N}(0, (\sigma^I)^2)$ and $\epsilon_{jt} \sim \mathcal{N}(0, (\sigma^C)^2)$. We assume $\rho^I = \rho^C = 0.9$ and the idiosyncratic shocks are larger than common cost shocks ($\sigma^I = 0.1, \sigma^C = 0.034$).

We simulate 200 sectors for 80 periods. Each sector is assigned a predetermined price stickiness, $\lambda_j \in [0, 0.8]$. We assume there are 40 sector groups z, within which the sectors have similar market structure and price stickiness.[31] To account for heterogeneity in market power across firms and sectors, we assume half of the sectors are highly concentrated, with 4 firms in total and the two largest firms accounting for 80% of the market share. The other half is slightly less concentrated with 10 firms in total and the two largest firms accounting for 40% of the market share. The cost shock process evolves according to (B.49)-(B.52). We assume that the timing of price and cost adjustments is perfectly synchronized and firms reset their prices according to Proposition 2. Finally, we set the elasticity of substitution $\theta = 5$ and the discount factor $\beta = 0.97^{1/12}$.

[31] That is, we have 5 similar sectors in each sector group z. Having a few similar sectors ensures that we have enough observations to conduct our estimation procedure when prices become very sticky.

Estimation. After simulating the data, we implement our two-step empirical procedure assuming that only P_{ijt} and Q_{ijt} are observed (as is the case in our data). Specifically, in the first step, we decompose the observed changes of log purchase prices, $\Delta \ln(Q_{ijt}) = \ln(Q_{ijt}) - \ln(Q_{ijt-1})$, into common and idiosyncratic components by estimating an unweighted fixed-effect OLS regression:

$$\Delta \ln(Q_{ijt}) = \mathcal{F}_{jt} + \mathcal{F}_{ijt}, \tag{B.53}$$

where $\mathcal{F}_{jt}$ represents the sector-month fixed effects and $\mathcal{F}_{ijt}$ is the residual.[32] In the second step, for each industry group z, we estimate the pass-through of these shocks to wholesalers' selling prices conditional on adjustment ($\Delta \ln(P_{ijt}) \neq 0$):

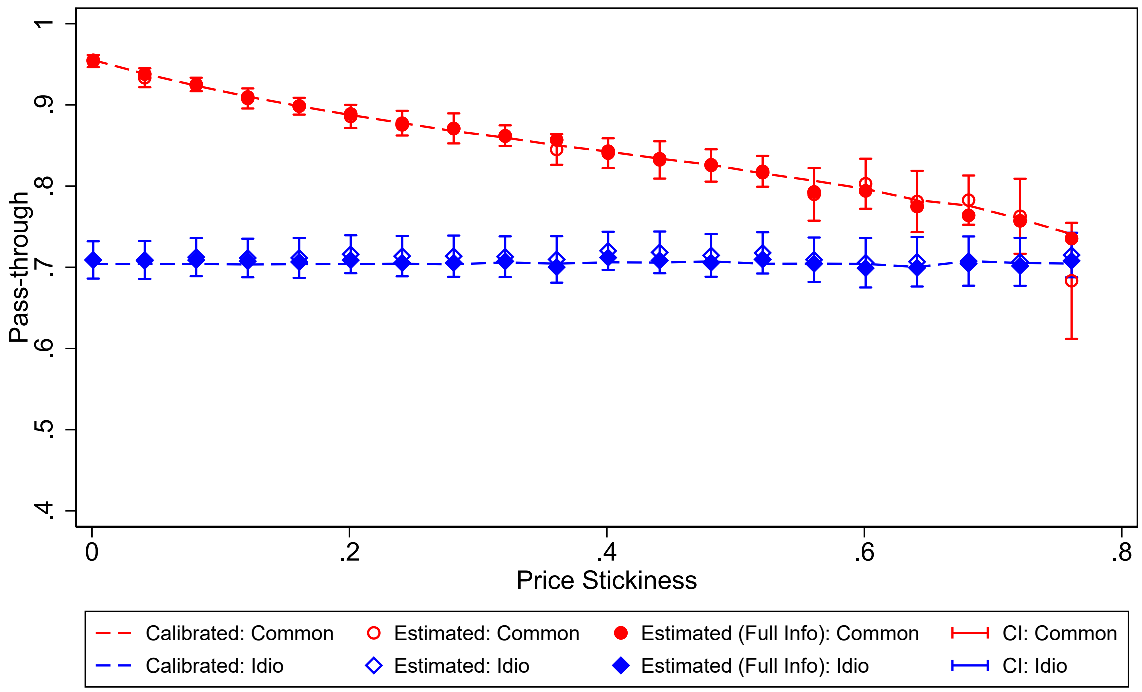
$$\Delta \ln(P_{ijt}) = \psi_z \mathcal{F}^{Est}_{ijt} + \Psi_z \mathcal{F}^{Est}_{jt} + FE_{ij} + \nu_{ijt}, \tag{B.54}$$

where FE_{ij} are firm-product fixed effects that absorb time-invariant heterogeneity in price adjustments across firm-products, and ν_{ijt} is the residual term. ψ_z and Ψ_z are the idiosyncratic and common cost pass-through coefficients for sector group z, respectively.

Results. Figure B6 compares the estimates using our proposed two-step procedure with their theoretical counterparts. Panel (a) shows the estimation results for the 100 less concentrated sectors. The red and blue colors show the results for common and idiosyncratic pass-through coefficients, respectively. The empty circles and diamonds give the pass-through estimates from (B.54) based on our two-step empirical procedure. Each point represents a separate estimate from a particular sector group z. The vertical lines with end caps show the 95% confidence interval of the corresponding estimate. The dashed lines show the average theoretical pass-through of firms in the simulated sector group z. Finally, the solid circles and diamonds give the counterfactual *full information estimates* if we were estimating (B.54) using the true underlying cost components from the simulated data based on (B.51)-(B.52) rather than the estimated ones from (B.53). The difference between our baseline estimates (i.e., empty circles and diamonds) and the full information estimates (i.e., solid circles and diamonds) indicates the extent to which our step 1 estimation using

[32] Note that, after conditioning on a price change, $\Delta \ln(Q_{ijt}) = \ln(Q_{ijt}) - \ln(Q_{ijt-1}) = \ln(Q_{ijt,t}) - \ln(Q_{ijt-l,t-l})$.

(a) Less concentrated: 10 firms with top-2 firms accounting for 40% market share



(b) More concentrated: 4 firms with top-2 firms accounting for 80% market share

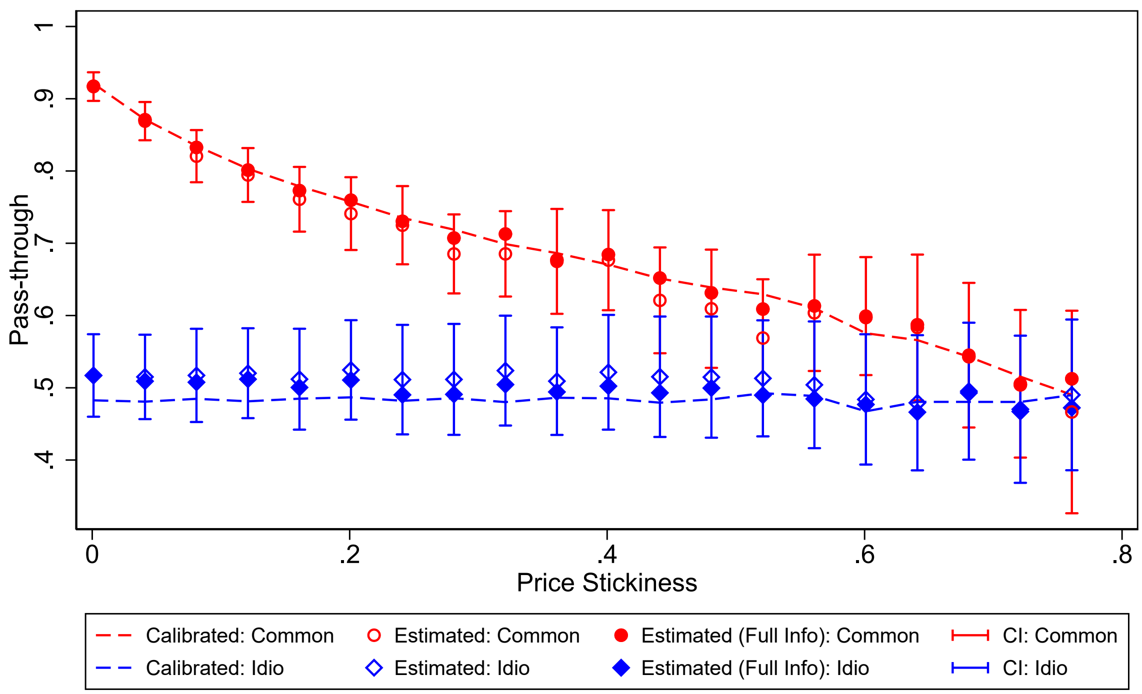


Figure B6: Comparing calibrated versus estimated coefficients

(B.53) provides a good proxy for the true underlying cost shock components.

Overall, our estimated pass-through coefficients are very close to their calibrated theoretical counterparts. Especially in panel (a), our baseline estimates (the empty circles and squares) closely align with the calibrated theoretical responses. The small difference between our baseline estimates and the theoretical average is largely driven by the fact that we do not directly observe all the underlying cost shocks and need to approximate these shocks using (B.53), as the full information estimates are almost exactly the same as the theoretical averages. In panel (b), we see the difference between our baseline estimates and the full information estimates is larger when the sector is more concentrated. This is because, with a smaller number of firms, it is harder to correctly isolate the common cost changes from idiosyncratic ones under price and cost stickiness. In addition, we note that the full information estimates of the idiosyncratic cost pass-through may not exactly reflect the theoretical average when there is a high degree of heterogeneity in the market shares (and market power) across firms within a sector.

Finally, we have been focusing on simple estimation approaches with no structural assumptions imposed since the true data-generating process may not be exactly the same as the one we assume in the model. The accuracy of the estimations can be improved by exploiting information on the data-generating process and imposing additional structural restrictions. Results from that approach are available upon request.

B.8 Derivation of sufficient statistic φ under Kimball demand

In this appendix, we show how the key statistic for the degree of strategic complementarity in our model φ_{ij} can be derived under Kimball demand.

Elasticities under a general demand function. The pricing problem of the distributor under a general demand function can be written as

$$\max_{P_{ijt,t}} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda)^{\tau} \frac{U_c(C_{t+\tau})/P_{t+\tau}}{U_c(c_t)/P_t} \left(P_{ijt,t} - Q^*_{ijt+\tau}\right) c_{ijt+\tau},$$

where $Q^*_{ijt+\tau}$ is the nominal marginal cost of distributor i of sector j in period $t+\tau$.

First order condition w.r.t. the reset price $P_{ijt,t}$ is:

$$\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda)^\tau \frac{U_c(C_{t+\tau})/P_{t+\tau}}{U_c(C_t)/P_t} \left[1 + \left(1 - \frac{Q^*_{ijt+\tau}}{P_{ijt,t}}\right) \vartheta_{ijt+\tau,t}\right] c_{ijt+\tau} = 0,$$

where $\vartheta_{ijt+\tau,t}$ is the demand elasticity:

$$\vartheta_{ijt+\tau,t} \equiv -\frac{\partial c_{ijt+\tau}}{\partial P_{ijt,t}} \frac{P_{ijt,t}}{c_{ijt+\tau}}.$$

With the assumption of log utility, $U_c(c_{t+\tau}) = 1/c_{t+\tau}$, the optimal reset price can be written as

$$P_{ijt,t} = \frac{\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda_j)^\tau \vartheta_{ijt+\tau,t} c_{ijt+\tau,t}}{\mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta\lambda_j)^\tau (\vartheta_{ijt+\tau,t} - 1) c_{ijt+\tau,t}/Q^*_{ijt+\tau}}.$$

Therefore, we get the same solution as in our benchmark model. Under the assumption of Kimball demand, we have[33]

$$c_{ijt} \equiv \left[1 - \xi \ln\left(\frac{P_{ijt}}{P_{jt}}\right)\right]^{\frac{\theta}{\xi}} c_{jt},$$

where ξ is the superelasticity that governs the extent to which the firm adjusts its markup to cost shocks. The effective demand elasticity is given by

$$\mathbb{E}_t \vartheta_{ijt+\tau,t} = \mathbb{E}_t \left[\frac{\theta}{1 - \xi \ln\left(\frac{P_{ijt+\tau,t}}{P_{jt+\tau}}\right)}\right]. \tag{B.55}$$

In the more general demand system developed by Amiti, Itskhoki and Konings (2019) that nests the Kimball and Atkeson and Burstein (2008) as special cases, the demand elasticity can be derived as[34]

$$\mathbb{E}_t \vartheta_{ijt+\tau,t} = \mathbb{E}_t \left[s_{ijt+\tau,t} + \chi_{ijt+\tau,t}\left(1 - \frac{s_{ijt+\tau,t}\chi_{ijt+\tau,t}}{\sum_i s_{ijt+\tau,t}\chi_{ijt+\tau,t}}\right)\right] \quad \text{with} \quad \chi_{ijt+\tau,t} \equiv \frac{\theta}{1 - \xi \ln\left(\frac{P_{ijt+\tau,t}}{P_{jt+\tau}}\right)}. \tag{B.56}$$

[33] We use the functional form of Klenow and Willis (2016). See Appendix B of Gopinath and Itskhoki (2010*b*) for more details.

[34] See Appendix D of Amiti, Itskhoki and Konings (2019) for more details.

Re-deriving the theoretical results. It is worthwhile noting that, if we could express the expected markup as a function of the relative prices, then all of our previous steps in deriving the closed-form solutions will carry through. That is, we need to find the expression of φ_{ij} such that the following relationship holds:

$$E_t\widehat{\mu}_{ijt+\tau,t} \approx -\frac{1}{\vartheta_{ij}-1}E_t\widehat{\vartheta}_{ijt+\tau,t} = -\varphi_{ij}\left[\widehat{P}_{ijt,t} - E_t\widehat{P}_{jt+\tau}\right].$$

In our benchmark setting, we have

$$\varphi_{ij} \equiv (\theta-1)\frac{s_{ij}}{1-s_{ij}} = (\theta-1)\left(\frac{\theta-1}{\theta}\mu_{ij}-1\right).$$

Under Kimball demand, it can be shown that

$$\varphi_{ij} \equiv \frac{\xi}{\theta}\frac{\vartheta_{ij}}{\vartheta_{ij}-1}.$$

When firms are *ex ante* homogeneous, $\vartheta_{ij}=\theta$ and

$$\varphi_{ij} = \frac{\xi}{\theta-1}. \tag{B.57}$$

With the sufficient statistic φ_{ij}, we can follow the same steps to obtain the closed-form solutions of the firms optimal reset prices in Propositions 1 and 2 and calculate the sector and aggregate dynamics according to Proposition 3.

Comparison. Under a first-order approximation, we could obtain the same firm-level, sectoral, and aggregate dynamics in our benchmark sticky-price oligopolistic competition model as in the alternative multi-sector monopolistic competition Kimball model if there exist calibrations of the superelasticity ξ_j such that $\varphi_{ij}^{\text{Benchmark}} = \varphi_{ij}^{\text{Kimball}}$. However, due to the differences in the underlying microfoundations of market power φ_{ij} in the two models, achieving an exact match at the firm level is often difficult.

When firms are symmetric within a sector, it is possible to calibrate the superelasticity ξ_j to achieve an exact match, resulting in $\varphi_j^{\text{Benchmark}} = \varphi_j^{\text{Kimball}}$. In this case, the aggregate dynamics in the homogeneous firm sticky-price oligopolistic competition model will be the same as those in the alternative multi-sector monopolistic competition Kimball model. The caveat is that, in each sector, the superelasticity ξ_j needs to be arbitrarily chosen to match the market power endogenously generated in the oligopolistic competition model.

Finally, if the primary concern is matching the *total* real impact of monetary policy, it is possible to calibrate a one-sector Kimball model to simultaneously match (i) the average degree of price stickiness observed in the data and (ii) the *cumulative* output response to a permanent monetary policy shock produced in our benchmark multi-sector model presented in column 5 of Table 3. Specifically, one can calibrate ξ such that:

$$\frac{\Lambda^{\text{Kimball}}(\xi)}{1 - \Lambda^{\text{Kimball}}(\xi)} = \sum_j \alpha_j \frac{\Lambda_j^{\text{Benchmark}}}{1 - \Lambda_j^{\text{Benchmark}}}.$$

B.9 Mapping to Amiti, Itskhoki and Konings (2019)

B.9.1 Background—The AIK framework

AIK provide a general *static* framework that decomposes a firm's price responses into two components: (1) the reaction to its own cost shocks and (2) the reaction to its competitors' price adjustments. The core theoretical insights of this framework are encapsulated in their Propositions 1 and 2, which are succinctly restated below. These findings are applicable to all industries and, for the sake of brevity, we omit the industry-specific subscript j.

AIK Proposition 1 *For any given invertible demand system and competition structure, there exists a markup function $\mu_{it} = \mu_i(p_{it}, \boldsymbol{p}_{-it}; \boldsymbol{\xi}_t)$, such that the firm's static profit-maximizing price $\tilde{p}_{it}$ is the solution to the following fixed-point equation for any given price vector of the competitors $\boldsymbol{p}_{-it}$:*

$$\tilde{p}_{it} = mc_{it} + \mu_i(\tilde{p}_{it}, \boldsymbol{p}_{-it}; \boldsymbol{\xi}_t), \tag{B.58}$$

where $\boldsymbol{\xi}_t = (\xi_{1t}, ..., \xi_{Nt})$ is a vector of exogenous demand shifters and N is the number of firms in the industry.

Totally differentiating the best response condition (B.58) around some admissible point $(\tilde{p}_{it}, \boldsymbol{p}_{-it}; \boldsymbol{\xi}_t)$, e.g., any equilibrium point $(\boldsymbol{p}_t; \boldsymbol{\xi}_t)$, we obtain the following decomposition for the firm's log price differential:

$$\mathrm{d}p_{it} = \mathrm{d}mc_{it} + \frac{\partial \mu_i\left(\boldsymbol{p}_t; \boldsymbol{\xi}_t\right)}{\partial p_{it}}\ \mathrm{d}p_{it} + \sum_{k \neq i} \frac{\partial \mu_i\left(\boldsymbol{p}_t; \boldsymbol{\xi}_t\right)}{\partial p_{kt}}\ \mathrm{d}p_{kt} + \sum_{k=1}^{N} \frac{\partial \mu_i\left(\boldsymbol{p}_t; \boldsymbol{\xi}_t\right)}{\partial \xi_{kt}}\ \mathrm{d}\xi_{kt} \tag{B.59}$$

The markup function $\mu_i(\cdot)$ can be evaluated for an arbitrary price vector $\boldsymbol{p}_t = (p_{it}, \boldsymbol{p}_{-it})$, and therefore (B.59) characterizes all possible perturbations to the firm's price in response to shocks to its marginal cost $\mathrm{d}mc_{it}$, the prices of its competitors $\{\mathrm{d}p_{kt}\}_{k \neq i}$, and the demand shifters $\{\mathrm{d}\xi_{kt}\}_{k=1}^{N}$. Solving the fixed point for $\mathrm{d}p_{it}$ in (B.59) results in:

$$\mathrm{d}p_{it} = \frac{1}{1+\Gamma_{it}}\ \mathrm{d}mc_{it} + \frac{\Gamma_{-it}}{1+\Gamma_{it}}\ \mathrm{d}p_{-it} + \frac{1}{1+\Gamma_{it}} \varepsilon_{it}, \tag{B.60}$$

where

$$\Gamma_{it} \equiv -\frac{\partial \mu_i\left(\boldsymbol{p}_t; \boldsymbol{\xi}_t\right)}{\partial p_{it}} \quad \text{and} \quad \Gamma_{-it} \equiv \sum_{k \neq i} \frac{\partial \mu_i\left(\boldsymbol{p}_t; \boldsymbol{\xi}_t\right)}{\partial p_{kt}},$$

$$\mathrm{d}p_{-it} \equiv \sum_{k \neq i} \omega_{kt}\ \mathrm{d}p_{kt} \quad \text{with} \quad \omega_{it} \equiv \frac{\partial \mu_i\left(p_t; \xi_t\right)/\partial p_{kt}}{\sum_{k \neq i} \partial \mu_i\left(p_t; \xi_t\right)/\partial p_{kt}},$$

$$\varepsilon_{it} \equiv \sum_{k=1}^{N} \frac{\partial \mu_i\left(\boldsymbol{p}_t; \xi_t\right)}{\partial \xi_{kt}}\ \mathrm{d}\xi_{kt}.$$

AIK Proposition 2 *(i) If the log expenditure function* p_t *is a sufficient statistic for competitor prices, i.e., if the demand can be written as* $q_{it} = q_i\left(p_{it}, \mathrm{p}_t; \xi_t\right)$*, then the weights in the competitor price index are proportional to the competitor revenue market shares* s_{kt}*, for* $k \neq i$*, and given by* $\omega_{kt} \equiv s_{kt}/\left(1 - s_{kt}\right)$*. Therefore, the index of competitor price changes simplifies to*

$$\mathrm{d}p_{-it} \equiv \sum_{k \neq i} \frac{s_{kt}}{1 - s_{kt}}\ \mathrm{d}p_{kt}. \tag{B.61}$$

(ii) Under the stronger assumption that the perceived demand elasticity is a function of the price of the firm relative to the industry expenditure function, $\sigma_{it} = \sigma_i\left(p_{it} - \mathrm{p}_t; \xi_t\right)$*, the following two markup elasticities are equal:*

$$\Gamma_{-it} \equiv \Gamma_{it}. \tag{B.62}$$

A key implication of AIK Proposition 2 is that, under the relatively mild conditions imposed by AIK, the pass-through to the firm's own cost shock and the firm's competitors' price changes (i.e., the first two coefficients in the price decomposition (B.60)) should sum to one:

$$\frac{1}{1+\Gamma_{it}} + \frac{\Gamma_{-it}}{1+\Gamma_{it}} = 1. \tag{B.63}$$

AIK empirically test (B.63) with Belgian data and find strong empirical support of this theoretical relationship.

Remarks. It is worth noting that the decomposition (B.60) cannot be applied directly in empirical estimations. This is because in an oligopolistic competition model the firms' prices are jointly determined. Since a firm's competitors' price changes $\mathrm{d}p_{-it}$ are endogenous and depend on the firm's price change $\mathrm{d}p_{it}$, directly estimating (B.60) can result in substantial bias. To address this concern, AIK use proxies of the competitors' cost changes as instruments for the competitors' price changes.

B.9.2 Response to cost shocks under the AIK framework

In what follows, we derive an alternative decomposition in terms of exogenous shocks, which can be estimated directly using observed cost shocks.

First, note that we can rewrite the price change decomposition (B.60) as follows:

$$\begin{aligned}
& \mathrm{d}p_{it} = \frac{1}{1+\Gamma_{it}}\ \mathrm{d}mc_{it} + \frac{\Gamma_{-it}}{1+\Gamma_{it}}\ \mathrm{d}p_{-it} + \frac{1}{1+\Gamma_{it}}\varepsilon_{it} \\
\Leftrightarrow\ \ & \mathrm{d}p_{it} = \frac{1}{1+\Gamma_{it}}\ \mathrm{d}mc_{it} + \frac{\Gamma_{it}}{1+\Gamma_{it}}\ \mathrm{d}p_{-it} + \frac{1}{1+\Gamma_{it}}\varepsilon_{it} && \text{(B.64)} \\
\Leftrightarrow\ \ & (1-s_{it})(1+\Gamma_{it})\mathrm{d}p_{it} = (1-S_{it})\ \mathrm{d}mc_{it} + \Gamma_{it}\sum_{k\neq i} s_{kt}\ \mathrm{d}p_{kt} + (1-s_{it})\varepsilon_{it} && \text{(B.65)} \\
\Leftrightarrow\ \ & \mathrm{d}p_{it} = \frac{1-s_{it}}{1-S_{it}+\Gamma_{it}}\ \mathrm{d}mc_{it} + \frac{\Gamma_{it}}{1-s_{it}+\Gamma_{it}}\ \mathrm{d}p_{t} + \frac{1-s_{it}}{1-s_{it}+\Gamma_{it}}\varepsilon_{it} && \text{(B.66)}
\end{aligned}$$

where (B.64) uses relationship (B.62); (B.65) uses relationship (B.61); and (B.66) uses the definition of the sector price index such that $\mathrm{d}p_t = \sum_k s_{kt}\ \mathrm{d}p_{kt}$. Note that the only endogenous variable in (B.66) is the changes in the sector price index $\mathrm{d}p_t$.

Next, to solve for $\mathrm{d}p_t$, we aggregate expression (B.66) across all firms:

$$\sum_i s_{it}\mathrm{d}p_{it} = \sum_i \frac{s_{it}(1-s_{it})}{1-s_{it}+\Gamma_{it}}\ \mathrm{d}mc_{it} + \sum_i \frac{\Gamma_{it}s_{it}}{1-s_{it}+\Gamma_{it}}\ \mathrm{d}p_t + \sum_i \frac{s_{it}(1-s_{it})}{1-s_{it}+\Gamma_{it}}\varepsilon_{it} \tag{B.67}$$

Rearranging (B.67), we can express the changes in the sector price index $\mathrm{d}p_t$ as a function of exogenous marginal cost and demand shocks:

$$\mathrm{d}p_t = \sum_i \widetilde{\varphi}_{it}\ \mathrm{d}mc_{it} + \sum_i \widetilde{\varphi}_{it}\varepsilon_{it} \tag{B.68}$$

with

$$\varphi_{it} \equiv \frac{1-s_{it}}{1-s_{it}+\Gamma_{it}} \quad \text{and} \quad \widetilde{\varphi}_{it} \equiv \frac{\varphi_{it}s_{it}}{\sum_k \varphi_{kt}s_{kt}},$$

where, as we show below in (B.71), $\varphi_{it} > 0$ is the firm's response to idiosyncratic shocks and $\widehat{\varphi}_{it} > 0$ is the implicit importance weight of the idiosyncratic shocks with $\sum_i \widetilde{\varphi}_{it} = 1$. When $\varepsilon_{it} = 0\ \forall i$, expression (B.68) is equivalent to the expression in AIK Proposition 3.

Finally, substitute (B.68) into (B.66) and we get the *solved* version of the price change decomposition:

$$\mathrm{d}p_{it} = \underbrace{\left[\varphi_{it} + (1-\varphi_{it})\widetilde{\varphi}_{it}\right](mc_{it}+\varepsilon_{it})}_{\text{pass-through to } own \text{ cost and demand shocks}} + \underbrace{(1-\varphi_{it})\left[\sum_{k\neq i}\widetilde{\varphi}_{kt}\ \mathrm{d}mc_{kt} + \sum_{k\neq i}\widetilde{\varphi}_{kt}\varepsilon_{kt}\right]}_{\text{pass-through to } competitors' \text{ cost and demand shocks}} \tag{B.69}$$

It can be shown that, under a common cost or demand shock, the price pass-through of *each firm* is 100% as

$$\left[\varphi_{it} + (1-\varphi_{it})\widetilde{\varphi}_{it}\right] + (1-\varphi_{it})\sum_{k\neq i}\widetilde{\varphi}_{kt} = 1.$$

Defining the common cost and demand shocks as

$$\mathrm{d}mc_t \equiv \sum_i \widetilde{\varphi}_{it}\ \mathrm{d}mc_{it} \quad \text{and} \quad \varepsilon_t \equiv \sum_i \widetilde{\varphi}_{it}\varepsilon_{it}, \tag{B.70}$$

the price change decomposition can be re-expressed in terms of common versus idiosyncratic shocks:

$$\mathrm{d}p_{it} = \varphi_{it}(\mathrm{d}mc_{it} - \mathrm{d}mc_t) + \ \mathrm{d}mc_t + \varphi_{it}(\varepsilon_{it} - \varepsilon_t) + \varepsilon_t. \tag{B.71}$$

The first term of (B.71) shows that the pass-through rate to an idiosyncratic cost shock ($\mathrm{d}mc_{it} - \mathrm{d}mc_t$) is well defined and given by φ_{it}. The second term shows that, in this static framework, the pass-through rate to a common cost shock is always equal to 100%. Under the structural assumptions of Atkeson and Burstein (2008), φ_{it} is a strictly *decreasing* function of market share s_{it}. Intuitively, this is because large firms with market power absorb part of their cost shocks into markups, while small firms do not adjust markups and thus fully pass-through any idiosyncratic cost shock. It is worth noting that, different from Γ_{it}, which is hump-shaped in market share, φ_{it} is a strictly decreasing function of market share (see Figure B7).[35]

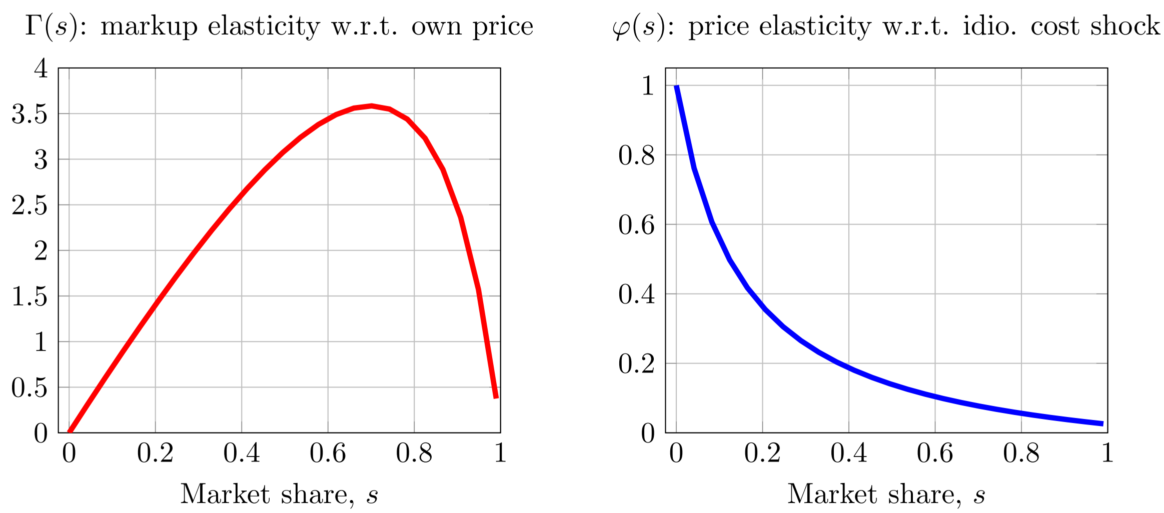


Figure B7: Market share and key elasticities

Note: The two figures plot $\Gamma(s)$ and $\varphi(s)$ under the nested-CES demand preference of Atkeson and Burstein (2008), where the within-industry elasticity of substitution is set to 10 and the cross-industry elasticity of substitution is set to 1.2.

[35] From the definition of $\varphi_{it} = 1/[1 + \Gamma(s_{it})/(1 - s_{it})]$, we see there are two market share effects as a firm becomes larger: (1) a direct market share effect captured by $(1 - s_{it})$ and (2) an indirect effect through markup adjustment captured by $\Gamma(s_{it})$. The two effects go in the same direction and reduce price pass-through to an idiosyncratic shock until the firm becomes extremely large (e.g., when it accounts for over 80% of the market share). For those extremely large firms, the two effects go in opposite directions: as a firm becomes extremely large it cares less about the cost shocks of other smaller firms (captured by effect 1) and makes smaller markup adjustments (captured by effect 2). It turns out that the direct effect (1) dominates as a firm becomes extremely large, and, therefore, the price pass-through to an idiosyncratic shock is strictly decreasing in the firm's market share.

Unlike AIK's original decomposition (B.60), our decomposition (B.71) involves no endogenous variable and thus does not need an instrument. Assuming the demand shocks are exogenous and i.i.d. (as in AIK), equation (B.71) can be directly estimated using OLS provided that a good measure of the common cost shock $\mathrm{d}mc_t$ can be constructed.

B.9.3 Cournot vs Bertrand Competition

Consistent with the literature, we have assumed Cournot competition in our benchmark model as it tends to better match the relationship between the estimated pass-through rates and empirical market share distributions (see Atkeson and Burstein 2008 and Amiti, Itskhoki and Konings 2019). Figure B8 contrasts the sufficient statistic $\varphi(\theta, s)$ in our model under Bertrand and Cournot competition. We observe that Cournot competition results in larger strategic complementarity (measured by φ) for a given market share, s, and is more sensitive to the assumed elasticity of substitution, θ.

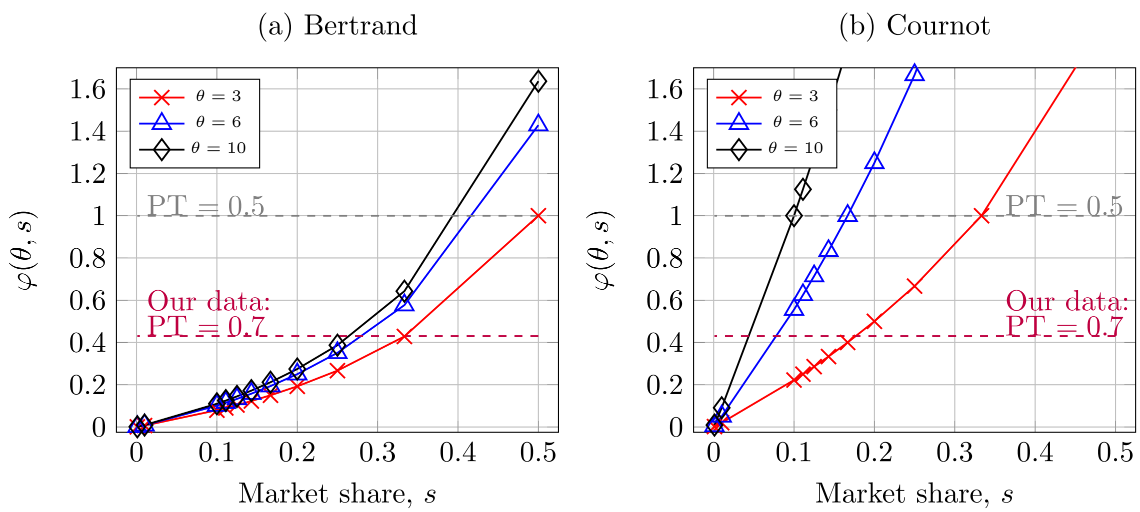


Figure B8: Sufficient statistic $\varphi(\theta, s)$ under Bertrand vs Cournot competition