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SECTORAL INFLATION PERSISTENCE, MARKET CONCENTRATION AND IMPERFECT COMMON KNOWLEDGE

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Sectoral inflation persistence, market concentration, and imperfect common knowledge*

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Abstract

Previous studies have stressed that inflation dynamics exhibit substantial dispersion across sectors. Using US producer price data, we present evidence that sectoral inflation persistence is negatively correlated with market concentration, which is difficult to reconcile with the prediction of the standard model of monopolistic competition. To better explain the data, we incorporate imperfect common knowledge into the monopolistic competition model introduced by Melitz and Ottaviano (2008). In the model, pricing complementarity among firms increases as market concentration decreases. Because higher pricing complementarity generates greater inflation persistence, our model successfully replicates the observed negative correlation between inflation persistence and market concentration across sectors.

JEL Classification: E31, D40, L16

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1 Introduction

Inflation has long been a cornerstone issue in monetary economics. Researchers consider disaggregated inflation at the industry level (hereafter, sectoral inflation) as a fundamental building block for aggregate inflation dynamics. Not surprisingly, sectoral inflation dynamics exhibit substantial heterogeneity across industries. For instance, Leith and Malley (2007) and Imbs et al. (2011) estimate sector-level Phillips curves and conclude that sectoral inflation dynamics are significantly dispersed.[1] Boivin et al. (2009, hereafter BGM) and Altissimo et al. (2009) incorporate sector-specific shocks in their models to replicate the heterogeneous dynamics of sectoral prices and inflation. Further, Bils and Klenow (2004) report a negative correlation between inflation persistence and the degree of price stickiness, while Clark (2006) reveals little correlation between inflation persistence and price stickiness across sectors. Together, these previous studies suggest that substantial heterogeneity in sectoral inflation dynamics remains an important challenge.

This paper explores factors that give rise to the substantial dispersion in sectoral inflation persistence. We focus on the relationship between sectoral inflation persistence and market concentration. Using US producer price index (PPI) data, we reveal that sectoral inflation persistence, as measured by the first-order autocorrelation, exhibits a negative correlation with market concentration. Figure 1 provides a scatter plot of the first-order autocorrelation against the Herfindahl–Hirschman Index (HHI) across 145 US manufacturing sectors. As shown, while the scatter plot is somewhat noisy, the regression line indeed suggests a negative correlation.

The negative correlation observed between inflation persistence and market concentration is robust. The correlation is estimated to be negative in various specifications with alternative measures of inflation persistence. A negative correlation is also present in nonmanufacturing sectors. Quantitatively, benchmark regressions suggest that an increase in HHI by 2,000

[1] See also Byrne et al. (2013) and Luengo-Prado et al. (2018).

would reduce the first-order autocorrelation of sectoral inflation by 0.10–0.14.

The canonical models of monopolistic competition under constant elasticity of substitution (CES) preferences fail to reconcile this observed negative correlation. The standard Dixit–Stiglitz monopolistic competition model implicitly assumes that market concentration is invariant. Notably, the quadratic preferences proposed by Melitz and Ottaviano (2008, hereafter MO) allow the degree of market concentration to vary across sectors in the otherwise standard model of monopolistic competition.[2] Here, for convenience, we refer to this setup as the MO model. In the MO model, if the market concentration is high, firms set their prices with positive markup as in the standard Dixit–Stiglitz model. The MO model can also represent a perfectly competitive market as a limiting case where market concentration is at its lowest. Nevertheless, the flexible specification of preferences in the MO model is not sufficient: inflation persistence has no correlation with market concentration.

We find that incorporating information rigidity into the MO model can account for the observed negative correlation. Remarkably, our model with a reasonable degree of information rigidity predicts that the first-order autocorrelation decreases by 0.12 as HHI increases from 0 to 2,000, compared with 0.10–0.14 in the data.

In the MO model, the information rigidity can be a powerful mechanism for linking inflation persistence with market concentration. The information rigidity that we consider is imperfect common knowledge as developed by Woodford (2003) and Morris and Shin (2002). Among others, Woodford (2003) demonstrates that higher pricing complementarity under imperfect common knowledge generates greater inflation persistence.[3] In the MO model, higher market concentration weakens the pricing complementarity. Thus, our model can successfully generate less inflation persistence in more concentrated markets.[4]

[2]Vives (1990) and Ottaviano et al. (2002) consider similar quadratic utility functions in the context of trade theory.

[3]See also Fukunaga (2007), Nimark (2008), and Angeletos and La'O (2009). Crucini et al. (2015) and Candian (2019) apply a model with imperfect common knowledge to examine the persistence of real exchange rates.

[4]Sbordone (2010) discusses the effects of variable market concentration on pricing complementarities using Kimball (1995) preferences. In a similar spirit, our model relies on MO preferences.

Empirical studies have long discussed the effect of market concentration on pricing. Examples include Carlton (1986), Leith and Malley (2007), and Gopinath and Itskhoki (2011). These studies examine US data and argue that the sensitivity of individual prices is smaller in more concentrated markets. Koga et al. (2020) employ survey data on Japanese firms and explore the sensitivity of individual prices to their competitor's prices (i.e., the pricing complementarities). Specifically, Koga et al. (2020) find that pricing complementarity is weaker in more concentrated markets. This existing evidence supports the key ingredient of the MO model in generating our main result.

Some theoretical studies have also argued for the importance of market structure on the pricing of firms. Among others, MO discuss how the toughness of competition affects markups. While their model structure is well known, our paper focuses on one aspect of the MO model that they do not highlight. That is, pricing complementarity decreases with market concentration. Other theoretical studies also consider the effect of market structure on firms' pricing, but the motivations differ from ours. Sbordone (2010) discusses the effects of increases in traded goods on the slope of the Phillips curve. Afrouzi (2019) argues that pricing complementarity in an oligopolistic market enhances monetary non-neutrality. Amiti et al. (2019) develop a model of incomplete pass-through in which endogenous markups vary with firm characteristics in an oligopolistic market.[5]

Our explanation of the observed negative correlation between inflation persistence and market concentration does not necessarily invalidate the importance of sticky prices. Angeletos and La'O (2009) discuss the interaction of sticky prices, imperfect common knowledge, and pricing complementarity. They also show how pricing complementarities generate inflation persistence under both imperfect common knowledge and sticky prices. Our model can be cast as a special case in the Angeletos and La'O (2009) framework, whereas we include an additional dimension such that pricing complementarity systematically depends on

[5]In the empirical part of their paper, they show that the prices set by large firms are less sensitive to marginal cost (incomplete pass-through) and more sensitive to the competitor's prices than those for small firms.

market concentration following MO. In this way, we reaffirm the importance of information rigidity in accounting for the negative correlation between inflation persistence and market concentration, which is difficult to explain by sticky prices per se.

The remainder of the paper is organized as follows. Section 2 discusses the empirical evidence. Section 3 introduces the basic model with comparative statistics and numerical examples. Section 4 extends the basic model. Section 5 discusses the Calvo sticky price model in the context of our empirical findings. Section 6 concludes.

2 Evidence

2.1 Data

We use US (seasonally adjusted) PPI at the six-digit level of the North American Industry Classification System (NAICS) code to explore the empirical characteristics of sectoral inflation persistence and market concentration. The PPI is more convenient than the consumer price index (CPI) because we examine the linkage between sectoral inflation persistence and the degree of market concentration of sectors. The market concentration data are from the Economic Census. To inspect the linkage, we match the NAICS codes of the PPI with those of the market concentration data.

Two datasets are available for the PPI. The first dataset is from BGM.[6] This dataset includes the PPI prices of 152 manufacturing sectors at monthly frequency.[7] The sample period runs from February 1976 to June 2005. The second dataset covers the more recent period running from January 2004 to December 2020. We include 270 manufacturing sectors and 79 nonmanufacturing sectors in this second dataset, which we call the extended dataset.

We use these two datasets separately because the sample periods and the coverage of

[6] The data are available on the American Economic Association website, https://www.aeaweb.org/articles?id=10.1257/aer.99.1.350

[7] From 154 sectors in the original BGM dataset, we drop two sectors (311119p and 324393 in the six-digit NAICS codes) for which market concentration data are not available.

sectors differ between them. The BGM dataset covers the period from 1976:2 to 2005:6, and the extended dataset is from 2004:1 to 2020:12. In addition, the coverage of sectors differs between the two datasets. In particular, only 93 of the 152 manufacturing sectors in the BGM dataset are included in the 270 manufacturing sectors in the extended dataset. This difference arises because the highly disaggregated prices in the PPI data are likely to be discontinued and replaced by new items. Thus, many sectors are unique to one of the two datasets.

Concerning the measurement of market concentration, two indicators are available. The first is the HHI. The second is the share of the top-four largest firms in the sector, often referred to as the C4 ratio. Given that the two PPI datasets cover different sample periods, we use the HHI and the C4 ratio in 2002 for the BGM dataset and those in 2007 for the extended dataset. While the C4 ratio is available for all sectors, the HHI is available only for manufacturing sectors.

Table 1 suggests that inflation persistence exhibits substantial dispersion across sectors in both datasets. We define the first-order autocorrelation of the difference in log prices in a particular sector (i.e., sector-level aggregate price) as our measure of sectoral inflation persistence. Here, the first-order autocorrelation is estimated from the first-order autoregressive process or AR(1). For the within-industry comparison, we focus on manufacturers, i.e., the first and second columns in Table 1. The standard deviations of manufacturers are 0.20 and 0.23, both of which are similarly large. The inflation persistence ranges from a maximum of 0.65 (0.71) to a minimum of -0.42 (-0.44) in the BGM dataset (the extended dataset). Compared with manufacturers, the dispersion observed among nonmanufacturers is similarly significant as that for manufacturers. The standard deviation for nonmanufacturers is 0.18, which is close to that for manufacturers.

This considerable dispersion does not appear to be an artifact arising from idiosyncratic shocks in highly disaggregated data. Each sector (at the NAICS six-digit level) includes, on average, 375 firms in the BGM dataset and 806 (manufacturing) firms in the extended dataset. This large number of firms in each sector ensures that the influence of idiosyncratic shocks for individual firms is washed out at the sector level.

2.2 Regressions

We run regressions specifying sectoral inflation persistence $\rho_{\pi,i}$ as the dependent variable, where i denotes the sector. The explanatory variable of interest is the indicator of market concentration. Typically, our estimation equation is

$$\rho_{\pi,i} = a + b\frac{HHI_i}{1000} + \text{controls}_i + u_i, \tag{1}$$

where b measures how much the first-order autocorrelation $\rho_{\pi,i}$ changes if the HHI of one sector is 1,000 points higher.

Table 2 provides the benchmark regression results. Since the HHI is available only in manufacturers, the results here are for manufacturers. Each panel reports the coefficient on the HHI in (1) for the cases with and without sector dummies, $D_{31,i}$ and $D_{32,i}$.[8] We report the results based only on the BGM dataset in the left panel and those based only on the extended dataset in the middle panel. In the right panel, we pool the two datasets and report the estimated coefficient on HHI along with the coefficient on the dummy variable indicating the BGM dataset ($D_{BGM,i}$).

The estimated coefficients on HHI range between -0.07 and -0.05, depending on the datasets and the presence of the sector dummies. All the estimated coefficients on HHI are negative and statistically significant at the conventional significance levels. The coefficient on $D_{BGM,i}$ is estimated to be positive and is statistically different from zero. This significantly positive estimate suggests that sectoral inflation tends to be more persistent during the earlier (1976:2–2005:6) than the later (2004:1–2020:12) period.

[8] The sector dummies $D_{31,i}$ and $D_{32,i}$ control for some manufacturing sectors at the two-digit level of the NAICS code. The NAICS codes for manufacturers start with 31, 32, or 33. Of these, $D_{31,i}$ controls for sectors with a NAICS code starting with 31 (e.g., food and textile industries) whereas $D_{32,i}$ controls for those with a NAICS code starting with 32 (e.g., paper, wood, and chemical industries).

Table 3 provides the results where we change the explanatory variable in (1) from $HHI_i/1000$ to $C4_i$. The results are qualitatively similar to those in Table 2. That is, the coefficient on the market concentration indicator is negative and statistically significant.

In Table 4, we use the data for nonmanufacturers in the extended dataset and compare the regression results with those for manufacturers. Comparisons of specifications (1) and (2) suggest that the negative correlation between inflation persistence and market concentration is quantitatively similar to each other. While the coefficient on $C4_i$ for manufacturers is -0.16, that for nonmanufacturers is -0.20. We also run a regression pooling both manufacturers and nonmanufacturers. As shown in specification (3) in the same table, the sector dummy controlling for manufacturers ($D_{3,i}$) is economically and statistically significant. This implies that while average inflation persistence differs between manufacturers and nonmanufacturers, market concentration matters for both.

Quantitatively, the estimated coefficients in Table 2 suggest that if the HHI of one sector is 1,000 points higher, the inflation persistence of that sector is lower by 0.05–0.07. The estimation results can be reconfirmed from the slope of the regression line in Figure 1, in which the BGM dataset is used for the regression (i.e., specification (1-1)). A cursory look at the regression line suggests that inflation persistence decreases from around 0.2 to slightly below 0.1 against a range of HHI from 0 to over 2,000.

2.3 Robustness

This subsection examines whether the above result is robust to changes in specification. Table 5 summarizes the results. In the following robustness analysis, we take $HHI_i/1000$ as an explanatory variable in regressions.[9]

Measures of inflation persistence The first robustness check replaces the dependent variable in (1) with alternative measures of inflation persistence. One alternative persistence

[9]Table A.1 in the not-for-publication appendix complements the exercises in Table 5 by replacing $HHI_i/1000$ with $C4_i$.

measure is the sum of the autoregressive coefficients (SAR) that allows for a general AR process.[10] Another alternative measure is the first-order autocorrelation of year-on-year inflation. We take a year-on-year difference of seasonally unadjusted log prices to check robustness to the methods of removing the seasonality. Specifications (1) and (2) in Table 5 describe the regression results under these alternative measures of inflation persistence. Our main finding remains unchanged.

Controlling for heterogeneity in sectors In the benchmark regression, only two sector dummies $D_{31,i}$ and $D_{32,i}$ deal with heterogeneity in inflation persistence across sectors. We thus elaborate sector dummies using the more detailed three-digit level. The results are reported in specification (3) in Table 5. The estimated coefficients on HHI remain broadly unchanged compared with the benchmark regressions in Table 2.

Dropping possible outliers We also run a regression excluding the influence of outliers in the data. We drop sectors with the top-10% HHI from the sample. As shown in specification (4) in Table 5, this subsample analysis also detects a significant negative correlation similar to the main results.

3 The basic model

This section introduces the basic model, which describes a firm's pricing behavior within a particular sector. Unless otherwise noted, any variable without the index j represents that variable at the sector level. In contrast, variables indexed by j denote the variables of individual firms. In parallel with the previous section, the first-order autocorrelation is the persistence measure in our model.

[10] BGM and Furher (2010) employ the SAR as a measure of inflation persistence. In our analysis, we set the maximum lag length to 13 as in BGM and select the lag length based on the Bayesian Information Criterion. The detailed regression results using the SAR can also be found in Section A of the not-for-publication appendix.

In the basic model, all firms are subject to a sector-level common shock to marginal cost that is assumed to be i.i.d. The i.i.d. assumption means that there is no inherited inflation persistence in the basic model, which helps crystallize the role of an endogenous mechanism that generates persistent inflation dynamics. Another benefit of inspecting the basic model is that it provides a simple analytical solution for the sectoral inflation in equilibrium. Later in Section 4, we extend the model by incorporating both permanent and temporary shocks and numerically examine whether the property of the basic model remains unchanged.

3.1 Preferences and technology

The consumer maximizes utility by choosing a quantity of consumption of indexed goods, $q_t(j)$ for $j \in [0, N]$ and the numeraire q_A. Following MO, we assume that her preferences are quadratic,

$$U_t = \alpha \int_{j\in[0,N]} q_t(j)dj - \frac{\beta}{2} \int_{j\in[0,N]} (q_t(j))^2 dj - \frac{\gamma}{2} \left[\int_{j\in[0,N]} q_t(j)dj\right]^2 + q_A. \tag{2}$$

We refer to $\alpha(> 0)$ as the demand shifter because a larger α shifts out the demand for differentiated varieties.[11] As $\gamma(> 0)$ increases, the total demand for the differentiated goods compared with the numeraire decreases, amplifying the degree of competition among firms. The parameter $\beta(\geq 0)$ indicates the degree of love of variety. If $\beta = 0$, the differentiated varieties are perfect substitutes and, hence, the consumer is interested only in the total consumption of the differentiated goods ($\int_{j\in[0,N]} q_t(j)dj$). As β increases, the consumer cares more about the consumption distribution across varieties.

The consumer's budget constraint is given by,

$$\int_{j\in[0,N]} q_t(j)p_t(j)dj + q_A \leq \overline{q}_A, \tag{3}$$

where $p_t(j)$ is the price of each good and $\overline{q}_A$ is the endowment of the numeraire which is

[11] We assume that α is constant for simplicity. If a time-varying $\alpha = \alpha_t$ follows the same stochastic process as that of c_t, our main results remain unchanged.

exogenously provided at the same amount in each period. Note that this inequality always binds because of the monotonicity of the utility function U_t.

As shown in Appendix A, we can derive the following linear demand function:

$$q_t(j) = \frac{\alpha h}{1+\beta h} - \frac{p_t(j)}{\beta} + \frac{p_t}{\beta\,(1+\beta h)}, \tag{4}$$

where the average price is given by,

$$p_t \equiv \frac{1}{N}\int_{j\in[0,N]} p_t(j)dj,$$

and $h \equiv (\gamma N)^{-1} \in [0,\infty]$. If we assume that $\gamma = 10^{-4}$ and all firms are identical in size, h can be interpreted as the HHI.[12] We maintain these assumptions for the rest of the analysis.

We treat h as the key indicator representing the degree of market concentration. A notable characteristic of (4) is that the sensitivity of the demand for good j with respect to average price p_t varies with h. This variable sensitivity is in sharp contrast to CES preferences, where demand elasticity is assumed to be constant regardless of market concentration.

We turn to the firms' decision-making. There is a continuum of firms, indexed by $j \in [0,N]$. Every firm operates under monopolistic competition, and the population of firms implies a mass of product varieties. Given marginal cost c_t, firm j solves the following maximization problem:

$$\max_{\{p_t(j)\}} \ \mathbb{E}_{j,t}[(p_t(j) - c_t)q_t(j)], \tag{5}$$

subject to (4). Here c_t is common for all firms in the sector. In (5) and hereafter, $\mathbb{E}_{j,t}[\cdot] \equiv \mathbb{E}[\cdot|\mathcal{H}_t\,(j)]$ denotes the expectations operator of firm j conditional on information set $\mathcal{H}_t\,(j)$ available in period t, which we specify in the next section.

[12] If N is interpreted as the number of firms in a sector, the share of each firm is given by $(100/N)\%$. Accordingly, the HHI is calculated as $(100/N)^2 \times N = 10^4/N$.

3.2 Shocks and information structure

In the basic model, c_t follows a stochastic process given by,

$$c_t = c_{t-1} + \varepsilon_t, \tag{6}$$

where ε_t is drawn from a Gaussian white noise process $\mathcal{N}(0, \sigma^2)$.[13] Early studies assume that firms do not precisely observe their marginal cost. For example, Maćkowiak and Wiederholt (2009) argue that firms pay only limited attention to common shocks. Following Woodford (2003), our model incorporates private signals regarding firms' costs. Specifically, firms cannot observe $\{c_s\}_{s=1}^t$ in our model. Instead, firm j receives private signal $x_t(j)$ given by,

$$x_t(j) = c_t + \delta_t(j), \tag{7}$$

where $\delta_t(j)$ is drawn from $\mathcal{N}(0, \tau^2)$, and recall that c_t is common across firms. With this information structure, firm j's information set $\mathcal{H}_t(j)$ includes $\left\{c_0, \{x_s(j)\}_{s=0}^t\right\}$ and all the parameter values, including h. In a special case of perfect information where $\tau = 0$, there is no noise in the signals and, therefore, $\mathcal{H}_t(j)$ includes the entire history of firms' marginal costs, $\{c_s\}_{s=0}^t$ together with the parameter values.

3.3 Equilibrium

3.3.1 Equilibrium under perfect information

We first derive the equilibrium prices under perfect information. Plugging (4) into the firm's profit function (5) and then taking derivatives with respect to $p_t(j)$ leaves the best-response function for a firm to choose its best price as follows.

$$p_t(j) = \left(\frac{1}{2} - r\right)\alpha + r\mathbb{E}_{j,t}[p_t] + \frac{\mathbb{E}_{j,t}[c_t]}{2}, \tag{8}$$

[13] In our model, we implicitly assume that c_0 is sufficiently large. This effectively allows us to ignore the possibility that $c_t < 0$.

where r represents the degree of pricing complementarity, defined as,

$$r(h) \equiv \frac{1}{2(1+\beta h)}. \tag{9}$$

Note that $r(h)$ is decreasing in h. The intuition is that when the market is more concentrated, firms' products are more differentiated and less substitutable. As substitution becomes more difficult across products, the price of a firm's product becomes less sensitive to its competitors' prices. Thus, pricing complementarity becomes weaker. This dependence of r on h is not present in the Dixit–Stiglitz models under CES preferences.

In the case of $\tau = 0$, both $\mathbb{E}_{j,t}[p_t] = p_t(j) = p_t$ and $\mathbb{E}_{j,t}[c_t] = c_t$ hold for any j because there is no heterogeneity across firms. Therefore, (8) can easily be solved for the equilibrium individual price $p_t(j)$ and the average price p_t such that,

$$p_t(j) = p_t = \kappa\alpha + (1-\kappa)c_t, \tag{10}$$

where $\kappa(h) \equiv \beta/\left(2\beta + h^{-1}\right)$. Further, we define the quasi-inflation rate as $\Delta p_t \equiv p_t - p_{t-1}$. This is now written as,

$$\Delta p_t = (1-\kappa)\varepsilon_t. \tag{11}$$

Note that sectoral inflation without private signals follows a white noise process.[14]

3.3.2 Equilibrium under imperfect common knowledge

We turn to the case under imperfect common knowledge, that is, $\tau > 0$ in (7). Here, we define average and higher-order expectations denoted recursively as,

$$\overline{\mathbb{E}}_t^1[\cdot] \equiv \overline{\mathbb{E}}_t[\cdot] \equiv \frac{1}{N}\int_{j\in[0,N]} \mathbb{E}_{j,t}[\cdot]dj,$$

[14]Hereafter, we refer to Δp_t simply as inflation, instead of *quasi*-inflation.

and $\overline{\mathbb{E}}_t^{k+1} \equiv \overline{\mathbb{E}}_t \left[\overline{\mathbb{E}}_t^k [\cdot] \right]$ for every $k \geq 1$. With these notations, the average of $p_t(j)$ in (8) over j is now expressed as,

$$p_t = \left(\frac{1}{2} - r \right) \alpha + r \overline{\mathbb{E}}_t^1 [p_t] + \frac{1}{2} \overline{\mathbb{E}}_t^1 [c_t], \tag{12}$$

where $\overline{\mathbb{E}}_t^1 [p_t]$ is no longer equal to p_t in general because of the private signals. Plugging p_t recursively into $\overline{\mathbb{E}}_t^1 [p_t]$ in (12) leaves the equilibrium price expressed as,

$$p_t = \kappa \alpha + (1 - \kappa)(1 - r) \sum_{k=0}^{\infty} r^k \overline{\mathbb{E}}_t^{k+1} [c_t]. \tag{13}$$

Note that prices adjust more slowly as r increases. Intuitively, when pricing complementarity is stronger, firms' pricing places more weight on higher-order expectations of c_t. This equation is the same as that presented for general linear-quadratic problems by Morris and Shin (2002).

By simplifying (13) and taking the limit of t to infinity, we now provide the explicit solution forms for p_t in the basic model, namely, a linear combination of the past marginal costs such that,

$$p_t = \kappa \alpha + (1 - \kappa) (1 - \mu) \sum_{s=0}^{\infty} \mu^s c_{t-s}. \tag{14}$$

This equation implies,

$$\Delta p_t = \mu \Delta p_{t-1} + (1 - \kappa) (1 - \mu) \varepsilon_t, \tag{15}$$

where μ is given by,

$$\mu \equiv \frac{(1 + \lambda) / \lambda - \sqrt{((1 + \lambda) / \lambda)^2 - 4}}{2},$$

and $\lambda(r)$ is increasing in r and is given by,

$$\lambda(r) \equiv \frac{\tau^2}{\tau^2 + (1 - r) \sigma^2}. \tag{16}$$

In a limiting case where $r = 0$, $1 - \lambda$ coincides with the Kalman gain of steady-state Kalman filtering.[15] If private signals are imprecise (i.e., τ^2 / σ^2 is large), the Kalman gain is low. A

[15] We assume that t is sufficiently large so that $\lambda(r)$ can be dealt with as a time-invariant parameter.

lower Kalman gain implies that firms place more weight on the priors in their belief updating process, generating slower dynamics for price and inflation. The same logic applies to a large r. That is, under a larger r, firms place more weight on the priors in their belief-updating process.

In the standard model with perfect common knowledge, $\delta_t(j)$ is common across firms. In this special case, the equilibrium price shown in (13) is independent of r since $\bar{\mathbb{E}}_t^k[\cdot] = \bar{\mathbb{E}}_t[\cdot]$ for all k. We can also show that λ in (16) reduces to $\tau^2/(\tau^2+\sigma^2)$. In other words, λ is not affected by r under perfect common knowledge.

3.4 Comparative statics

The explicit solution forms given by (11) and (15) predict how inflation persistence depends on market concentration in our model. To express the relationship, we denote the predicted first-order autocorrelation by $\rho_\pi(h)$, where h represents the HHI as discussed in Section 3.1.

In the case of perfect information, (11) indicates $\rho_\pi(h) = 0$ for any h because Δp_t is i.i.d. By contrast, in the case of imperfect common knowledge, (15) implies $\rho_\pi(h) = \mu(\lambda) > 0$ because Δp_t follows AR(1). Because (16) shows that λ depends on r, $\mu(\lambda(r))$ also depends on r. Therefore, applying the implicit function theorem and the chain rule, we have,

$$\frac{d\rho_\pi(h)}{dh} = \underbrace{\frac{d\mu}{d\lambda}\frac{d\lambda}{dr}}_{ICK}\underbrace{\frac{dr}{dh}}_{MO} \leq 0, \tag{17}$$

where ICK and MO point to the role of imperfect common knowledge and the prediction of the MO model, respectively. The derivation of (17) is in Appendix B.

The inequality in (17) indicates that incorporating imperfect common knowledge into the MO model is critical in explaining the negative correlation between inflation persistence and market concentration. The intuition behind (17) can be obtained via two steps. The first step is to recall that pricing complementarity is higher in less concentrated markets ($dr/dh < 0$), as shown by (9). This negative correlation between h and r is a unique feature of the MO model and is absent in monopolistic competition models under CES preferences.

The second step is to adopt the common mechanism in the models of imperfect common knowledge, which makes inflation persistence $\mu(\lambda(r))$ increasing in r. In markets where pricing complementarity is high, firms place more weight on their priors ($d\lambda/dr \geq 0$) and less on private signals in the belief-updating process. Under a larger λ, firms revise their prices more slowly ($d\mu/d\lambda \geq 0$). This positive correlation between r and μ is a unique feature of imperfect common knowledge and is absent in the model with perfect common knowledge.

3.5 Numerical examples

To visualize the results of the basic model, we provide some numerical examples. In our numerical examples, we set $\gamma = 10^{-4}$ so that h can be interpreted as the HHI. For the other parameters, we assume $\beta = 10^{-3}$ and $\sigma = 1$.

Figure 2 illustrates how inflation persistence varies against market concentration. The left panel plots the inflation persistence under perfect common knowledge (i.e., signals $x_t(j)$ are common across all j). The right panel shows the inflation persistence under imperfect common knowledge (i.e., heterogeneous signals). Each panel presents inflation persistence under $\tau = 0, 1.0, 1.5$, and 2.0 to examine to what extent imperfect information generates inflation persistence.

Comparing the two panels highlights the role of imperfect common knowledge. In the left panel, the lines for inflation persistence shift upward as τ increases but are flat against h. Thus, the model with perfect common knowledge succeeds in generating persistence but fails to reconcile the observed negative correlation between inflation persistence and market concentration. This is because inflation persistence is independent of r under perfect common knowledge.

In the right panel, however, the lines for inflation persistence not only shift upward as τ increases but also are downward sloping against h if $\tau > 0$. Thus, the model can explain the observed negative correlations as well as the intrinsic persistence. This implies that imperfect common knowledge is necessary for explaining the observed negative correlation.

While our numerical examples reconfirm the main analytical result of the basic model, the model does not quantitatively perform well in explaining the magnitude of inflation persistence. In particular, if τ is positive, inflation persistence in Figure 2 ranges between 0.4 and 0.7, much larger than the median of inflation persistence reported in Table 1. In the next section, we consider a more general stochastic process for c_t to reconcile the data. We also check the robustness of our main result under the general stochastic process for c_t.

4 Extending the basic model

This section extends the basic model for two purposes. First, we improve the model's predictions for inflation persistence while confirming the robustness of our results concerning the negative correlation. For this purpose, we generalize the marginal cost stochastic process. Second, we derive the macroeconomic implications of our model. For this purpose, we develop a simple general equilibrium model.

4.1 Generalizing the marginal cost stochastic process

4.1.1 Setup

We allow for (i) temporary deviations of the marginal cost from the stochastic trend η_t and (ii) the persistence of ε_t parameterized by ρ. Consider the following stochastic process for c_t,

$$c_t = \tilde{c}_t + \eta_t, \tag{18}$$

$$\tilde{c}_t = \tilde{c}_{t-1} + \varepsilon_t, \tag{19}$$

$$\varepsilon_t = \rho\varepsilon_{t-1} + e_t, \tag{20}$$

where $\eta_t \sim \mathcal{N}(0, \zeta^2)$ and $e_t \sim \mathcal{N}(0, \sigma^2)$ are Gaussian white noise processes. Recall that ε_t was assumed to be i.i.d. and $c_t = \tilde{c}_t$ in the basic model. In the extended model, c_t follows an autoregressive integrated moving average process, specifically, ARIMA(1,1,2) process, which generalizes the random walk process assumed for c_t in the basic model.

The generalized stochastic process of c_t generates much richer inflation dynamics, consistent with the data. The model introduces a temporary shock to c_t (i.e., η_t) and can replicate a wide range of levels of inflation persistence, including negative values. In fact, Table 1 shows that the minimum value of inflation persistence is negative. Further, our specification distinguishes between intrinsic and inherited inflation persistence, as emphasized in the literature.[16] Note that ρ in (20) represents the degree of inherited inflation persistence because the persistence of $\Delta\tilde{c}_t$ is ρ from (19) and (20).[17]

Before we move to the numerical results, we note that the equilibrium price continues to be expressed as a linear combination of past marginal costs and α owing to the linear-quadratic nature of the problem. Specifically, it is given by,

$$p_t = \kappa\alpha + (1-\kappa)\sum_{s=0}^{t}\phi_{t-s}c_{t-s}, \tag{21}$$

and, accordingly, inflation is,

$$\Delta p_t = (1-\kappa)\sum_{s=0}^{t}\phi_{t-s}\Delta c_{t-s}, \tag{22}$$

where each ϕ_{t-s} is a nonlinear function of h. Note that (21) generalizes (14) in the basic model. In what follows, we numerically compute ϕ_{t-s} and examine the inflation dynamics under various parameter values.[18]

[16]See Fuhrer (2010) for a discussion of intrinsic and inherited inflation persistence.

[17]In addition, the generalized process can generate consistent prediction with the findings by BGM regarding the contrasting responses of inflation to sector-specific and macroeconomic shocks. If η_t and e_t in (18)-(20) correspond to the sector-specific shock and the macroeconomic shock identified by BGM, respectively, the solution for inflation, (22), implies that the inflation dynamics exhibit quicker responses to sector-specific shocks than to macroeconomic shocks.

[18]See Appendix C for details of the numerical methods.

4.1.2 Results

Given plausible dynamics of marginal cost, we numerically check whether the model can generate inflation persistence that is consistent with the data. We also confirm the robustness of the negative correlation between inflation persistence and market concentration when $\eta_t \neq 0$ and $\rho \in [0, 1)$. We compute inflation persistence under (i) $\eta_t = 0$ or $\eta_t \neq 0$ and (ii) $\rho \in \{0.00, 0.35, 0.70\}$. In the computation, $\tau = 1.5$ and $\zeta = 1$ and the other parameters remain unchanged.

Figure 3 illustrates the result. All lines in the figure are downward sloping against h. Thus, our results are robust to the general stochastic process of the marginal cost. Next, solid lines in all panels indicate that the presence of η_t significantly lowers inflation persistence. For example, see panel (a) under $\rho = 0$. Inflation persistence ranges between 0.54 and 0.63 when $\eta_t = 0$ for all t (see the dashed line). However, when a temporary shock η_t is present, the range is now between -0.08 and 0.03, much closer to the data. Panels (b) and (c) show that, as inherited inflation persistence increases (i.e., ρ increases), both the dashed and solid lines move upward.

Given the stochastic process of c_t, we estimate unknown parameters ρ and τ that are consistent with the data at the sector level. For estimation, we use $\rho_{\pi,i}$ and HHI_i of the pooled dataset. Define the predicted inflation persistence as $\rho_\pi(HHI_i, \theta)$, where θ is the parameter vector of $\theta' = (\rho, \tau)$. We then estimate θ by nonlinear least squares (NLS) that solve $\min_\theta \sum_i [\rho_{\pi,i} - \rho_\pi(HHI_i, \theta))]^2$. The resulting NLS estimates are $\hat{\theta}' = (\hat{\rho}, \hat{\tau}) = (0.66 \times 10^{-4}, 2.01)$. The standard errors are 1.82×10^{-4} for $\hat{\rho}$ and 0.54 for $\hat{\tau}$, respectively.[19]

Figure 4 depicts that the size of the declines in inflation persistence predicted by the model is close to the data. The solid line, which is the model's prediction under $\hat{\theta}' = (\hat{\rho}, \hat{\tau})$, shows that inflation persistence decreases by 0.12 from 0.17 to 0.05 as the HHI increases from 0 to

[19]We added $D_{BGM,i}$ as an explanatory variable to control for a difference in the mean between the BGM and extended datasets. Our estimation also imposes the restriction that $\hat{\rho}$ is strictly positive.

2,000.[20] The dashed line, which is the regression line based on specification (3-1) in Table 2, indicates that inflation persistence decreases by 0.12 from 0.14 to 0.02, alongside the HHI increasing from 0 to 2,000. The shaded area indicates the range of one-standard deviation from the linear regression line, showing that the model's prediction is in proximity to the regression result.

4.2 A general equilibrium model

4.2.1 Setup

We next develop a general equilibrium model with multiple sectors in each of which firms are engaged in the monopolistic competition described in Section 3. The general equilibrium analysis aims to understand how market concentration affects monetary non-neutrality. It also derives some implications on the rise of market power and the relevant industrial policies.[21]

A sketch of our general equilibrium model is as follows.[22] The model is a simple closed economy model with a representative household and multiple sectors. The model has two levels of aggregation. At the "wholesale level," aggregation is done by intermediate-good producers in each sector with MO technology, similar to the MO preferences. Outputs of firm j are aggregated at sector i: $q_{i,t} = \int_{j\in[0,N_i]} q_{i,t}(j)dj$, where $q_{i,t}$ is the sectoral output and $q_{i,t}(j)$ is outputs of firm j. The sectoral price is given by $p_{i,t} = (1/N_i)\int_{j\in[0,N_i]} p_{i,t}(j)dj$. In this model, N_i is heterogeneous across sectors. As a result, the degrees of market concentration $h_i = (\gamma N_i)^{-1}$ is also heterogeneous. The "retail level" aggregation is done by the final-good producer using standard CES technology: $Q_t = [(1/N_A)^{1/\upsilon}\sum_{i=1}^{N_A} q_{i,t}^{(\upsilon-1)/\upsilon}]^{\upsilon/(\upsilon-1)}$, where Q_t is the real GDP and υ is the elasticity of substitution satisfying $\upsilon > 1$. The price index for final goods is $P_t = [(1/N_A)\sum_{i=1}^{N_A} p_{i,t}^{1-\upsilon}]^{1/(1-\upsilon)}$.

The representative household maximizes its lifetime utility subject to the budget and cash-

[20]The data presented in Section 2 indicate that the HHIs of 94.2% of sectors are less than 2,000.

[21]For recent discussions on the rise of market power, see Autor et al. (2017), Grullon et al. (2019), and De Loecker et al. (2020).

[22]We leave the details of the model setup to Section B in the not-for-publication appendix.

in-advance constraints. The period utility is given by $\ln Q_t - L_t$ where L_t is hours worked. Turning to firms, we assume that the production function for firm j in sector i is linear in labor: $q_{i,t}(j) = l_{i,t}(j)$, where $l_{i,t}(j)$ are the labor inputs of firms. There is no government expenditure in this model.

The above assumptions lead to an equality between the nominal marginal cost c_t and the nominal money supply M_t. Firms solve the same maximization problem as (5), but now the money supply explicitly affects their prices. If the money supply follows the stochastic process specified by (18) – (20), we can derive the solution for P_t from $c_t = M_t$. We then compute output Q_t from the cash-in-advance constraint $M_t = P_t Q_t$. In computing the solutions, we use the parameter values consistent with the NLS estimates in Section 4.1. We calibrate the distribution of h_i to the actual distribution of HHI_i in the regressions and refer to this as the baseline distribution.[23]

4.2.2 Results

We are now ready to discuss the macroeconomic implications of our model.

Baseline distribution The solid lines in Figure 5 plot the impulse response functions of aggregate inflation ($\Delta \ln P_t$) and the log deviations of aggregate output from the steady state ($\ln Q_t - \ln Q_{ss}$) to a 1% increase in money supply under the baseline distribution. In what follows, we discuss the impulse responses under two counterfactual distributions in comparison with the baseline distribution. The impulse functions allow us to assess how monetary non-neutrality varies depending on the distribution of h_i. In the left panel, the initial responses of aggregate inflation are standardized at 1.0 to facilitate the comparison across calibrations.

Effects of pro-competition policy The dotted lines in Figure 5 represent the impulse responses in the case where all sectors are homogeneous and perfectly competitive (i.e., $h_i = 0$

[23] We use the distribution of HHI_i in the pooled dataset. The impulse responses are not substantially different, even if we use either the BGM dataset or the extended dataset.

for all i). In this case, goods produced by firms are fully substitutable in the MO preferences and pricing complementarity is at its strongest. Therefore, taking other parameters as given, the degree of monetary non-neutrality would also be the strongest. Under the counterfactual distribution of $h_i = 0$ for all i, inflation converges more slowly to the steady state than under the baseline distribution. Quantitatively, output under the baseline distribution increases by 0.45% on impact while the output response is now 0.64% under the counterfactual distribution.

An interpretation of this case is that an industrial policy achieves perfect competition in all sectors. Thus, according to our model, the impact of the pro-competition industrial policy can potentially be large.

Rise of market concentration (or market power) The dashed lines in Figure 5 are the impulse responses in the case where all observed HHI_i are hypothetically doubled. Compared with the baseline distribution, output responds less under the increased market concentration (or market power). The response on impact declines from 0.45% in the baseline distribution to 0.38% in the counterfactual distribution. Thus, the impact of the increased market concentration weakens monetary non-neutrality, but quantitatively, the effects would be marginal.

The result is a straightforward outcome from (9). As (9) shows, the declines in pricing complementarity become smaller as h increases. Therefore, declines in inflation persistence are also small when the HHI is high. We can reconfirm this result from Figure 4. The solid line indicates that the slope is steep when h is low but becomes flatter when h is high.

5 An alternative approach: The Calvo model

Apart from our arguments so far, some early studies emphasize the linkage between price stickiness and market concentration. If (i) the degree of price stickiness varies depending on market concentration and (ii) price stickiness increases inflation persistence, we can arrive at a reasonable hypothesis that can account for the observed correlation between inflation persistence and market concentration. Along with this argument, Carlton (1986) reports a positive correlation between the degree of price rigidity and market concentration. BGM argue that the price adjusts more sluggishly in more concentrated markets.[24]

In what follows, we explore the prediction of a Calvo model with standard CES preferences where the degree of price stickiness increases as market concentration rises. Let ξ be the probability of no price changes. In the Calvo model, the (log-linearized) price index is a weighted average of the lagged price and the newly reset prices. Here, we maintain the same assumption as in our basic model that the (log of) marginal cost follows a random walk. Then, sectoral inflation follows an AR(1) process as, for instance, shown by Bils and Klenow (2004), such that,

$$\Delta \ln p_t = \xi \Delta \ln p_{t-1} + (1-\xi)\varepsilon_t, \tag{23}$$

where ξ now coincides with inflation persistence in the sector. Given the findings by Carlton (1986) and BGM, the Calvo model predicts that inflation persistence would positively correlate with market concentration. Namely,

$$\frac{\partial \rho_\pi}{\partial h} = \frac{d\xi}{dh} > 0,$$

which contradicts the empirical findings presented in Section 2.

The key to reconciling the seemingly contradicting predictions given by the Calvo model and our model lies in the relationship between the degree of price stickiness and inflation persistence. Bils and Klenow (2004) report empirical findings that point to a *negative* correlation between the degree of price stickiness and inflation persistence across sectors.[25] Although the degree of price stickiness could positively correlate with market concentration, greater price

[24]However, Bils and Klenow (2004) conclude that market concentration does not have robust explanatory power for the degree of price stickiness as measured by the (in)frequency of price changes.

[25]See Figures 2 and 3 in Bils and Klenow (2004). Table 4 of their paper also shows the correlation between (sectoral) inflation persistence and the frequency of price changes.

stickiness does not ensure higher inflation persistence. As suggested by studies of information rigidity models, inflation persistence cannot solely be explained by models of sticky prices.

6 Conclusion

Many previous studies have confirmed the role of information rigidities in firms' price-setting decisions. Our contribution to the literature on inflation dynamics is twofold. First, using US PPI data, we present evidence that sectoral inflation persistence is negatively correlated with market concentration. Second, we find that pricing complementarity among monopolistically competitive firms decreases as market concentration increases, given quadratic preferences over the variety. Because of the varying pricing complementarity, our model with imperfect common knowledge can generate the observed negative correlation between inflation persistence and market concentration across sectors.

One caveat in this paper is that our simple general equilibrium model in Section 4 may not fully quantify the importance of the rise of market power on monetary non-neutrality. Our model predicts that the rise of market power may weaken monetary non-neutrality. However, the model is small-scale, and its quantitative impact may differ in a full-fledged medium-scale model. The interaction of changes in market power with the imperfect formation in full-fledged, medium-scale models would be worth exploring for future work.

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A Consumer demand under MO preferences

The consumers' problem is to maximize (2) subject to (3). The first-order condition is obtained as,

$$p_t(j) = \alpha - \beta q_t(j) - \gamma \int_{j\in[0,N]} q_t(j)dj. \tag{24}$$

By integrating $p_t(j)$ over $j \in [0, N]$ and dividing it by N, we obtain,

$$p_t = \frac{1}{N}\int_{j\in[0,N]} p_t(j)dj = \alpha - \frac{\beta}{N}\int_{j\in[0,N]} q_t(j)dj - \gamma \int_{j\in[0,N]} q_t(j)dj. \tag{25}$$

Using (24), $\int_{j\in[0,N]} q_t(j)dj$ is eliminated from (25), resulting in the demand function given by (4).

B Comparative statics

We first derive the equilibrium price from individual prices. Given (4), the firm's maximization problem (5) can be rewritten as,

$$\max_{p_t(j)} : -\frac{1}{\beta}\mathbb{E}_t\left[(p_t(j) - p_t)^2 r + \{p_t(j) - (\kappa\alpha + (1-\kappa)c_t)\}^2 (1-r)\right] + \Psi, \tag{26}$$

where Ψ represents all exogenous terms for firm j. Notice that the structure of this optimization problem is exactly the same as those introduced by Morris and Shin (2002). Due to the linear-quadratic nature of the problem, the optimal price set by firm j has a linear form given by,

$$p_t(j) = \kappa\alpha + (1-\kappa)\,\boldsymbol{\phi}_t(\lambda)\,\mathbf{x}_t(j)', \tag{27}$$

where $\boldsymbol{\phi}_t = [\phi_t\ \phi_{t-1} \cdots\ \phi_0]$ and $\mathbf{x}_t(j) = [x_t(j)\ x_{t-1}(j) \cdots\ x_0(j)]$. Given the assumption that information structure converged in $t = 0$, we conjecture that ϕ_t takes the following form independent of t such that $\phi_{t-j} = (1-\mu)\mu^j$, where μ is the smaller root of $\lambda z^2 - (1+\lambda) z + \lambda =$

0. Consequently, firm j's optimally chosen price should take the form,

$$p_t(j) = \mu p_{t-1}(j) + (1-\mu)\left\{\kappa\alpha + (1-\kappa)\, x_t(j)\right\}. \tag{28}$$

This conjecture (28) is substituted back into (26) and it can be confirmed that there exists a unique $\mu \in [0,1]$ that solves the optimization problem. Integrating (28) over j leads to the equilibrium price given by (14).

The comparative statics take three steps. First, we inspect $d\mu/d\lambda$. Because $\mu \in [0,1]$ is the smaller root of $\lambda z^2 - (1+\lambda)\, z + \lambda = 0$, applying the implicit function theorem leaves,

$$\frac{d\mu}{d\lambda} = \frac{\mu}{\lambda^2}\left\{(1-\mu) + \left(\frac{1}{\lambda} - \mu\right)\right\}^{-1} > 0.$$

The second step is to examine $d\lambda/dr$, which is clearly positive as shown by (16). In the third step, $dr/dh < 0$ is assured by the definition of pricing complementarity given by (9). Finally, the chain rule combines the three inequalities, which results in (17).

C Numerical solutions of the extended model

C.1 The solution form

We redefine the vector $\boldsymbol{\phi}_t = [\phi_t \ \phi_{t-1} \cdots \ \phi_0]$ as,

$$\begin{aligned}\boldsymbol{\phi}_t = \arg\min_{\{\phi_0,\phi_1,\ldots\phi_t\}} \mathbb{E}\Bigg[r\sum_{s=0}^{t-1}\phi_{t-s}^2\tau^2 + (1-r)\left\{(\phi_t - 1)^2\zeta^2 + \phi_t^2\tau^2 + \sum_{s=1}^{t-1}\phi_{t-s}^2\left(\tau^2+\zeta^2\right)\right\} \\ +(1-r)\left\{\sum_{s=0}^{t}\left(\sum_{u=0}^{s}\phi_{t-u}\frac{1-\rho^{s-u+1}}{1-\rho} - \frac{1-\rho^{s+1}}{1-\rho}\right)^2\sigma^2\right\}\Bigg].\end{aligned} \tag{29}$$

The terms in the square bracket on the right-hand side of (29) are obtained by substituting (21) and (27) into (26) under the assumption that c_t follows the general process specified in

(18)–(20). It can be confirmed that $\{\phi_t, \phi_{t-1}, \cdots, \phi_0\}$ satisfies the following $t+1$ conditions.

$$\phi_t = \Gamma_1 + \Gamma_2(1+\rho)\phi_{t-1} - \Gamma_2\rho\phi_{t-2}, \tag{30}$$

$$\begin{aligned}\phi_{t-s} &= (1-\Gamma_2)\left\{\frac{1-\rho^{s+1}}{1-\rho} - \sum_{k=1}^{s}\left(\frac{1-\rho^{s+2-k}}{1-\rho}\right)\phi_{t+1-k}\right\} \\ &\quad +\Gamma_2(1+\rho)\phi_{t-s-1} - \Gamma_2\rho\phi_{t-s-2},\end{aligned} \tag{31}$$

for $s \in \{1, 2, ...t-2\}$ and,

$$\begin{aligned}\phi_1 &= (1-\Gamma_2)\left\{\frac{1-\rho^{t}}{1-\rho} - \sum_{k=1}^{t-1}\left(\frac{1-\rho^{t+1-k}}{1-\rho}\right)\phi_{t+1-k}\right\} + \Gamma_2(1+\rho)\phi_0, \\ \phi_0 &= \frac{1-\rho^{t+1}}{1-\rho} - \sum_{k=1}^{t}\left(\frac{1-\rho^{t+2-k}}{1-\rho}\right)\phi_{t+1-k},\end{aligned}$$

where,

$$\Gamma_1 \equiv \frac{(1-r)\left(\sigma^2+\zeta^2\right)}{r\tau^2+(1-r)\left(\tau^2+\sigma^2+\zeta^2\right)},\ \Gamma_2 \equiv \frac{r\tau^2+(1-r)(\tau^2+\zeta^2)}{r\tau^2+(1-r)\left(\tau^2+\sigma^2+\zeta^2\right)}.$$

Then, the solution form is given by,

$$p_t = \kappa\alpha + (1-\kappa)\,\boldsymbol{\phi}_t\boldsymbol{c}_t',$$

where $\boldsymbol{c}_t = [c_t\ c_{t-1} \cdots\ c_0]$.

C.2 Approximation

When t is extremely large, it is not feasible to deal with $t \times t$ matrices numerically. Therefore, we further assume that for a large $T < t$, all elements in $[\phi_{t-T-1}\ \phi_{t-T-2}...\phi_0]$ should be zero. This additional assumption reduces the dimension of the matrices needed to compute the solution numerically.

Define a $1 \times (T+1)$ vector $\boldsymbol{\phi}_{t,T} = [\phi_t\ \phi_{t-1} \cdots\ \phi_{t-T}]$ which satisfies the $T+1$ conditions given by (30) and (31) for $s \in \{1, 2, ...T+1\}$. Then, $\boldsymbol{\phi}_{t,T}'$ can be obtained by,

$$\boldsymbol{\phi}_{t,T}' = (\mathbf{I} - \mathbf{M})^{-1}\mathbf{G}', \tag{32}$$

where $\mathbf{I}_{(T+1)\times(T+1)}$ is an identity matrix and $\mathbf{M}_{(T+1)\times(T+1)}$ and $\mathbf{G}_{1\times(T+1)}$ are given by,

$$\mathbf{M} = \begin{bmatrix} 0 & \Gamma_2\frac{1-\rho^2}{1-\rho} & -\Gamma_2\rho & 0 & \cdots & 0 \\ -\left(1-\Gamma_2\right)\frac{1-\rho^2}{1-\rho} & 0 & \Gamma_2\frac{1-\rho^2}{1-\rho} & -\Gamma_2\rho & \ddots & \vdots \\ -\left(1-\Gamma_2\right)\frac{1-\rho^3}{1-\rho} & -\left(1-\Gamma_2\right)\frac{1-\rho^2}{1-\rho} & 0 & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & -\Gamma_2\rho \\ \vdots & \ddots & \ddots & \ddots & 0 & \Gamma_2\frac{1-\rho^2}{1-\rho} \\ -\left(1-\Gamma_2\right)\frac{1-\rho^{T+1}}{1-\rho} & -\left(1-\Gamma_2\right)\frac{1-\rho^T}{1-\rho} & \cdots & -\left(1-\Gamma_2\right)\frac{1-\rho^3}{1-\rho} & -\left(1-\Gamma_2\right)\frac{1-\rho^2}{1-\rho} & 0 \end{bmatrix},$$

$$\mathbf{G} = \left[\ \Gamma_1 \quad \left(1-\Gamma_2\right)\left(1+\rho\right) \quad \ldots \quad \left(1-\Gamma_2\right)\left(1+...+\rho^T\right)\ \right].$$

C.3 Inflation persistence

The inflation is now approximated by,

$$\Delta p_t \simeq \left(1-\kappa\right)\boldsymbol{\phi}_{t,T}\Delta\boldsymbol{c}'_{t,T},$$

where $\Delta\boldsymbol{c}_{t,T} = [\Delta c_t\ \Delta c_{t-1}\cdots\Delta c_{t-T}]$. Using this approximated form, inflation persistence is calculated as follows.

$$Corr\left(\Delta p_t, \Delta p_{t-1}\right) = \frac{\sum_{s=0}^{T} a_{t-s}a_{t-s-1}\sigma^2 + \sum_{s=0}^{T} b_{t-s}b_{t-s-1}\zeta^2}{\sum_{s=0}^{T} a_{t-s}^2\sigma^2 + \sum_{s=0}^{T} b_{t-s}^2\zeta^2},$$

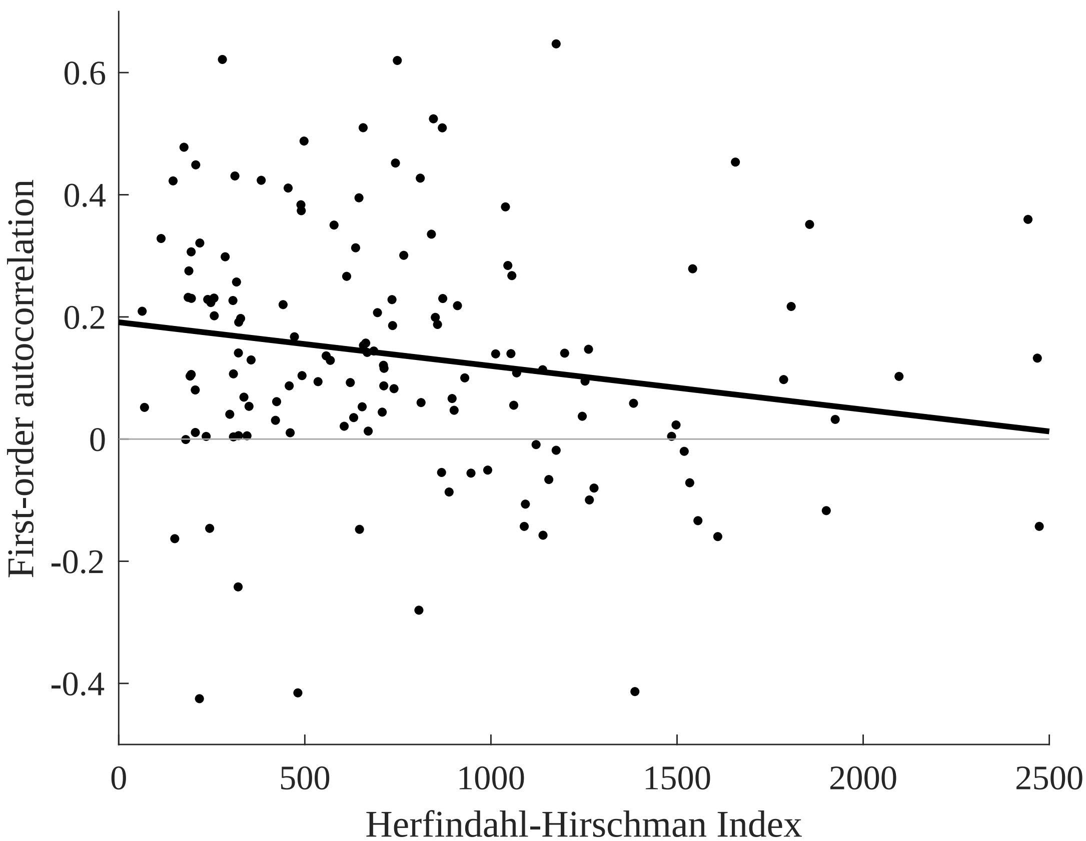
where a_{t-s} and b_{t-s} for $s \in \{0,1,2,..T\}$ are characterized by $\mathbf{A}' = (\mathbf{I}-\mathbf{P})^{-1}\boldsymbol{\phi}'_{t,T}$ and $\mathbf{B}' = \mathbf{Q}\boldsymbol{\phi}'_{t,T}$ given by,

$$\mathbf{A} = \left[\ a_t \quad a_{t-1} \quad \ldots \quad a_{t-T}\ \right],$$

$$\mathbf{B} = \left[\ b_t \quad b_{t-1} \quad \ldots \quad b_{t-T}\ \right],$$

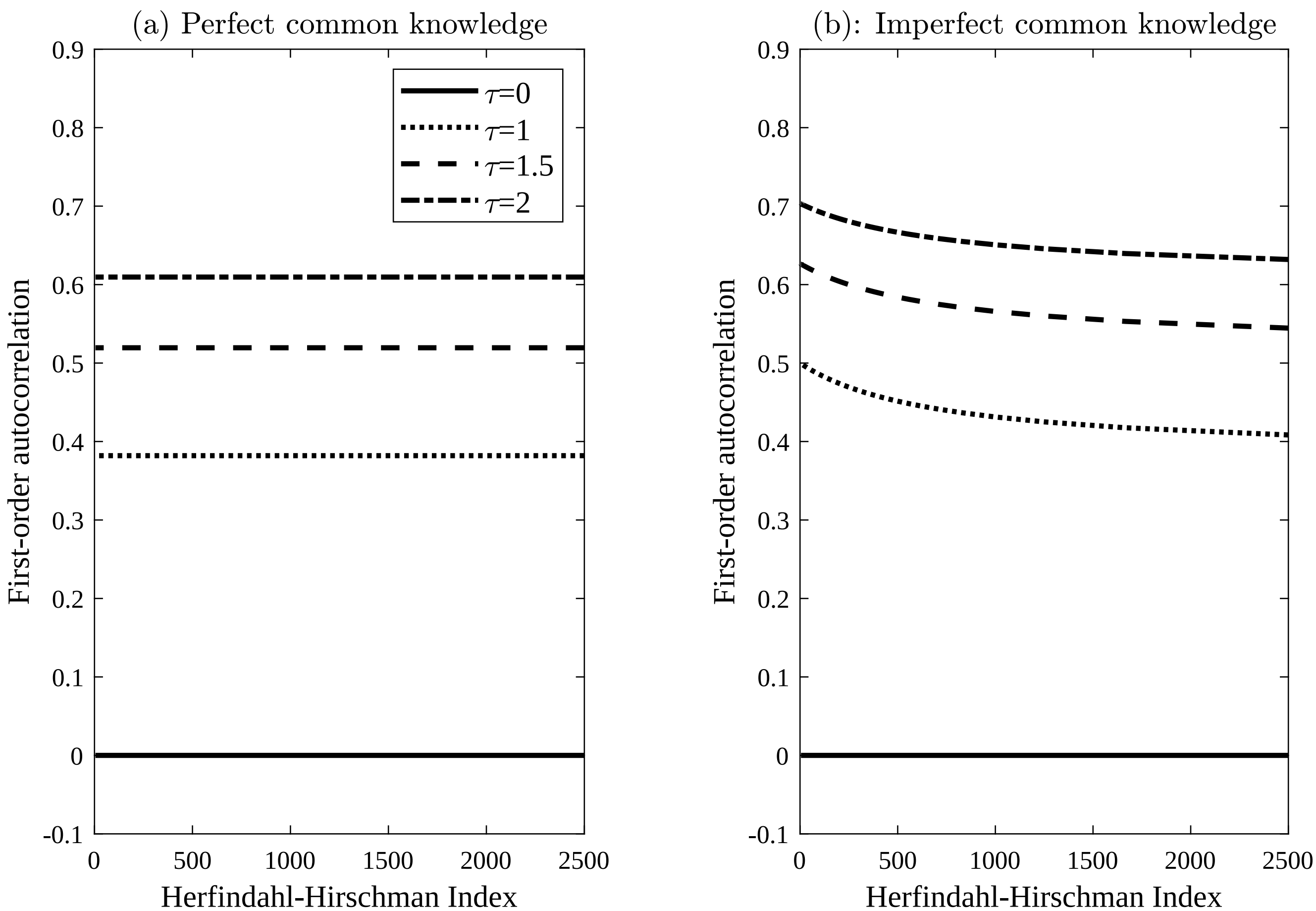
$$\mathbf{P} = \begin{bmatrix} 0 & \cdots & \cdots & \cdots & 0 \\ \rho & \ddots & \ddots & \ddots & \vdots \\ 0 & \rho & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & \cdots & \rho & 0 \end{bmatrix}, \text{and } \mathbf{Q} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ -1 & 1 & \ddots & \ddots & \vdots \\ 0 & -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & -1 & 1 \end{bmatrix}.$$

Figure 1: Scatter plot of inflation persistence and market concentration



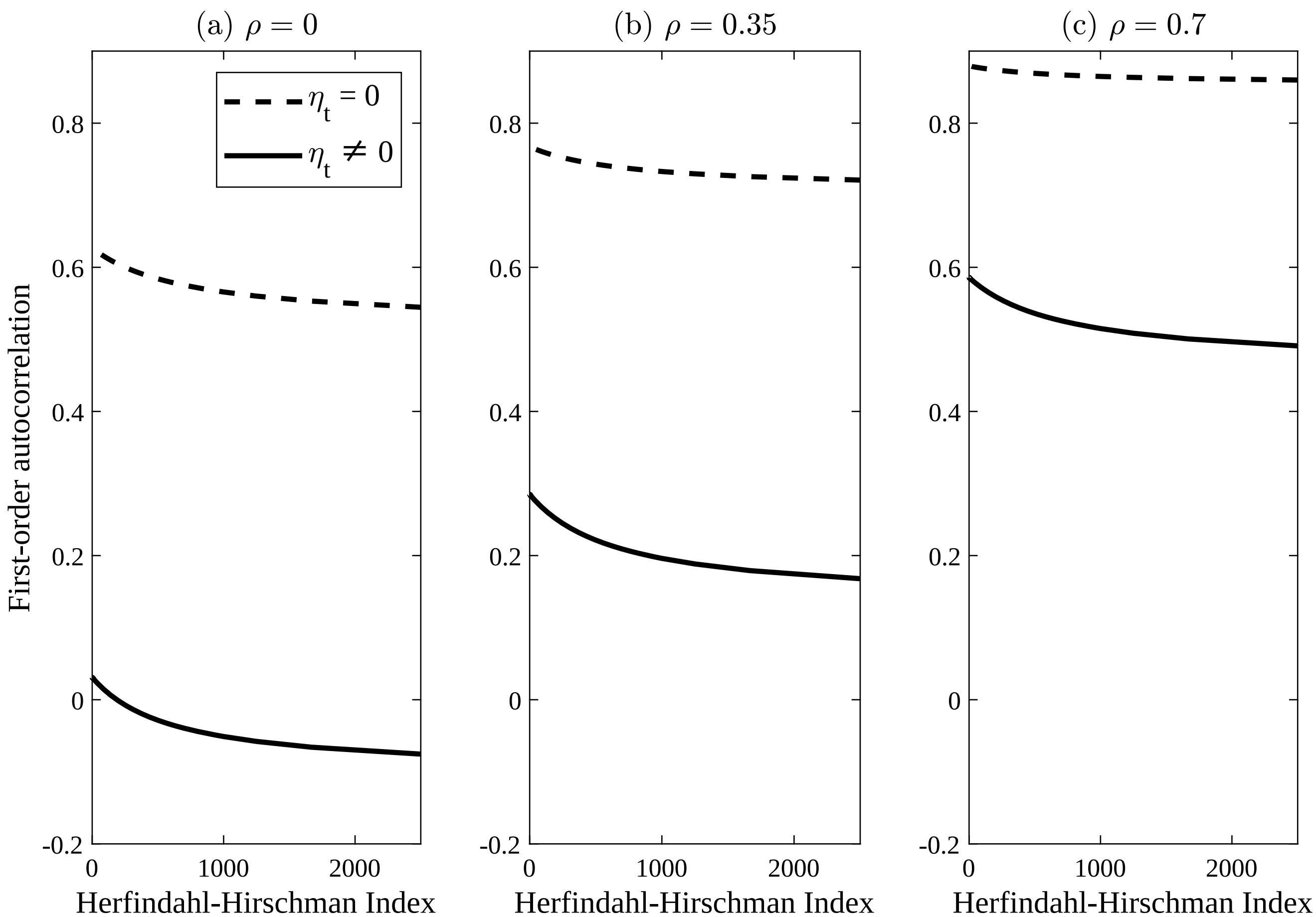
Notes: The vertical axis is inflation persistence measured by the first-order autocorrelation of the seasonally adjusted monthly difference of the sectoral (log) prices taken from BGM. The horizontal axis is the Herfindahl–Hirschman Index.

Figure 2: Inflation persistence in the basic model



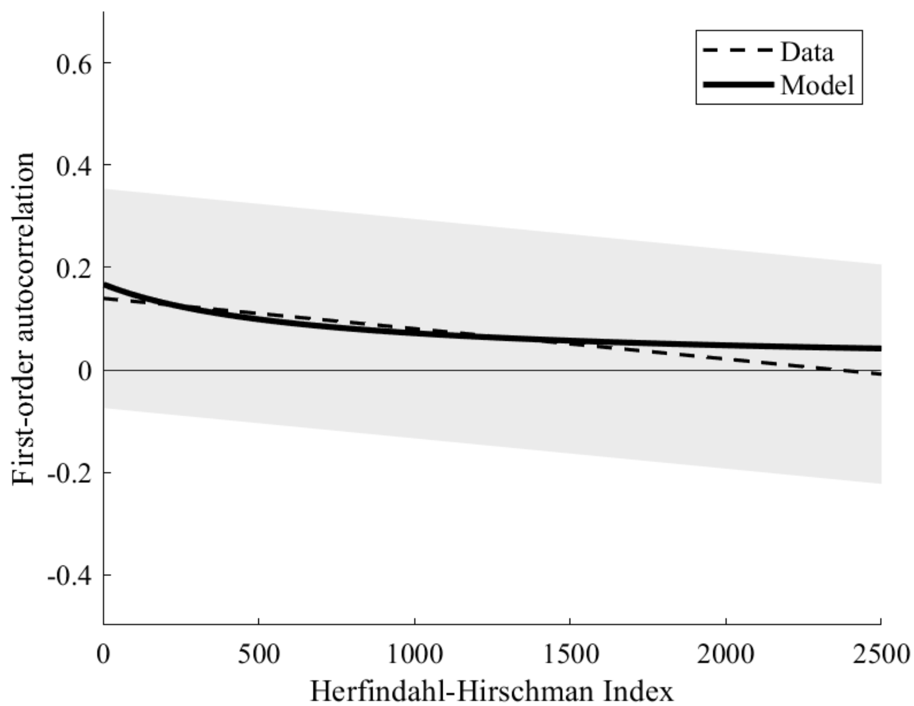
Notes: The vertical axis is inflation persistence measured by the first-order autocorrelation. The horizontal axis is the Herfindahl–Hirschman Index. In the left panel, signals are common across all j. In the right panel, heterogeneous signals are assumed.

Figure 3: Inflation persistence under the generalized stochastic process of marginal cost



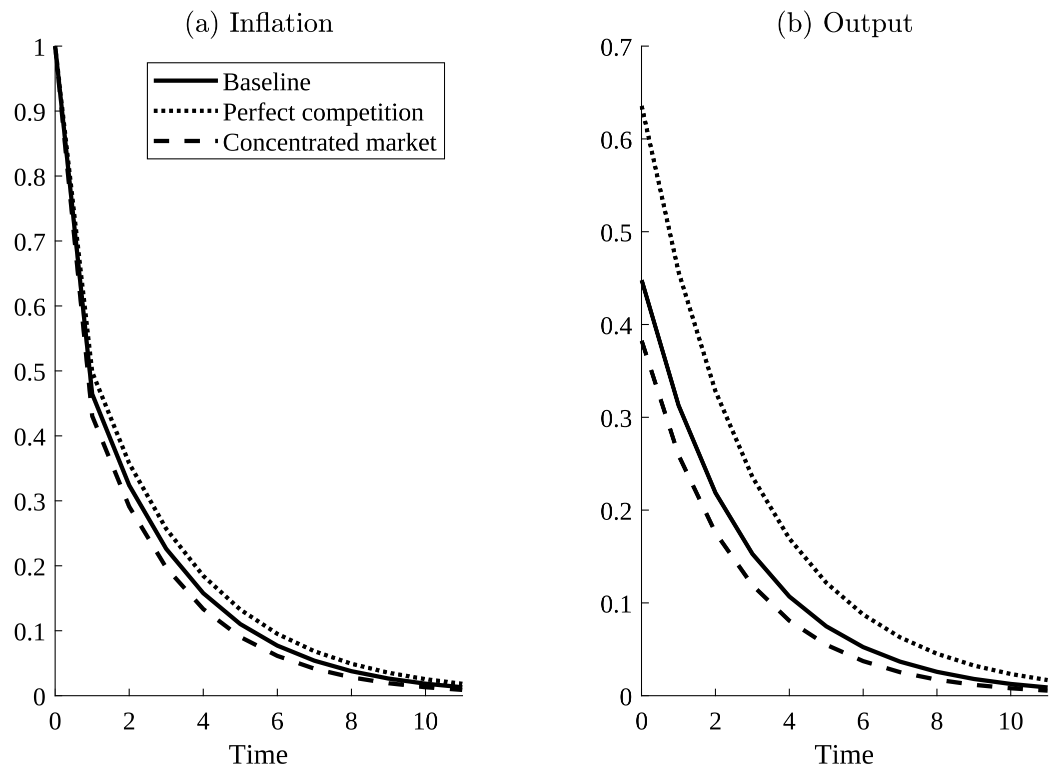
Notes: The marginal cost follows the generalized stochastic process specified by (18) – (20). The vertical axis is inflation persistence measured by the first-order autocorrelation. The horizontal axis is the Herfindahl–Hirschman Index.

Figure 4: Predicted size of declines in inflation persistence



Notes: The vertical axis is inflation persistence measured by the first-order autocorrelation. The horizontal axis is the Herfindahl–Hirschman Index. "Data" indicates the regression line of specification (3-1) in Table 2. "Model" presents the prediction of the model with $\hat{\rho} = 0.00$ and $\hat{\tau} = 2.01$. The shaded area indicates the range of ± 1 standard deviations from the regression line calculated using the residuals of regression in specification (3-1) of Table 2.

Figure 5: Impulse response function of aggregate inflation and aggregate output



Notes: Panels (a) and (b) show the impulse response function of aggregate inflation and the log-deviation of aggregate output from its steady state, respectively. In both panels, we calibrate ρ and τ at the NLS estimates of $\hat{\rho} = 0.00$ and $\hat{\tau} = 2.01$. The solid lines indicate the case of the baseline distribution in which we calibrate the distribution of h_i to the actual distribution of HHI_i. The dotted lines correspond to the case where all sectors are homogeneous and perfectly competitive (i.e., $h_i = 0$ for all i). The dashed lines show the case where all observed HHI_i are hypothetically doubled.

Table 1: Descriptive statistics of sectoral inflation persistence

	BGM dataset:	Extended dataset:	
Sample period	1976:2 – 2005:6	2004:1 – 2020:12	
Industries	Manufactureres	Manufactureres	Nonmanufactureres
Average	0.13	0.10	-0.07
Median	0.11	0.06	-0.09
Minimum	-0.42	-0.44	-0.38
Maximum	0.65	0.71	0.50
Standard deviation	0.20	0.23	0.18
Observations	152	270	79

Notes: The inflation persistence is measured by the first-order autocorrelation estimated from an AR(1) model. Inflation is the monthly difference of seasonally adjusted sectoral log prices (NAICS six-digit classification).

Table 2: Benchmark regression results

Dependent variable: $\rho_{\pi,i}$						
	BGM dataset: 1976:2 – 2005:6		Extended dataset: 2004:1 – 2020:12		Pooled dataset: -	
	(1-1)	(1-2)	(2-1)	(2-2)	(3-1)	(3-2)
$HHI_i/1000$	-0.071***	-0.073***	-0.052**	-0.057***	-0.059***	-0.063***
	(0.024)	(0.025)	(0.021)	(0.021)	(0.016)	(0.016)
$D_{31,i}$		-0.068*		0.059		0.007
		(0.040)		(0.041)		(0.030)
$D_{32,i}$		0.036		0.076**		0.061**
		(0.047)		(0.032)		(0.026)
$D_{BGM,i}$					0.041*	0.045**
					(0.022)	(0.022)
Observations	145	145	262	262	407	407
Adjusted-R^2	0.042	0.061	0.017	0.034	0.029	0.040
F-statistics	9.208	4.786	6.406	4.632	8.072	5.592
p-value	0.003	0.003	0.012	0.004	0.000	0.000

Notes: Regression results for manufacturers. The dependent variable $\rho_{\pi,i}$ is the first-order autocorrelation of inflation estimated from an AR(1) model. Inflation is the seasonally adjusted monthly difference of the sectoral log prices and i denotes sectors. HHI_i is the Herfindahl–Hirschman Index from the Economic Census. $D_{31,i}$ is a dummy variable controlling for food and textile industries (NAICS codes starting with 31) while $D_{32,i}$ is a dummy variable controlling for paper, wood, and chemical industries (NAICS codes starting with 32). $D_{BGM,i}$ is a dummy variable that equals one if the data are from the BGM dataset. Constant terms are suppressed in all specifications. The numbers in parentheses are the heteroskedasticity-consistent standard errors.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table 3: Regression results: C4 ratio

Dependent variable: $\rho_{\pi,i}$						
	BGM dataset:		Extended dataset:		Pooled dataset:	
	1976:2 – 2005:6		2004:1 – 2020:12		-	
	(1-1)	(1-2)	(2-1)	(2-2)	(3-1)	(3-2)
$C4_i$	-0.216***	-0.199**	-0.160**	-0.180***	-0.179***	-0.190***
	(0.079)	(0.084)	(0.067)	(0.068)	(0.052)	(0.053)
$D_{31,i}$		-0.070*		0.055		0.003
		(0.039)		(0.040)		(0.029)
$D_{32,i}$		0.014		0.079**		0.057**
		(0.046)		(0.032)		(0.026)
$D_{BGM,i}$					0.042*	0.046**
					(0.021)	(0.022)
Observations	152	152	270	270	422	422
Adjusted-R^2	0.035	0.049	0.015	0.034	0.025	0.034
F-statistics	7.445	4.015	5.711	4.610	6.791	4.882
p-value	0.007	0.009	0.018	0.004	0.001	0.001

Notes: Regression results for manufacturers. $C4_i$ is the market share of the top-four largest firms included in the Economic Census. See the notes for Table 2 for the other details.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table 4: Regression results for manufacturers and nonmanufacturers

Dependent variable: $\rho_{\pi,i}$			
	Extended dataset: 2004:1 – 2020:12		
	Manufacturers	Nonmanufacturers	Pooled
	(1)	(2)	(3)
$C4_i$	-0.160**	-0.199*	-0.169***
	(0.067)	(0.102)	(0.056)
$D_{3,i}$			0.181***
			(0.024)
Observations	270	79	349
Adjusted-R^2	0.015	0.039	0.111
F-statistics	5.711	3.810	31.867
p-value	0.018	0.055	0.000

Notes: Regression results using the extended dataset. $C4_i$ is used as the explanatory variable because HHI_i is not available for nonmanufacturers. $D_{3,i}$ is a dummy variable controlling for manufacturing sector (NAICS codes starting with 3). See the notes for Table 2 for the other details.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.

Table 5: Robustness

Dependent variable:	SAR	$\rho_{\pi,i}$ (year-on-year inflation)	$\rho_{\pi,i}$	$\rho_{\pi,i}$
	(1)	(2)	(3)	(4)
$HHI_i/1000$	-0.082***	-0.007**	-0.046***	-0.106***
	(0.022)	(0.004)	(0.015)	(0.027)
$D_{31,i}$	-0.054	-0.014		0.012
	(0.044)	(0.009)		(0.033)
$D_{32,i}$	0.078**	0.008**		0.062**
	(0.033)	(0.004)		(0.028)
$D_{BGM,i}$	0.176***	0.025***	0.046**	0.051**
	(0.032)	(0.004)	(0.020)	(0.024)
Controling for the 3 digit NAICS industries	N	N	Y	N
Observations	407	407	407	366
Adjusted-R^2	0.099	0.088	0.225	0.042
F-statistics	11.114	9.451	25.866	5.064
p-value	0.000	0.000	0.000	0.001

Notes: Regression results for manufacturers. The sample includes both the BGM and the extended datasets. The dependent variable in specification (1) is the sum of the autoregressive coefficients (SAR) estimated from a higher-order autoregressive model. The lag length is chosen by the Bayesian Information Criterion. In specification (2), the dependent variable is the first-order autocorrelation estimated from an AR(1) model, but inflation is the year-on-year difference of the seasonally unadjusted sectoral log prices. Specifications (3) and (4) have the same dependent variable as specifications in Tables 2 and 3, but the explanatory variables are different. In specification (3), the sector dummy is based on the three-digit NAICS code. In specification (4), the top-10% of sectors for HHI are removed from the sample as possible outliers. See the notes for Table 2 for the other details.
*** $p < 0.01$,
** $p < 0.05$,
* $p < 0.1$.