Imperfect Information, Heterogeneous Demand Shocks, and Inflation Dynamics*

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Abstract

Using sector-level survey data for the universe of Japanese firms, we establish the positive co-movement in the firm's expectations about aggregate and sector-specific demand shocks. We show that a simple model with imperfect information on the current aggregate and sector-specific components of demand explains the positive co-movement of expectations in the data. The model predicts that an increase in the relative volatility of sector-specific demand shocks compared to aggregate demand shocks reduces the sensitivity of inflation to changes in aggregate demand. We test and corroborate the theoretical prediction on Japanese data and find that the observed decrease in the relative volatility of sector-specific demand has played a significant role for the decline in the sensitivity of inflation to movements in aggregate demand from mid-1980s to mid-2000s.

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1 Introduction

A large class of macroeconomic models builds on the premise that firms set prices to fulfil demand. Several studies show that shocks to demand are heterogeneous and reflect aggregate and sector-specific disturbances.[1] Knowing the source that originates the change in demand is important for setting the price consistent with profit maximization. Ball and Mankiw (1995) shows that the price should adjust if the change in demand originates from the aggregate shock, but it should remain unchanged if the change originates from the sector-specific shock. In reality, firms cannot observe the source of any change in demand. They therefore form expectations of aggregate and sector-specific components of demand based on the observed total demand and accrued knowledge from past aggregate and sector-specific shocks. Our analysis establishes important empirical regularities about firms' expectations on the different aggregate and sector-specific components of total demand, it develops a parsimonious model of imperfect information that explains the co-movements in the expectations, and it studies the implications of empirically-congruous expectations for the sensitivity of inflation to changes in aggregate demand.

The first contribution of our analysis is to establish novel evidence on the firms' expectations about aggregate and sector-specific components of total sectoral demand, using a sector-level survey to the universe of Japanese firms across 21 sectors. The survey requires each firm to provide its own expectations about expected changes in aggregate and sector-specific demand, therefore offering for the first time a consistent overview on the firms' expectations on the separate components of demand. Our analysis establishes a positive co-movement between expectations on the aggregate and sector-specific components of demand.

The second contribution of the analysis is to develop a simple model of imperfect information that sheds light on the mechanism that explains the positive co-movement in the expectations about the different components of demand. The theoretical framework builds on the Lucas (1972) seminal island framework where firms cannot separately observe the different aggregate and sector-specific components that jointly move the observed total sectoral demand. Imperfect information on the source of shocks that move total sectoral demand induces the firm to attribute part of the observed change in total sectoral demand to each separate aggregate and sector-specific component, and expectations on the separate compo-

[1] See di Giovanni et al. (2014) and references therein.

nents of demand positively co-move. We prove analytically that the positive co-movement of expectations on the *current* components of demand implies a positive co-movement in the expectations on the *future* components of demand, which explains the positive co-movement observed in the survey data.

The third contribution of the analysis is to use the model to study the implication of the data-congruous formation of expectations for the sensitivity of inflation to changes in aggregate demand. To link the expectations of total sectoral demand to inflation, we enrich the model with nominal price rigidities, such that movements in inflation depend on the expectations of total sectoral demand, which reflects the expectations on the different aggregate and sector-specific components. We show that the degree of heterogeneity in demand shocks, encapsulated by the ratio of volatility of sector-specific demand shocks compared to the volatility of aggregate demand shocks, is important for the response of inflation to aggregate demand. Under perfect information, if the change in total sectoral demand originates from the aggregate component of demand, the price adjustment is large as a result of strategic complementarity in price setting because the aggregate shock should be common to all firms. If instead the change in total sectoral demand originates from the sector-specific component of demand specific to each sector, the price adjustment in the sector is contained since firms would either lose customers (if the price rises) or forego earnings for a lower markup (if the price falls), given competitors in other sectors retain prices unchanged. The presence of imperfect information in our model prevents firms from perfectly disentangling the single contribution of aggregate and sector-specific components to total demand. Therefore, firms optimally attribute part of a change in total sectoral demand to movements in the sector-specific component of demand, and consequently, the response of prices to the aggregate component of demand is smaller than the case under perfect information. A central prediction of our theoretical framework is that the negative relationship between the ratio of volatility of sector-specific shocks compared to the aggregate shocks decreases the sensitivity of inflation to movements in aggregate demand.

The fourth and final contribution of the analysis is to test empirically the negative relation between the volatility of sector-specific shocks relative to aggregate demand shocks and the sensitivity of inflation to movements in aggregate demand on Japanese data.[2] We estimate

[2] Several studies show a decline in the sensitivity of inflation to real activity. See survey by Mavroeidis et al. (2014) for a recent review of the literature on U.S. data. Kaihatsu et al. (2017) and Bundick and Smith (2020) provide evidence on the reduced sensitivity of inflation to real activity on Japanese data.

the volatility of the sector-specific component of demand relative to the volatility of the aggregate component of demand through principal component analysis on sector-level data for Japanese firms across 29 sectors for the period 1975-2018. In line with the theory, we establish a robust inverse relationship between shock heterogeneity and the sensitivity of inflation to movements in aggregate demand. We find that the increase in the volatility of sector-specific demand relative to aggregate demand is a significant factor to explain the observed reduction in the sensitivity of inflation to movements in aggregate demand since the early 2000s.

The analysis is linked to three strands of literature. First, it is related to studies that focus on imperfect information. This realm of research develops imperfect information in models with flexible prices (Woodford, 2003; Hellwig and Venkateswaran, 2009; Mackowiak et al., 2009; Crucini et al., 2015; Kato and Okuda, 2017; Afrouzi, 2018; and Kato et al., 2020) and nominal price rigidities (Fukunaga, 2007; Nimark, 2008; Angeletos and La'O, 2009; Melosi, 2017; and L'Huillier, 2020). It is also related to studies that allow for coexistence of aggregate and disaggregate shocks in the presence of costly information acquisition (Veldkamp and Wolfers, 2007; and Acharya, 2017). Coibion et al. (2018b) and Coibion et al. (2019) provide broad evidence on the relevance of firms' expectations to firms' decisions. Andrade et al. (2020) examine the empirical plausibility of information frictions in the Lucas-island model (Lucas, 1972) by studying the relationship between firms' expectations about aggregate variables and estimated industry-specific shocks. Different from those studies, we provide new evidence on firms' expectations about aggregate and disaggregate components of demand and assess the role of expectations for the sensitivity of inflation to aggregate demand.

Second, the analysis relates to the literature that investigates the effect of imperfect information on the Phillips curve. Mankiw and Reis (2002) and Dupor et al. (2010) develop sticky-information models to investigate the effect of informational frictions on the empirical performance of the Phillips curve. Coibion and Gorodnichenko (2015) establish that information frictions are critical in generating an empirically-consistent formation of expectations that explain the missing disinflation between 2009 and 2011. Coibion et al. (2018a) show that information frictions are important to address puzzling shortcomings to the Phillips curve that arise under the assumption of full-information rational expectations. Mackowiak and Wiederholt (2009) investigate the effect of rational inattention on the Phillips curve, establishing a positive relationship between the relative variance of aggregate shocks to disaggregate shocks and the sensitivity of inflation to aggregate shocks.

Finally, the analysis is closely related to studies that investigate changes in the relationship between inflation and economic slack, as generated by the anchoring effect of inflation targets (Roberts, 2004 and L'Huillier and Zame, 2020), the increase in competition in the goods market (Sbordone, 2008 and Zanetti, 2009), downward wage rigidities (Akerlof et al., 1996), structural reforms (Thomas and Zanetti, 2009, Zanetti, 2011, and Cacciatore and Fiori, 2016), and lower trend inflation (Ball and Mazumder, 2011). Unlike these studies, our focus is on the relationship between imperfect information and the sensitivity of inflation to changes in aggregate demand.

The remainder of the paper is organized as follows. Section 2 provides evidence on the co-movement in expectations about aggregate and sector-specific demand from survey data. It develops a simple model with imperfect information that explains the positive co-movement in the expectations of the separate components of demand. Section 3 augments the model to incorporate general equilibrium and derive equilibrium pricing with and without nominal rigidities. Section 4 studies the effect of data-congruous expectations for the sensitivity of inflation dynamics to demand, and it shows that the data corroborates the theoretical predictions. Section 5 concludes.

2 Evidence from Survey Data

We study expectations of firms on aggregate and sector-specific components of demand based on data assembled from the Annual Survey of Corporate Behavior (ASCB), administered by the Cabinet Office of Japan across 21 sectors in the economy over the period 2003-2017. The survey collects expectations from the same firm about total sectoral demand and aggregate demand, asking each firm to distinguish those two. This makes it possible to separately observe the aggregate and the sector-specific components that constitute firms' expectations. Appendix G provides a description and summary statistics for the ASCB.[3]

Our central focus is the co-movement between expectations of aggregate and sector-specific components of demand. If the expectations on the separate components of demand are independent from each other, as it would happen if firms perfectly observe the two separate components under perfect information, the co-movement in the expectations is

[3] Appendix A and B show consistency of the survey data with the Dixit-Stiglitz demand function that we use in the model.

insignificantly different from zero. Table 1 shows in panel (a) and column (1) the estimated co-movement in the expectations obtained from regressing the firm's expectations of the growth rate of aggregate demand on the firm's expectations about the growth rate of sector-specific demand. The regression coefficient (bold entry) that captures the co-movements between the expectations in aggregate and sector-specific demand is positive and significant, establishing a positive co-movement in the separate expectations. To ensure that these results are not driven by the heterogeneity across specific sectors, column (2) shows estimates from a regression that includes sector-specific fixed effects, and it establishes that the positive correlation between aggregate and sector-specific components of demand remains significant and positive.

To establish whether the co-movements in expectations are a distinctive attribute of the firms' expectations, or instead are a mere reflection of the underlying positive co-movements in *realized* aggregate and sector-specific components of total demand, we estimate the co-movement in the aggregate and sector-specific components of *realized* demand from the National Account Data for Japan.[4] Table 1 in panel (b) shows results from regressing the growth rate of realized aggregate demand on the growth rate of realized sector-specific demand. The regression coefficient (bold entry) on the growth rate of sector-specific demand is statistically insignificant in the benchmark regression (column 1) and in the regression that includes a sector-specific fixed effect (column 2). Hence, the positive relationship between firms' expectations about aggregate and sector-specific components of demand is a distinctive feature of firms' expectations, and it is not a by-product of the co-movements in the *realized* components of total sectoral demand.

As a final robustness check, we regress firms' expectations on the growth rate of aggregate demand on the growth rate of aggregate and sector-specific demands to test whether both shocks affect the firms' expectations. Table 1 in panel (c) shows that the regression coefficients on the growth rate of aggregate and sector-specific demands are positive and statistically significant for both the benchmark regression (column 1) and the specification with sector-specific fixed effect (column 2). Taken together, these findings consistently show that the positive co-movement in the firms' expectations on the growth rates of aggregate and sector-specific demand is a distinctive feature of firm's expectations.[5]

[4] Appendix G provides a description of National Account Data.

[5] Appendix H provides additional evidence on this point by using the extended cross-sectional dataset of ASCB that also includes small firms.

Table 1: Firms' expectations on aggregate and sector-specific demands

(a) Expectations data

Dataset: Annual survey of corporate behavior; 21 sectors; 2003y-2017y

Dependent Variable: firms' expectations on the growth rate of the aggregate demand

	One year ahead expectations	
	(1) Pooled OLS model	*(2) fixed effect model*
Constant	1.05***	1.07***
	(0.05)	(0.05)
Firms' expectations on the growth rate of the sector-specific demand	**0.19*****	**0.25*****
	(0.07)	(0.08)
Observations	315	315
Adjusted-R^2	0.05	0.01

(b) Realized data

Dataset: SNA statistics; 21 sectors; 2004y-2018y

Dependent Variable: the growth rate of the aggregate demand

	One year ahead expectations	
	(1) Pooled OLS model	*(2) fixed effect model*
Constant	0.27	0.27
	(0.83)	(0.86)
the growth rate of the sector-specific demand	**0.81**	**0.81**
	(0.52)	(0.54)
Observations	315	315
Adjusted-R^2	0.08	0.10

(c) Expectations and realized data

Dataset: Annual survey of corporate behavior, SNA statistics; 21 sectors; 2003y-2017y, 2004y-2018y

Dependent Variable: firms' expectations on the growth rate of the aggregate demand

	One year ahead expectations	
	(1) Pooled OLS model	*(2) fixed effect model*
Constant	0.89***	0.89***
	(0.04)	(0.04)
The growth rate of the aggregate demand	**0.24*****	**0.24*****
	(0.02)	(0.02)
The growth rate of the sector-specific demand	**0.02****	**0.02*****
	(0.01)	(0.01)
Observations	315	315
Adjusted-R^2	0.41	0.38

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators.
**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

2.1 Expectations under Imperfect Information

In what follows, we develop a parsimonious model of imperfect information that explains the positive co-movement in the firms' expectations about the different components of demand. We will embed these expectations in a general equilibrium framework to study inflation dynamics in Section 3.

We assume the economy is populated by a representative household and a continuum of monopolistic competitive firms that produce differentiated goods indexed by $j \in [0, 1]$ in a continuum of sectors indexed by $i \in [0, 1]$. Each firm j in sector i observes total sectoral demand ($x_t(i)$) that changes in response to aggregate demand and sector-specific demand, according to $x_t(i) = q_t + v_t(i)$, without observing the separate realizations for the aggregate (q_t) and sector-specific components ($v_t(i)$).[6] Aggregate demand follows the stochastic process:

$$q_t = q_{t-1} + u_t, \tag{1}$$

where u_t is an AR(1) process:

$$u_t = \rho_u u_{t-1} + e_t, \tag{2}$$

with $0 \leq \rho_u < 1$, and $e_t \sim \mathcal{N}(0, \sigma^2)$. The sector-specific demand follows the AR(1) process:

$$v_t(i) = \rho_v v_{t-1}(i) + \epsilon_t(i), \tag{3}$$

where $0 \leq \rho_v < 1$, and $\epsilon_t(i) \sim \mathcal{N}(0, \tau^2)$.

In each period t, firms set prices simultaneously without observing the current aggregate and sector-specific components of total sectoral demand and therefore are unable to infer the current aggregate price.[7] Thus, each firm uses information from the common signal of total sectoral demand (i.e., $x_t(i) = q_t + v_t(i)$) and the past realizations of aggregate and sector-specific components of demand to make inference on the current components of aggregate (q_t) and sector-specific demand ($v_t(i)$), such that $q_t \sim \mathcal{N}\left(q_{t-1} + \rho_u u_{t-1}, \sigma^2\right)$ and $v_t(i) \sim \mathcal{N}\left(\rho_v v_{t-1}(i), \tau^2\right)$. Hence, in each period t, the information set for the firms in sector i is:

$$\mathcal{H}_t(i) \equiv \left\{ \{x_s(i)\}_{s=0}^{t}, \{q_s, u_s, v_s(i), e_s, \epsilon_s(i)\}_{s=0}^{t-1} \right\}, \tag{4}$$

[6] We will derive and revisit this relation in a general equilibrium framework in Section 3. A recent study by Chahrour and Ulbricht (2019) shows that imperfect information on disaggregate shocks of the type we have in our simple model generate realistic business cycle statistics.

[7] Assuming that q_t is unobservable in period t implies that the labor market clears after firms set prices. Therefore, firms base their profit-maximizing decisions on the expected nominal wage in period t, as in Angeletos and La'O (2009).

and hereafter we denote the expectations under imperfect information as: $\mathbb{E}_t \equiv \mathbb{E}\left[\bullet|\mathcal{H}_t(i)\right]$.

In what follows, we show that imperfect information explains the observed positive correlation between firms' expectations on aggregate and sector-specific components of total demand.

Mapping the model to the data. The model characterizes the expectations on the *level* of total demand and its different components whereas the data refer to the expectations on the *changes* of total demand and its aggregate and sector-specific components. To link the model with the empirical measurements, we derive the changes in total sectoral demand and its separate components by taking the first difference of $x_t(i)$: $\Delta x_t(i) = \Delta q_t + \Delta v_t(i)$. Thus, the model now provides a measure of changes in expectations in aggregate and sector-specific demands, Δq_t and $\Delta v_t(i)$, respectively, that is the equivalent measurement in the data.

To simplify notation, we label $\widetilde{x}_t(i) = \Delta x_t(i)$, $\widetilde{v}_t(i) = \Delta v_t(i)$, and by using equation (1), $u_t = \Delta q_t$. Combining equations (2)-(3), we write the change in total sectoral demand, $\widetilde{x}_t(i)$, as the sum of the change in aggregate demand, u_t, and the change in sector-specific demand, $\widetilde{v}_t(i)$:

$$\widetilde{x}_t(i) = u_t + \widetilde{v}_t(i). \tag{5}$$

Equation (5) shows that the change in total sectoral demand in the model compounds the changes in aggregate and sector-specific demand, as in the data. In the remaining part of this section, we use equation (5) to study the effect of imperfect information for the co-movement between the changes in expectations about aggregate and sector-specific demand.

The formation of expectations and co-movements in the components of total sectoral demand. Using equation (5), expectations in the current period t about total demand in k-period ahead are equal to:

$$\mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{x}_{t+h}(i)\right] = \mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right] + \mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]. \tag{6}$$

Equation (6) shows that the expectations at period t of total demand k-period ahead depend on the expectations of the separate aggregate and sector-specific components of demand in k-period ahead. If firms were able to observe separately the components of aggregate and sector-specific demand, such that $\mathbb{E}_t\left[u_t\right] = u_t$ and $\mathbb{E}_t\left[\widetilde{v}_t\right] = \widetilde{v}_t$, the expectations of the different components of total sectoral demand are independent from each other and the co-movement between them equal to zero. The next proposition shows that imperfect information renders the expectations on the separate components of demand dependent on the common change in total sectoral demand, therefore generating a co-movement in expectations.

Proposition 1 *Under imperfect information, the expectations at time t about the changes in aggregate and sector-specific demands are equal to:*

$$\mathbb{E}_t\left[u_t\right] = \rho_u u_{t-1} + \frac{\sigma^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right] \tag{7}$$

and

$$\mathbb{E}_t\left[\tilde{v}_t(i)\right] = (\rho_v - 1)v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right], \tag{8}$$

respectively.

Proof: See Appendix F.1. □

Equations (7) and (8) show that the firm's expectations on the changes in aggregate and sector-specific demand depend on the changes in total sectoral demand, which compounds shocks to aggregate and sector-specific shocks ($e_t + \epsilon_t(i)$) that the firm cannot separately observe. The response of each expectation to movement in total sectoral demand depends on the ratio τ/σ that encapsulates the relative volatility of sector-specific shocks compared to aggregate shocks. If the volatility of the shock to sector-specific demand is larger than the volatility of the shock to aggregate demand (i.e., $\tau/\sigma > 1$), reflecting the fact that changes in total sectoral demand are predominantly driven by the sector-specific component of demand, the response of firms' expectations on the sector-specific component of demand to the change in total sector demand increases while the response of firms' expectations on the aggregate component of demand to total sectoral demand decreases.

The next propositions characterize the sign of the co-movement between the current expectations of aggregate and sector-specific demand and the resulting co-movement in the *expectations* between the separate components of demand.

Proposition 2 *Under imperfect information, the co-movement in the current expectations about aggregate and sector-specific demand is equal to:*

$$\mathbb{C}(\mathbb{E}_t\left[u_t\right], \mathbb{E}_t\left[\tilde{v}_t\right]) = \frac{\sigma^2\tau^2}{\sigma^2+\tau^2} > 0, \tag{9}$$

where $\mathbb{C}(\cdot)$ is the unconditional covariance operator.

Proof: See Appendix F.2. □

Proposition 2 shows that the presence of imperfect information generates a positive co-movement between the current expectations of aggregate and sector-specific components of total sectoral demand. This implies a positive co-movement between the expectations about the components of k-period ahead demand, as shown in the next proposition.

Proposition 3 *If total demand compounds unobservable aggregate and sector-specific components (i.e., $\widetilde{x}_t(i) = u_t + \widetilde{v}_t(i)$), the positive co-moment in the expectations at time t generates the positive co-movement in the k-period ahead expectations:*

$$\mathbb{C}(\mathbb{E}_t [u_t], \mathbb{E}_t [\tilde{v}_t]) > 0 \Rightarrow \mathbb{C}\left(\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right], \mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]\right) > 0.$$

Proof: See Appendix F.3. □

Proposition 3 provides the theoretical underpinning that explains the positive co-movement in expectations on aggregate and sector-specific demand observed in the data. If we use the model to estimate the regression coefficients in Table 1, it yields:

$$\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right] = \beta_0 + \beta_1 \mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right], \tag{10}$$

where β_0 is the constant term in the regression and β_1 is the coefficient that captures the correlation between changes in aggregate and sector-specific demand. The value for β_1 is equal to:

$$\beta_1 = \frac{\mathbb{C}\left(\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right], \mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]\right)}{\mathbb{V}\left(\mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]\right)}. \tag{11}$$

Equation (11) shows that the value for the correlation coefficient β_1 depends on the covariance of expectations about future realizations of aggregate and sector-specific demand, which Proposition 3 shows is determined by the correlation between the *current* expectations on these components. To sum up, the analysis shows that imperfect information on the current components of total sectoral demand is critical to generate a positive co-movement in the expectations of aggregate and sector-specific components of demand, as observed in the data.

3 General Equilibrium

This section embeds the expectations under imperfect information in a general equilibrium framework to study the firms' equilibrium prices with and without nominal price rigidities.

3.1 Model

The model is based on Woodford (2003) and Angeletos and La'O (2009). We retain the same settings and information structure developed in the previous section. Time is discrete and indexed by t. The economy is populated by a representative household and a continuum of monopolistic competitive firms that produce differentiated goods indexed by $j \in [0,1]$ in a continuum of sectors indexed by $i \in [0,1]$. The representative household consumes the whole income with no saving in equilibrium. Monopolistic competitive firms face a total sectoral demand that compounds aggregate and sector-specific shocks as described in the equations (1), (2), and (3). Firms observe current total sectoral demand and the past realizations of aggregate and sector-specific shocks to demand, but they are unable to separately observe the realizations of aggregate and sector-specific components of total sectoral demand in real time. Namely, firms form expectations at time t using the information set $\mathcal{H}_t(i)$ in equation (4).

The rest of the section develops the model and derives the equilibrium price.

Households. A utility function describes the preferences of the representative household over consumption, C_t, and labor, N_t:

$$\sum_{t=0}^{\infty} \beta^t \left(\log C_t - N_t\right),$$

where $\beta \in (0,1)$ is the discount rate. The household's aggregate consumption, C_t, and consumption of goods in sector i, $C_t(i)$, are defined by the CES consumption aggregators:

$$C_t \equiv \left[\int_0^1 \left(C_t(i)\Theta_t(i)\right)^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}}, \text{and } C_t(i) \equiv \left[\int_0^1 \left(C_t(i,j)\right)^{\frac{\widetilde{\eta}-1}{\widetilde{\eta}}} dj\right]^{\frac{\widetilde{\eta}}{\widetilde{\eta}-1}},$$

where $\eta > 1$ is the elasticity of substitution across sectors, $\widetilde{\eta} > 1$ is the elasticity of substitution across goods within the same sector, $C_t(i,j)$ is consumption of good j in sector i, and $\Theta_t(i)$ is the sector-specific preference shocks (defined below).

Firms. Each firm j in sector i (we refer to as "firm (i,j)") faces the following demand:

$$C_t(i,j) = \Theta_t^{\eta-1}(i) \left(\frac{P_t(i,j)}{P_t(i)} \right)^{-\widetilde{\eta}} \left(\frac{P_t(i)}{P_t} \right)^{-\eta} C_t, \tag{12}$$

where $P_t(i) \equiv \left[\int_0^1 P_t^{1-\widetilde{\eta}}(i,j)dj \right]^{\frac{1}{1-\widetilde{\eta}}}$ is the price index for sector i, $P_t \equiv \left[\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di \right]^{\frac{1}{1-\eta}}$ is the aggregate price index, and the sector-specific preference shock, $\Theta_t(i)$, acts as an exogenous demand shifter for firm i.[8]

Each firm (i,j) manufactures a single good $Y(i,j)$, according to the production technology:

$$Y_t(i,j) = AL_t^{\epsilon}(i,j), \tag{13}$$

where A is aggregate productivity and $\epsilon \in (0,1)$ determines the degree of diminishing marginal returns in production.

Market Clearing. In a symmetric equilibrium, market clearing implies $Y_t(i,j) = C_t(i,j)$ for each firm (i,j), and thus $Y_t = C_t$ in the economy. Aggregate nominal demand, Q_t, is given by the following cash-in-advance constraint:

$$Q_t = P_t C_t.$$

In the rest of the analysis, we use lower-case variables to indicate logarithms of the corresponding upper-case variables (i.e., $x_t \equiv \log X_t$).

Optimal Price Setting Rule and Total Sectoral Demand. In what follows, we derive the optimal price-setting rule as a function of total sectoral demand under flexible prices, assuming perfect information about current shocks to aggregate and sector-specific demand, and we introduce imperfect information to study the co-movements in the expectations on aggregate and sector-specific components of total sectoral demand.

During each period t, the firm (i,j) sets the optimal price as a mark-up over the marginal cost:

$$p_t(i,j) = \mu + mc_t(i,j), \tag{14}$$

[8] See Appendix A for the derivation of the demand function for each firm (i,j) and price indexes. Appendix B shows that total sectoral demand in equation (12) entails independent aggregate and sector-specific components consistent with the empirical analysis.

where $\mu \equiv \widetilde{\eta}/(\widetilde{\eta}-1) > 0$ is the mark-up and $mc_t(i,j)$ is the nominal marginal cost faced by firm (i,j). The nominal marginal cost is the difference between the nominal wage, w_t, and the marginal product of labor:

$$mc_t(i,j) = w_t + (1-\epsilon)\, l_t(i,j) - a - log(\epsilon). \tag{15}$$

Using the production technology in equation (13), we express labor input as: $l_t(i,j) = [y_t(i,j) - a]/\epsilon$, and we use it in equation (15) to rewrite the nominal marginal cost as:

$$mc_t(i,j) = w_t + \frac{1-\epsilon}{\epsilon} y_t(i,j) - \frac{1}{\epsilon} a - log(\epsilon).$$

The optimal labor supply condition for the representative household is:

$$w_t - p_t = c_t, \tag{16}$$

and the linearized consumer demand in equation (12) is:

$$c_t(i,j) = -\widetilde{\eta}\,(p_t(i,j) - p_t(i)) - \eta\,(p_t(i) - p_t) + c_t + (\eta - 1)\,\theta_t(i), \tag{17}$$

where the sector-specific preference shock, $\theta_t(i)$, follows the AR(1) process:

$$\theta_t(i) = \rho_v \theta_{t-1}(i) + \widetilde{\epsilon}_t(i), \tag{18}$$

and $\widetilde{\epsilon}_t(i) \sim \mathcal{N}(0, (1-\epsilon)^{-2}\,(\eta-1)^{-2}\,\tau^2)$.[9]

We derive the optimal price-setting rule for firm (i,j) by using equations (16), (17), the equilibrium conditions, $y_t(i,j) = c_t(i,j)$, $y_t = c_t$, and the cash-in-advance constraint, $y_t = q_t - p_t$, which yields:[10]

$$p_t(i,j) = r_1 p_t(i) + r_2 p_t + (1 - r_1 - r_2)\, x_t(i) + \xi, \tag{19}$$

where

$$\begin{aligned}
x_t(i) &= q_t + v_t(i), & (20)\\
v_t(i) &= (1-\epsilon)\,(\eta-1)\,\theta_t(i), & (21)\\
\xi &= \frac{\epsilon}{\epsilon + \widetilde{\eta}\,(1-\epsilon)}(\mu - \frac{1}{\epsilon}a - log(\epsilon)), & (22)\\
r_1 &= \frac{(\widetilde{\eta}-\eta)\,(1-\epsilon)}{\epsilon + \widetilde{\eta}\,(1-\epsilon)}, & (23)\\
r_2 &= \frac{(\eta-1)\,(1-\epsilon)}{\epsilon + \widetilde{\eta}\,(1-\epsilon)}, & (24)
\end{aligned}$$

[9] Note that the information set is augmented with $p_s, \theta_s(i)$, and $\widetilde{\epsilon}_t(i)$. Namely, the following is the observed variables at time t: $\mathcal{H}_t(i) \equiv \left\{\{x_s(i)\}_{s=0}^{t}, \{p_s, q_s, u_s, v_s(i), \theta_s(i), e_s, \epsilon_s(i), \widetilde{\epsilon}_s(i)\}_{s=0}^{t-1}\right\}$. All propositions in the previous section continue to hold.

[10] Appendix D shows the derivation of the price setting rule.

and $p_t = \int_0^1 p_t(i)di$.[11] Equation (19) shows that the optimal pricing rule for firm (i, j) is a weighted average of the sectoral prices $(p_t(i))$, aggregate prices (p_t), and total sectoral demand $(x_t(i))$, which compounds together aggregate and sector-specific demand (i.e., $x_t(i) = q_t + v_t(i)$). The weights on each term of equation (19) are determined by parameters r_1 and r_2 that reflect the degree of strategic complementarity among firms in the same sector and across sectors, respectively. Equation (20) shows that total demand $(x_t(i))$ additively combines the aggregate (q_t) and sector-specific components $(v_t(i))$. Equation (21) shows that the sector-specific demand depends on the sector-specific preference shock $\theta_t(i)$. The constant parameter ξ, defined by equation (22), is a linear transformation of the level of aggregate productivity, a. By normalizing aggregate productivity such that $\xi = 0$, the price level for firm (i, j) is uniquely determined by sector-specific and aggregate prices and total sectoral demand.[12]

Since firms in the same sector face the same marginal costs and have access to the same information, $p_t(i) = p_t(i, j) = p_t(i, j')$ for $j \neq j'$ in equilibrium, and equation (19) reduces to:

$$p_t(i) = rp_t + (1 - r)\, x_t(i), \tag{25}$$

where

$$r \equiv \frac{r_2}{1 - r_1} = \frac{(\eta - 1)(1 - \epsilon)}{\epsilon + \eta(1 - \epsilon)}.$$

Equation (25) shows that the optimal pricing rule for firm (i, j) is a weighted average of aggregate prices (p_t) and total sectoral demand $(x_t(i))$. The weights for average prices and total sectoral demand are determined by the parameter r, which reflects the degree of strategic complementarity between firms in different sectors, consistent with equation (19).[13]

3.2 Nominal Price Rigidities

To link expectations about total sectoral demand to the price-setting behavior of the firm, we enrich the model with nominal price rigidities that prevent firms from optimally adjusting prices in each period. In this environment, the optimal price depends on the expecta-

[11] Appendix C shows the derivation of the index of aggregate prices.

[12] Note that setting $\xi = 0$ is irrelevant for inflation since ξ affects the price level only.

[13] Equation (25) shows that if production technology converges to constant returns (i.e., $\epsilon \to 1$), average prices become less important in the determination of the price for firm i (i.e., $r \to 0$) since the marginal cost converges to the aggregate nominal wage across firms (i.e., $mc_t(i) \to w_t$) and heterogeneity in the firms' prices decreases. The magnitude of the sector-specific shock decreases (i.e., $v_t(i) \to 0$) as the production technology converges to constant returns (i.e., $\epsilon \to 1$). As a result, in the limiting case of a linear production technology (i.e., $\epsilon = 1$), the optimal pricing rule is $p_t(i) = q_t + \xi$.

tions of future demand, which in our framework, reflects both the different aggregate and sector-specific components. Therefore, the co-movement between those expectations plays an important role for the price-setting decision and ultimately inflation dynamics.

We embed nominal price rigidities, as in Calvo (1983), by assuming that a firm maintains the same price with exogenous probability $\theta \in (0,1)$ and otherwise changes the price optimally based on the expectations of demand. The optimal price for firms in sector i, denoted as $p_t^*(i)$, depends on expectations formed at time t on present and future prices, as described by the pricing rule:

$$\begin{aligned} p_t^*(i) &= (1-\beta\theta)\sum_{j=0}^{\infty}(\beta\theta)^j \mathbb{E}_t[p_{t+j}(i)] \\ &= (1-\beta\theta)\sum_{j=0}^{\infty}(\beta\theta)^j \left[r\mathbb{E}_t[p_{t+j}] \ + (1-r)\mathbb{E}_t[x_{t+j}(i)]\right], \end{aligned} \tag{26}$$

where the second equation is derived by substituting the optimal pricing rule in equation (25). Unlike standard full-information rational expectations models, the expectations in equation (26) are formed under imperfect information, which must be consistent with the optimizing problem of the firm and the formation of expectations in Proposition 1. Equation (26) shows that each firm in sector i sets prices as a weighted average of the firm's expectations about current and *expected* future prices, whose expectations depend on the information set at time t. Since expectations about total sectoral demand ($\mathbb{E}_t[x_{t+j}(i)]$) depend on the different aggregate and sector-specific components of demand, as shown in equation (5), the co-movement of these components is important to determine the optimal price.

The Equilibrium Average Price. Equation (26) provides the equilibrium average price once we derive expectations for prices and total sectoral demand. The model is sufficiently simple to provide an analytical solution for the equilibrium average price, characterized in the next proposition.

Proposition 4 *The equilibrium average price is given by:*

$$p_t = [\theta + (1-\theta)a_1]\, p_{t-1} + (1-\theta)\, a_2 q_t + (1-\theta)\, a_3 q_{t-1} + (1-\theta)\, a_4 u_{t-1}, \tag{27}$$

where (a_1, a_2, a_3, a_4) are non-linear functions of the ratio in the volatility of sector-specific to aggregate shocks (τ/σ), and $u_{t-1} = \Delta q_{t-1} = q_{t-1} - q_{t-2}$.

Proof: See Appendix F.4. □

Equation (27) shows that the equilibrium average price depends on the equilibrium price in the period $t-1$ (p_{t-1}) and the sequence of present and past aggregate demand (q_t, q_{t-1}, q_{t-2}). Important to our subsequent analysis, the proposition shows that the relative volatility of sector-specific shocks compared to aggregate shocks, described by the ratio τ/σ, plays an important role for the sensitivity of the aggregate price to present and past aggregate demands.

4 Demand Shocks and Inflation Dynamics

This section studies the sensitivity of inflation to changes in aggregate demand using the model outlined in the previous section that entails empirically-congruous co-moment in the separate expectations of demand.

Using the definition of the average price in equation (27), we derive the analytical solution for the gross inflation rate, defined as the change in the average price from period $t-1$ to period t ($\pi_t \equiv p_t - p_{t-1}$), as characterized by the next proposition.

Proposition 5 *Under imperfect information on aggregate and sector-specific demand shocks, average price inflation is equal to:*

$$\begin{aligned} \pi_t &= [\theta + (1-\theta)a_1]\,\pi_{t-1} + (1-\theta)\,a_2 u_t + (1-\theta)\,(a_3+a_4)\,u_{t-1} - (1-\theta)\,a_4 u_{t-2} \\ &= \alpha_1 \pi_{t-1} + \alpha_2 u_t + \alpha_3 u_{t-1} + \alpha_4 u_{t-2}, \end{aligned} \tag{28}$$

where $\alpha_1 \equiv \theta + (1-\theta)a_1$, $\alpha_2 \equiv (1-\theta)a_2$, $\alpha_3 \equiv (1-\theta)(a_3+a_4)$, *and* $\alpha_4 \equiv -(1-\theta)a_4$.

Proof: See Appendix F.4. □

Equation (28) provides the analytical solution for inflation under imperfect information, which shows that current inflation (π_t) depends on past inflation (π_{t-1}) and current and past changes in aggregate demand (u_t, and u_{t-1}, respectively) for the assumption that demand in the past period $t-1$ is fully revealed in the current period t.[14] The effect of τ/σ on the

[14]The dynamics for inflation is related to Angeletos and La'O (2009), but it differs across two important dimensions. First, the coefficients ($\alpha_2, \alpha_3, \alpha_4$) depend on the volatility of sector-specific shocks (τ^2), and second, inflation depends on the changes in demand two period before u_{t-2} since aggregate shocks are persistent.

coefficients $(\alpha_2, \alpha_3, \alpha_4)$ is highly non-linear, and it interacts with the degree of nominal price rigidities θ.[15] Proposition 5 shows that if prices are flexible ($\theta = 0$), the parameter α_1 is equal to zero, showing that nominal price rigidities are the main driver of inflation persistence. Since the effect of τ/σ on coefficients $\alpha_1, \alpha_2, \alpha_3$, and α_4 in equation (28) is highly non-linear and interplays with the degree of nominal price rigidities, we rely on numerical simulations to study the sensitivity of inflation to aggregate demand, developed in the next subsection.

4.1 Numerical Assessment

The model shows that imperfect information makes the response of inflation to aggregate demand a non-linear function of the ratio of volatility of the sector-specific to aggregate shock (τ/σ) and the degree of nominal rigidities (θ), which jointly determine the response of inflation to aggregate demand, as encapsulated by the coefficients α_1, α_2, α_3 and α_4 in equation (28). In this section, we use numerical simulations to study the sensitivity of inflation to demand.

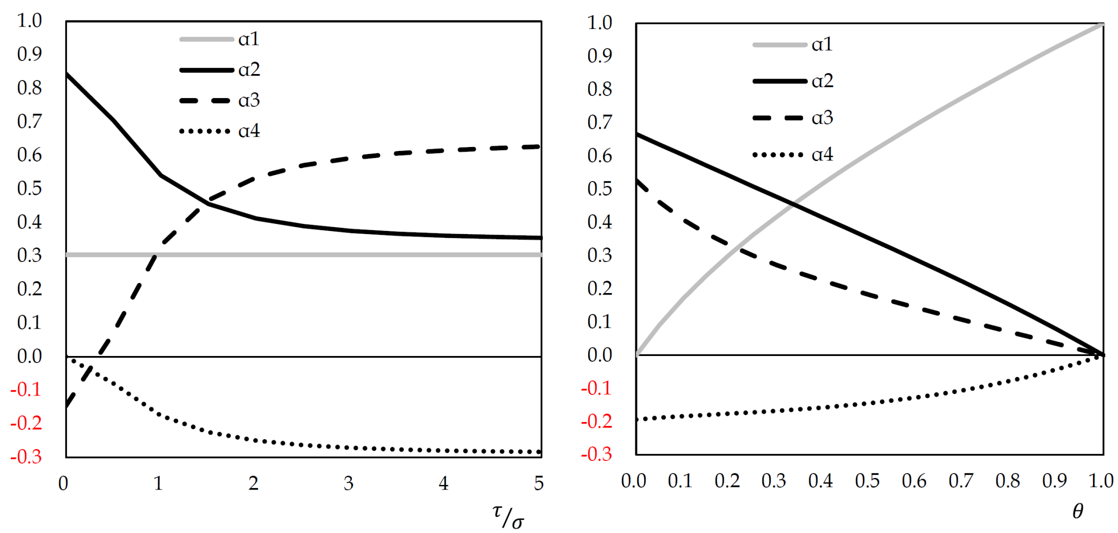
Sensitivity of Inflation to Changes in Demand. We calibrate the model using standard parameter values. We set $\eta = 3$, $\epsilon = 1/2$, $r = [(\eta - 1)(1 - \epsilon)]/[\epsilon + \eta(1 - \epsilon)] = 0.5$, and $\beta = 0.99$. To investigate the role of shock heterogeneity, we allow the ratio $\tau/\sigma \in [0, 6]$ to cover a wide range of values. We will estimate this parameter in the next section. Similarly, we allow the degree of nominal price rigidity $\theta \in [0, 1]$ to cover the whole range of admissible values. We set the parameters for the persistence of aggregate and sector-specific shocks equal to $\rho_u = 0.58$ and $\rho_v = 0.30$ so that the co-movement in the current and past year demand replicates the empirical auto-correlation in Table 6 for both the aggregate and sector-specific components of demand (i.e., $Corr\,(u_t, u_{t-4}) = 0.11$ and $Corr\,(\widehat{v}_t, \widehat{v}_{t-4}) = 0.01$).[16]

Figure 1 in panel (a) shows the coefficients α_1, α_2, α_3, and α_4 for different values of the relative volatility of sector-specific shocks (i.e., τ/σ). The coefficient α_1 on past inflation is insensitive to τ/σ, showing that the relative volatility of sector-specific shocks plays no role in the relationship between current inflation and past inflation, which instead is determined by the degree of nominal price rigidities, as we discuss below. The coefficient α_2 on current aggregate demand is instead highly sensitive to the relative volatility of sector-specific shocks, and inflation becomes less sensitive to changes in current aggregate demand (i.e., α_2

[15] See Appendix F.4 for the characterization of parameters a_1, a_2, a_3, and a_4.
[16] For the details of the calculation, see Appendix E

Figure 1: Sensitivity of coefficients

(a) The degree of shock heterogeneity (τ/σ) (b) The degree of nominal price rigidity (θ)

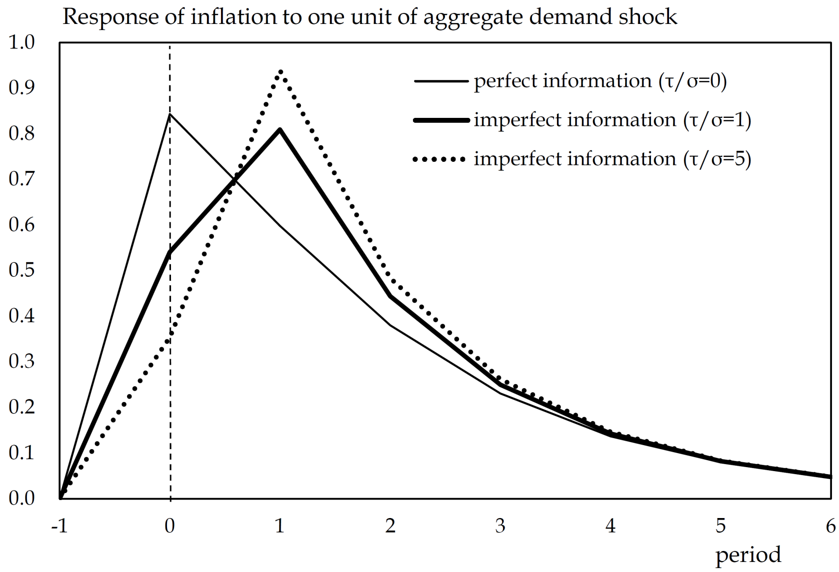


Notes: Parameters are $\tau/\sigma = 1,\ r = 0.5,\ \beta = 0.99,\ \rho_u = 0.58,\ \rho_v = 0.30$ *for (a), and* $\theta = 0.2\ r = 0.5,\ \beta = 0.99, \rho_u = 0.58,\ \rho_v = 0.30$ *for (b).*

decreases) when τ/σ increases. Strategic complementarity in the optimal price setting, encapsulated by $r > 0$ in equation (25), induces the firm to largely adjust prices if it perceives that the change in total sectoral demand is generated by the aggregate component common across all sectors in the economy. Therefore, *ceteris paribus*, an increase in the volatility of the sector-specific component of demand decreases the response of prices to changes in total sectoral demand. The coefficient α_3 (past lag of demand) increases while the coefficient α_4 (past two lags of demand) decreases in response to the increase in τ/σ. The response of inflation is on average more sensitive to movements in past lags of aggregate demand. Overall, the numerical simulations show that the parameter α_2, which internalizes the effect of changes in τ/σ, plays a critical role in the sensitivity of inflation to aggregate demand.

Figure 1 in panel (b) shows the sensitivity of coefficients α_1, α_2, α_3, and α_4 to changes in the degree of nominal price rigidity (θ) in the inflation equation (28). The increase in nominal price rigidities generates a rise in the coefficient α_1 since a low frequency of price adjustment increases the importance of past inflation in the determination of current inflation. The increase in the degree of nominal price rigidity generates a decrease in the absolute value of the coefficients α_2, α_3, and α_4 since the sensitivity of individual prices to movements in current aggregate demand is lowered to the extent the firm maintains the current price by the increased nominal price rigidity (θ).

Figure 2: Impulse response functions of aggregate inflation to aggregate shocks



Notes: Parameters are $\theta = 0.2$, $r = 0.5$, $\beta = 0.99, \rho_u = 0.58$, $\rho_v = 0.30$.

Impulse Response of Inflation to Aggregate Demand Shock. How does the relative volatility of sector-specific demand shocks to aggregate shocks influence the sensitivity of inflation to changes in aggregate demand? To address this central question in our analysis, we simulate the model and determine the response of inflation to a one-period, positive aggregate demand shock for different values of τ/σ. Figure 2 shows that an increase in the ratio τ/σ reduces the response of inflation to changes in aggregate demand. Since the firm cannot disentangle changes in aggregate and sector-specific demand, it attributes changes in total sectoral demand partially to changes in sector-specific demand, which have no effect on the price-setting decisions of firms in other sectors in the economy. Attributing part of the movement in total sectoral demand to sector-specific demand induces the firm to decrease the response of prices to aggregate shocks. Therefore, inflation becomes less responsive to changes in total sectoral demand. If the ratio of τ/σ is large, the firm conjectures that a large fraction of the changes in total sectoral demand occurs because of sector-specific shock. Consequently, the firm expects that the average price in the period remains almost the same as that in the previous period and adjusts its prices less strongly to changes in aggregate demand.

4.2 Empirical Assessment

This section estimates the ratio of the volatility of the sector-specific component to the aggregate component of demand using principal component analysis on Japanese data and observes a sharp decline in the ratio since the early 2000s. It then tests the empirical relevance of the decline in the ratio for the reduced sensitivity of inflation to movements in aggregate demand.

Estimation of τ/σ. To estimate the ratio τ/σ, we compute the variance of the changes in the aggregate and sector-specific components of demand (σ^2 and τ^2, respectively). We proxy changes in aggregate demand by the principal component of the movements in sales growth across sectors, following the approach in Boivin et al. (2009). We use quarterly data on sector-level sales of Japanese firms from the Financial Statements Statistics of Corporations by Industry, compiled by the Ministry of Finance of Japan. The data cover the period 1975:Q3-2018:Q3 for 29 major sectors in the economy.[17]

We proxy the changes in the aggregate component of demand with sales, u_t, by the first principal component of $\widetilde{x}_t(i)$ across sectors, $i \in \{1, 2, ..., 29\}$, by calculating it as $u_t = \left(\Sigma_{i=1}^{29}\Lambda_i\right)^{-1} \Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$, where Λ_i is the loading factor of $\widetilde{x}_t(i)$ and the term $\left(\Sigma_{i=1}^{29}\Lambda_i\right)^{-1}$ normalizes $\Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$.[18] We proxy sector-specific demand, $\widetilde{v}_t(i)$, by subtracting the estimated principal component from changes in total sectoral demand:[19] $\widetilde{x}_t(i) - u_t = \widetilde{x}_t(i) - \left(\Sigma_{i=1}^{29}\Lambda_i\right)^{-1} \Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$.[20]

We proxy the variance of aggregate fluctuations, σ_t^2, with the average of the square of

[17] Appendix I provides a description of the data.

[18] The proportion of the variance of the first component is around 19%, which is considerably larger than the variance of the second component (7%), suggesting that the second principal component plays a limited role in aggregate shocks. Note that since the principal component is $\Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$ and changes in sectoral demand is $\widetilde{x}_t(i)$, the scale of the principal component $\Sigma_{i=1}^{29}\Lambda_i$ may differ from the scale of changes in sectoral demand. Estimation results reveal that $\Sigma_{i=1}^{29}\Lambda_i \approx 4.7$, which we use to normalize the principal component.

[19] To ensure results are robust to alternative normalization, we implement alternative specifications. First, we define $u_t = \Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$ and $\widetilde{x}_t(i) - u_t$, and second, we define $u_t = \left(\Sigma_{i=1}^{29}\Lambda_i\right)^{-1} \Sigma_{i=1}^{29}\Lambda_i\widetilde{x}_t(i)$ and $\widetilde{x}_t(i) - u_t$. Results remain unchanged across different normalization assumptions.

[20] Appendix J discusses the methodology we use to extract the sequence of shocks on aggregate and sector-specific components of total sectoral demand, and it provides summary statistics on the volatility of aggregate and sectoral-specific demand shocks. Appendix K shows that the changes in the series for aggregate demand extracted from the industry-level data are representative of aggregate movements in demand. Our series closely co-move with the average of industry-level data and with the measure of the output gap from the Bank of Japan that several studies use as a proxy for changes in aggregate demand.

residuals of equation (2) for alternative moving windows of size $2k+1$:

$$\sigma_t^2 = \frac{1}{2k+1}\Sigma_{s=-k}^{k}\widehat{e}_t^2. \tag{29}$$

Similarly, we proxy the variance of the sector-specific fluctuations, τ_t^2, with the average of the square of the averages of the residuals of (3) across sectors for alternative moving windows of size $2k+1$:

$$\tau_t^2 = \frac{1}{2k+1}\Sigma_{s=-k}^{k}\left(\frac{1}{29}\Sigma_{i=1}^{29}\frac{\left(\widehat{\epsilon}_t(i)-\widehat{\epsilon}_{t-1}(i)\right)^2}{2}\right). \tag{30}$$

To ensure robustness of results across the different time windows, we compute the variance of each of the shocks in equations (29) and (30), using four alternative time windows: two years ($k=4$), three years ($k=6$), five years ($k=10$), and ten years ($k=20$), excluding the upper and lower 10% of the samples as outliers. Finally, we measure shock heterogeneity as the ratio of the square root of the estimate of the variance of sector-specific shocks (τ_t) to that of aggregate shocks (σ_t).

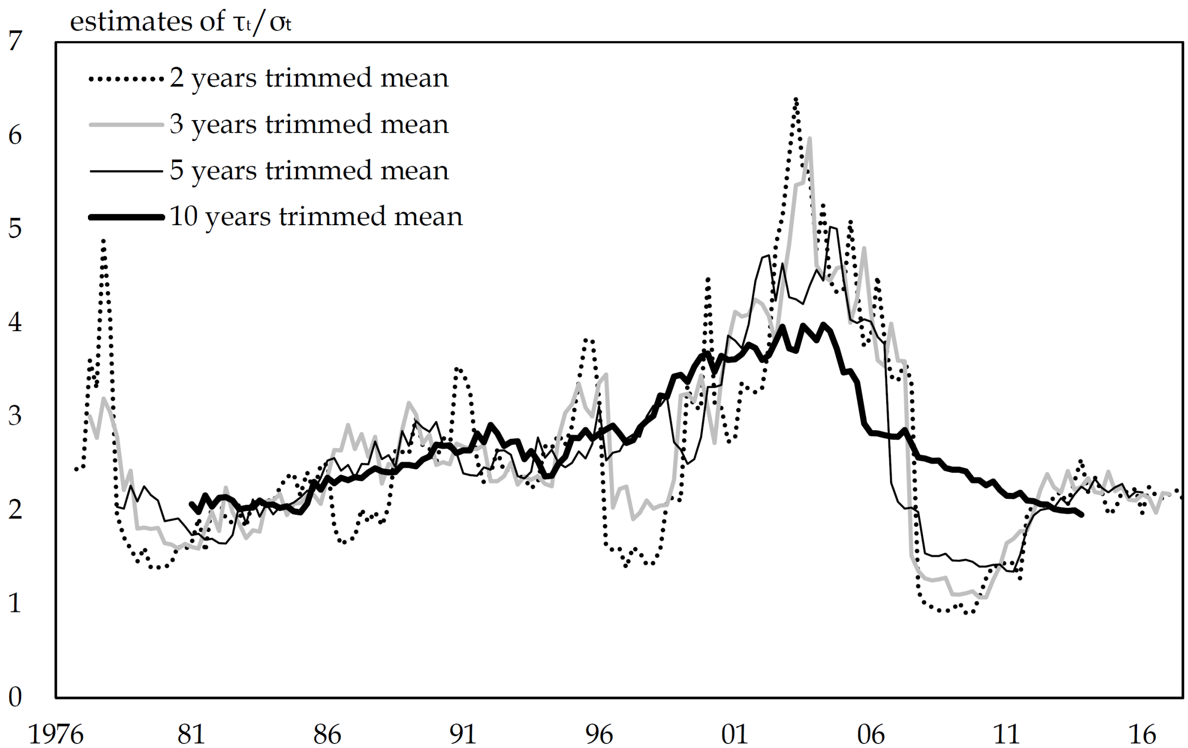
Figure 3 shows the estimated series for the ratio of the variance of sector-specific shocks to the variance of aggregate shocks (τ_t/σ_t) for the alternative time windows. Entries show that the ratio τ_t/σ_t substantially varies throughout the sample period, rising steadily from a value of 2 in the mid-1980s to 4 in the mid-2000s and returning quickly to a value of approximately 2 after 2010 for the 10-year window. The shorter the time window, the larger the volatility, but the overall dynamics of the changes are similar across the alternative estimates. Overall, the analysis establishes a substantial decrease in the τ_t/σ_t ratio during the 2000s.[21]

Sensitivity of Inflation to Aggregate Demand. We use our proxy for τ_t/σ_t to study the empirical relevance of the decreases in the ratio for the reduced sensitivity of inflation to changes in aggregate conditions since the mid-2000s, a robust empirical regularity (see recent studies by Kaihatsu et al., 2017 and Bundick and Smith, 2020).

We set up the empirical model using the insights from the price equation (28) that accounts for the effect of information frictions in the relationship between inflation and aggregate demand. We regress current inflation (π_t) on past inflation (π_{t-1}), changes in current aggregate demand (u_t), an interaction term between past inflation and the volatility ratio between sector-specific and aggregate shocks ($\pi_{t-1}\times\tau_t/\sigma_t$), and an interaction term

[21] Movements in τ_t/σ_t are primarily driven by changes in the volatility of sector-specific demand shocks (τ_t) while the value for volatility of aggregate demand shock (σ_t) remains broadly stable across the sample period, except during the period of the global financial crisis (2007:4Q to 2010:1Q).

Figure 3: Estimates of shock heterogeneity (τ_t/σ_t)



Notes: Upper and lower 10% of the samples are excluded in estimation.
Source: Ministry of Finance "Financial statements statistics of corporations by industry".

between changes in current aggregate demand and the volatility ratio between sector-specific and aggregate shocks ($u_t \times \tau_t/\sigma_t$). The terms $\pi_{t-1} \times \tau_t/\sigma_t$ and $u_t \times \tau_t/\sigma_t$ capture the differential effect of the ratio τ_t/σ_t for the effect of past inflation and aggregate demand on current inflation, respectively. In line with the theoretical model, we include aggregate demand with two lags and control for the degree of nominal price rigidities, motivated by the fact the comparative statics in the model described in section 4.1 show that the higher degree of nominal price rigidity increases the persistence of inflation and reduces the sensitivity of current inflation to changes in current aggregate demand. Specifically, we use an indicator variable equal to 1 for the period 2000-2018 ($\mathbf{1}_{\{2000-2018\}}$) when nominal price rigidities decrease (see evidence in Sudo et al., 2014 and Kurachi et al., 2016), and we enrich the estimation of the price equation with two additional interaction terms. The first term interacts the indicator variable for nominal price rigidities with past inflation ($\pi_{t-1} \times \mathbf{1}_{\{2000-2018\}}$) to capture the interplay between the degree of nominal price rigidity and the effect of past inflation on current inflation. The second term interacts the indicator variable for nominal price rigidities with current aggregate demand ($u_t \times \mathbf{1}_{\{2000-2018\}}$) to capture the interplay between nominal price rigidities and current aggregate demand. The empirical specification of the price inflation is summarized by the following equation:

$$\begin{aligned}\pi_t =& c_1 + \left(c_2 + c_3\mathbf{1}_{\{2000-2018\}} + c_4\left(\tau_t/\sigma_t\right)\right)\pi_{t-1} + \left(c_5 + c_6\mathbf{1}_{\{2000-2018\}} + c_7\left(\tau_t/\sigma_t\right)\right)u_t \\ &+ c_8 u_{t-1} + c_9 u_{t-2} + \varepsilon_t^c, \end{aligned} \tag{31}$$

where the coefficients $c_1, \ldots, c_9$ are regression coefficients, and ε_t^c is the error term.

Table 2 shows the estimates for equation (31), using the τ/σ ratio based on time-windows of two year (column 1), three-year (columns 2), five years (column 3) and ten years (column 4), respectively. All entries show that current inflation is positively correlated with past inflation and current demand. This finding is in line with the theoretical prediction in the price equation (27). The findings also show that the coefficient for the interaction term of past inflation with the indicator variable ($\pi_{t-1} \times \mathbf{1}_{\{2000-2018\}}$) is negative and that for the interaction term of past inflation with shock heterogeneity is not significant, indicating the positive correlation between current inflation and past inflation decreases with a decline in nominal price rigidities, again in line with the predictions of our model. The estimates for the interaction term of changes in demand with the indicator variable ($u_t \times \mathbf{1}_{\{2000-2018\}}$) are insignificant for all proxies of the τ/σ ratio. Important for our analysis, the interaction term between aggregate demand and the degree of shock heterogeneity ($u_t \times \tau_t/\sigma_t$) is negative and

Table 2: Estimation of inflation dynamics

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 sectors; 1976/2Q-2018/3Q				
Dependent Variable: Inflation rate (π_t, core consumer price index, seasonally adjusted, QoQ, annualized)				
	2 years trimmed mean	*3 years trimmed mean*	*5 years trimmed mean*	*10 years trimmed mean*
Constant	0.09	0.08	0.06	0.05
	(0.09)	(0.09)	(0.08)	(0.07)
Lag of inflation (π_{t-1})	0.72 ***	0.62 ***	0.71 ***	0.64 ***
	(0.12)	(0.16)	(0.17)	(0.23)
Lag of inflation×time dummy (2000-2018)	-0.33 ***	-0.32 ***	-0.35 ***	-0.38 ***
($\pi_{t-1} \times 1_{\{2000-2018\}}$)	(0.11)	(0.11)	(0.11)	(0.11)
Lag of inflation	0.03	0.06	0.03	0.06
×shock heterogeneity ($\pi_{t-1} \times {}^{\tau_t}/_{\sigma_t}$)	(0.03)	(0.05)	(0.07)	(0.09)
Changes in aggregate demand (u_t)	0.37 ***	0.37 ***	0.38 **	0.63 ***
	(0.11)	(0.13)	(0.15)	(0.22)
Changes in aggregate demand ×time	-0.13	-0.13	-0.13	-0.08
dummy (2000-2018) ($u_t \times 1_{\{2000-2018\}}$)	(0.09)	(0.09)	(0.10)	(0.09)
Changes in aggregate demand	**-0.08 *****	**-0.07 ***	**-0.07 ***	**-0.17 ****
×shock heterogeneity ($u_t \times {}^{\tau_t}/_{\sigma_t}$)	(0.03)	(0.04)	(0.04)	(0.07)
Observations	170	170	170	170
Adjusted-R^2	0.80	0.80	0.80	0.80

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators. First and second lags of changes in aggregate demand are included in estimation as control variables. Data extrapolation using the values in the closest periods is applied for the missing values in the estimates of shock heterogeneity. The series for the core consumer price index is "all items, less fresh food (impact of consumption taxes are adjusted)".
**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

significant, implying that a rise in the τ_t/σ_t ratio reduces the positive correlation between inflation and aggregate demand, in accordance with the results of our analysis. It also shows that the raise in shock heterogeneity plays an empirically significant part in the reduced sensitivity of inflation to aggregate demand.[22]

To account for the possibility that the absolute variances of the aggregate and sector-specific components of sectoral demand may play a role for the sensitivity of inflation to real activity, Table 3 provides estimates from the regression in equation (31), enriched by an interaction term between aggregate demand and the sum of the variances of the aggregate and sector-specific components of sectoral demand ($u_t \times (\sigma_t + \tau_t)$). While the interaction term with the sum of the variances is not significant, our baseline results continue to hold, suggesting that shock heterogeneity is important for the reduced sensitivity of inflation to real activity, as predicted by the theoretical model.

Finally, to ensure that decline in nominal price rigidities is not driving the significance of the negative relation between τ/σ and inflation, Table 4 presents results for the benchmark regression that abstracts from the indicator variable $\mathbf{1}_{\{2000-2018\}}$ by omitting the interaction

[22] As a robustness check, we also run the regression based on the changes in inflation as specified by equation (31). We observe that interaction term between aggregate demand and the degree of shock heterogeneity ($u_t \times \tau_t/\sigma_t$) is negative for all cases and significant if we use sufficiently volatile proxies for the degree of shock heterogeneity such as τ_t/σ_t for $k = 4$ and 8. For the details, see Appendix L.

Table 3: Estimation of inflation dynamics

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 sectors; 1976/2Q-2018/3Q

Dependent Variable: Inflation rate (π_t, core consumer price index, seasonally adjusted, QoQ, annualized)

	2 years trimmed mean	*3 years trimmed mean*	*5 years trimmed mean*	*10 years trimmed mean*
Constant	0.12	0.09	0.06	0.05
	(0.09)	(0.09)	(0.08)	(0.07)
Lag of inflation (π_{t-1})	0.26	0.52	0.64	0.93
	(0.58)	(0.36)	(0.66)	(1.39)
Lag of inflation×time dummy (2000-2018)	-0.58 ***	-0.38 **	-0.40 **	-0.32
($\pi_{t-1} \times 1_{\{2000-2018\}}$)	(0.20)	(0.16)	(0.18)	(0.31)
Lag of inflation	0.08	0.08	0.04	0.02
×shock heterogeneity ($\pi_{t-1} \times {}^{\tau_t}/_{\sigma_t}$)	(0.05)	(0.06)	(0.12)	(0.20)
Lag of inflation	0.06	0.01	0.01	-0.04
×size of total shock ($\pi_{t-1} \times (\sigma_t + \tau_t)$)	(0.05)	(0.04)	(0.08)	(0.19)
Changes in aggregate demand (u_t)	0.64 ***	0.77 **	0.71 *	1.04
	(0.23)	(0.29)	(0.38)	(0.71)
Changes in aggregate demand ×time	-0.02	0.02	-0.02	0.02
dummy (2000-2018) ($u_t \times 1_{\{2000-2018\}}$)	(0.08)	(0.07)	(0.07)	(0.15)
Changes in aggregate demand	**-0.13 ****	**-0.14 ****	**-0.12 ***	**-0.22 ****
×shock heterogeneity ($\boldsymbol{u_t \times {}^{\tau_t}/_{\sigma_t}}$)	(0.06)	(0.06)	(0.07)	(0.10)
Changes in aggregate demand	**-0.03**	**-0.04**	**-0.04**	**-0.06**
×size of total shock ($\boldsymbol{u_t \times (\sigma_t + \tau_t)}$)	(0.03)	(0.02)	(0.04)	(0.09)
Observations	170	170	170	170
Adjusted-R^2	0.80	0.80	0.80	0.80

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators. First and second lags of changes in aggregate demand are included in estimation as control variables. Data extrapolation using the values in the closest periods is applied for the missing values in the estimates of shock heterogeneity. The series for the core consumer price index is "all items, less fresh food (impact of consumption taxes are adjusted)".

**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

term between past inflation and the indicator variable (i.e., $\pi_{t-1} \times \mathbf{1}_{\{2000-2018\}}$) and the interaction term between changes in demand and the indicator variable ($u_t \times \mathbf{1}_{\{2000-2018\}}$) from equation (31). The regression coefficient on the term $u_t \times (\tau/\sigma)$ (bold entry) remains significant and negative, as in the benchmark regression.[23]

Our results suggest that the imperfect information on sectoral demand, together with the increased shock heterogeneity, has contributed to the reduced sensitivity of inflation to the aggregate demand shock in Japan during 1980s to mid-2000s.[24]

[23] While not the focus of this study, we also investigate the empirical validity of our model from the perspective of sectoral inflation dynamics. The empirical result supports our theoretical framework that an increase in shock heterogeneity induces sector-specific inflation, becoming less responsive to sector-specific demand. For details, see Appendix M.

[24] This result is relevant to the flattening of Philips curve in Japan, as discussed in Appendix N.

Table 4: Estimation of inflation dynamics

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 industries; 1976/2Q-2018/3Q

Dependent Variable: Inflation rate (π_t, core consumer price index, seasonally adjusted, QoQ)

	2 years trimmed mean	*3 years trimmed mean*	*5 years trimmed mean*	*10 years trimmed mean*
Constant	0.15 **	0.15 ***	0.13 **	0.10
	(0.07)	(0.07)	(0.07)	(0.06)
Lag of inflation (π_{t-1})	0.69 ***	0.69 ***	0.57 ***	0.92 ***
	(0.12)	(0.12)	(0.16)	(0.26)
Lag of inflation	0.04	0.04	0.08	-0.08
×*shock heterogeneity* ($u_t \times {}^{\tau_t}/_{\sigma_t}$)	(0.04)	(0.04)	(0.06)	(0.11)
Changes in aggregate demand (u_t)	0.29 ***	0.29 ***	0.27 ***	0.61 ***
	(0.08)	(0.08)	(0.10)	(0.22)
Changes in aggregate demand	**-0.07 ****	**-0.07 ****	**-0.05**	**-0.18 ****
×***shock heterogeneity*** ($\boldsymbol{u_t \times {}^{\tau_t}/_{\sigma_t}}$)	(0.03)	(0.03)	(0.04)	(0.08)
Observations	170	170	170	170
Adjusted-R²	0.79	0.79	0.78	0.79

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators. First and second lags of changes in aggregate demand are included in estimation as control variables. Data extrapolation using the values in the closest periods is applied for the missing values in the estimates of shock heterogeneity. The series for the core consumer price index is "all items, less fresh food (impact of consumption taxes are adjusted)".
**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

5 Conclusion

Our analysis establishes a positive co-movement in the expectations of aggregate and sector-specific demand using sector-level survey for the universe of Japanese firms and shows that a parsimonious model of imperfect information explains this empirical regularity. Our theoretical model with empirically-congruous expectations predicts that an increase in the volatility of sector-specific shocks relative to aggregate shocks generates a reduction in the sensitivity of inflation to aggregate demand. We test and corroborate the theoretical prediction using sector-level sales data for Japanese firms across 29 sectors and show that the increase in the volatility of sector-specific demand played a significant role for the reduced sensitivity of inflation to movements in aggregate demand from mid-1980s to mid-2000s in Japan.

The analysis opens interesting avenues for future research. Our theoretical framework can be extended to account for a richer information structure that allows firms to use additional signals to infer changes in aggregate and sector-specific components from total demand. It would also be interesting to extend the analysis to a network economy in which idiosyncratic shocks are an important source of business cycle fluctuations (e.g., Carvalho and Grassi, 2019) and study whether imperfect information significantly changes the propagation and influence of idiosyncratic shocks. We plan to pursue these ideas in future work.

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A Derivation of Demand Functions and Price Indexes

A.1 Demand Functions

The representative household first determines the allocation of consumption across sectors and then determines that to goods in each sector taking the expenditure level to each sector as given.

Define the expenditure level by $Z_t \equiv \int_0^1 P_t(i)C_t(i)di$, the Lagrangian is:

$$L = \left[\int_0^1 (C_t(i)\Theta_t(i))^{\frac{\eta-1}{\eta}} di\right]^{\frac{\eta}{\eta-1}} - \lambda_t \left(\int_0^1 P_t(i)C_t(i)di - Z_t\right), \tag{32}$$

and the first-order conditions are:

$$C_t(i)^{-\frac{1}{\eta}} C_t^{\frac{1}{\eta}} (\Theta_t(i))^{\frac{\eta-1}{\eta}} = \lambda_t P_t(i). \tag{33}$$

Thus, for any two sectors, the following equation holds:

$$C_t(i) = C_t(j)\left(\frac{P_t(i)}{P_t(j)}\right)^{-\eta}\left(\frac{\Theta_t(i)}{\Theta_t(j)}\right)^{\eta-1}. \tag{34}$$

By substituting equations (33) and (34) into the definition of consumption expenditures ($Z_t \equiv \int_0^1 P_t(i)C_t(i)di$), it yields:

$$\int_0^1 P_t(i)\left[C_t(j)\left(\frac{P_t(i)}{P_t(j)}\right)^{-\eta}\left(\frac{\Theta_t(i)}{\Theta_t(j)}\right)^{\eta-1}\right] di = Z_t$$

$$\Leftrightarrow \quad C_t(j) = P_t^{-\eta}(j)\Theta_t^{\eta-1}(j)Z_t\frac{1}{\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di}. \tag{35}$$

By substituting the equation:

$$\int_0^1 P_t(i)C_t(i)di = Z_t = P_tC_t,$$

into equation (35), it yields:

$$C_t(i) = \Theta_t^{\eta-1}(i)\left(\frac{P_t(i)}{P_t}\right)^{-\eta} C_t\frac{P_t^{1-\eta}}{\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di}. \tag{36}$$

Using the definition of the price level, $P_t \equiv \left[\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di\right]^{\frac{1}{1-\eta}}$, we can re-write equation (36) as:

$$C_t(i) = \Theta_t^{\eta-1}(i)\left(\frac{P_t(i)}{P_t}\right)^{-\eta} C_t. \tag{37}$$

Applying the same calculation for $C_t(i) = \left[\int_0^1 (C_t(i,j))^{\frac{\widetilde{\eta}-1}{\widetilde{\eta}}} dj\right]^{\frac{\widetilde{\eta}}{\widetilde{\eta}-1}}$, it yields:

$$C_t(i,j) = \left(\frac{P_t(i,j)}{P_t(i)}\right)^{-\widetilde{\eta}} C_t(i). \tag{38}$$

By combining equations (37) and (38), we obtain the demand for good (i,j) as follows:

$$C_t(i,j) = \Theta_t^{\eta-1}(i)\left(\frac{P_t(i,j)}{P_t(i)}\right)^{-\widetilde{\eta}}\left(\frac{P_t(i)}{P_t}\right)^{-\eta} C_t.$$

A.2 Price Indexes

We show the derivation of aggregate price index $P_t \equiv \left[\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di\right]^{\frac{1}{1-\eta}}$, and we omit the derivation of sectoral price index $P_t(i) \equiv \left[\int_0^1 P_t^{1-\widetilde{\eta}}(i,j)dj\right]^{\frac{1}{1-\widetilde{\eta}}}$ since it can be similarly derived.

Recall that λ_t^{-1} indicates the shadow price of one unit of utility. The first-order condition in equation (33) can be re-written as:

$$\begin{aligned}
& C_t(i)^{-\frac{1}{\eta}} C_t^{\frac{1}{\eta}} (\Theta_t(i))^{\frac{\eta-1}{\eta}} = \lambda_t P_t(i) \\
\Leftrightarrow\ & C_t(i)^{\frac{\eta-1}{\eta}} C_t^{\frac{1}{\eta}} (\Theta_t(i))^{\frac{\eta-1}{\eta}} = \lambda_t C_t(i) P_t(i) \\
\Leftrightarrow\ & \int_0^1 \left(C_t(i)^{\frac{\eta-1}{\eta}} (\Theta_t(i))^{\frac{\eta-1}{\eta}}\right) di C_t^{\frac{1}{\eta}} = \lambda_t \int_0^1 C_t(i) P_t(i) di \\
\Leftrightarrow\ & C_t \lambda_t^{-1} = Z.
\end{aligned}$$

From the first-order condition (33) we derive the aggregate price index:

$$\begin{aligned}
& C_t(i)^{-\frac{1}{\eta}} C_t^{\frac{1}{\eta}} (\Theta_t(i))^{\frac{\eta-1}{\eta}} = \lambda_t P_t(i) \\
\Leftrightarrow\ & (C_t(i)\Theta_t(i))^{-\frac{1}{\eta}} C_t^{\frac{1}{\eta}} \Theta_t(i) = \lambda_t P_t(i) \\
\Leftrightarrow\ & (C_t(i)\Theta_t(i))^{\frac{1}{\eta}} = C_t^{\frac{1}{\eta}} \Theta_t(i) \lambda_t^{-1} P_t^{-1}(i) \\
\Leftrightarrow\ & (C_t(i)\Theta_t(i))^{\frac{\eta-1}{\eta}} = C_t^{\frac{\eta-1}{\eta}} \Theta_t^{\eta-1}(i) \lambda_t^{1-\eta} P_t^{1-\eta}(i) \\
\Leftrightarrow\ & \int_0^1 (C_t(i)\Theta_t(i))^{\frac{\eta-1}{\eta}} di = C_t^{\frac{\eta-1}{\eta}} \lambda_t^{1-\eta} \int_0^1 \left(P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)\right) di \\
\Leftrightarrow\ & 1 = \lambda_t^{1-\eta} \int_0^1 \left(P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)\right) di \\
\Leftrightarrow\ & \lambda_t^{-1} = \left[\int_0^1 \left(P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)\right) di\right]^{\frac{1}{1-\eta}}.
\end{aligned}$$

B Total Sectoral Demand and Aggregate and Sector-Specific Components

As shown in Appendix A, the demand for firm j in sector i in equation (12), can be expressed as:

$$C_t(i,j) = \left(\frac{P_t(i,j)}{P_t(i)}\right)^{-\tilde{\eta}} C_t(i),$$

where the demand for sector i, $C_t(i)$, can be re-written as:

$$C_t(i) = \Theta_t^{\eta-1}(i)\left(\frac{P_t(i)}{P_t}\right)^{-\eta} C_t, \tag{39}$$

where C_t is the aggregate demand and $\left(\frac{P_t(i)}{P_t}\right)^{-\eta}$ is the cross-price elasticity term. $\Theta_t^{\eta-1}(i)$ is the sector-specific demand shifter driven by the preference shocks. We can express the demand in equation (39) in nominal terms as:

$$P_t C_t(i) = (P_t C_t)\,\Theta_t^{\eta-1}(i)\left(\frac{P_t(i)}{P_t}\right)^{-\eta}, \tag{40}$$

where we name $P_t C_t(i)$ is the total sectoral demand and the demand is composed of two components: the aggregate demand $P_t C_t$ and the sector-specific demand $\Theta_t^{\eta-1}(i)\left(\frac{P_t(i)}{P_t}\right)^{-\eta}$. By using $P_t \equiv \left[\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di\right]^{\frac{1}{1-\eta}}$ into equation (40), it yields the decomposition of the total sectoral demand $(P_t(i)C_t(i))$ into aggregate demand $(P_t C_t)$ and sector-specific demand $\left(\left(\frac{P_t(i)}{P_t}\right)^{-\eta}\Theta_t^{\eta-1}(i)/\left[\int_0^1\left(\frac{P_t(i)}{P_t}\right)^{1-\eta}\Theta_t^{\eta-1}(i)di\right]^{\frac{-\eta}{1-\eta}}\right)$, such that:

$$P_t C_t(i) = (P_t C_t)\left(\frac{\left(\frac{P_t(i)}{P_t}\right)^{-\eta}\Theta_t^{\eta-1}(i)}{\left[\int_0^1\left(\frac{P_t(i)}{P_t}\right)^{1-\eta}\Theta_t^{\eta-1}(i)di\right]^{\frac{-\eta}{1-\eta}}}\right). \tag{41}$$

In equation (41) the relative sectoral price $(P_t(i)/P_t)$ depends on the exogenous sector-specific demand shifter, $\Theta_t(i)$, and aggregate demand and sector-specific demand are independent from each other.

To link the demand function in equation (40) to the empirical framework in Section 2, we show that the growth rates of total sectoral demand in our model can be decomposed into that of aggregate and sector-specific demand, as in the survey data. The growth rate of these term is given by

$$\frac{P_t C_t(i)}{P_{t-1}C_{t-1}(i)} = \frac{P_t C_t}{P_{t-1}C_{t-1}}\frac{\Theta_t^{\eta-1}(i)}{\Theta_{t-1}^{\eta-1}(i)}\left(\frac{\frac{P_t(i)}{P_{t-1}(i)}}{\frac{P_t}{P_{t-1}}}\right)^{-\eta}.$$

The log-linearization around the symmetric equilibrium yields:

$$[\Delta p_t + \Delta c_t(i)] = [\Delta p_t + \Delta c_t] + [(\eta - 1)\,\Delta\theta_t(i) - \eta\,(\Delta p_t(i) - \Delta p_t)]\,, \tag{42}$$

where lower-case variables to indicate logarithms of the corresponding upper-case variables (i.e., $x_t \equiv \log X_t$) and Δ indicates the difference the variables between two periods ($\Delta x_t \equiv x_t - x_{t-1}$). Equation (42) shows that the growth of the total sectoral demand ($\Delta p_t + \Delta c_t(i)$) is composed of that of aggregate demand ($\Delta p_t + \Delta c_t$) and that of sector-specific demand ($(\eta - 1)\,\Delta\theta_t(i) - \eta\,(\Delta p_t(i) - \Delta p_t)$), as in the survey data.

C Derivation of the Index of Aggregate Prices

Recall that: $P_t \equiv \left[\int_0^1 P_t^{1-\eta}(i)\Theta_t^{\eta-1}(i)di\right]^{\frac{1}{1-\eta}}$ can be expressed as, $P_t = \left[\int_0^1 \left(\frac{P_t(i)}{\Theta_t(i)}\right)^{1-\eta} di\right]^{\frac{1}{1-\eta}} = \left[\int_0^1 \left(\widetilde{P}_t(i)\right)^{1-\eta} di\right]^{\frac{1}{1-\eta}}$, where $\widetilde{P}_t(i) \equiv \frac{P_t(i)}{\Theta_t(i)}$. We then define $p_t \equiv \int_0^1 \widetilde{p}_t(i)di$, such that:

$$p_t \equiv \int_0^1 \widetilde{p}_t(i)di = \int_0^1 p_t(i)di - \int_0^1 \theta_t(i)di = \int_0^1 p_t(i)di,$$

since $\theta_t(i) \sim \mathcal{N}(0, (1-\epsilon)^{-2}\,(\eta-1)^{-2}\,\tau^2)$ and $\int_0^1 \theta_t(i)di = 0$.

D Derivation of the Price Setting Rule

Using the following equations:

$$p_t(i,j) = \mu + mc_t(i,j),$$

$$c_t(i,j) = -\widetilde{\eta}\,(p_t(i,j) - p_t(i)) - \eta\,(p_t(i) - p_t) + c_t + (\eta - 1)\,\theta_t(i),$$

and

$$mc_t(i,j) = w_t + \frac{1-\epsilon}{\epsilon} y_t(i,j) - \frac{1}{\epsilon} a - log(\epsilon),$$

the price of firm j in sector i, $p_t(i,j)$, is equal to:

$$\begin{aligned}
p_t(i,j) &= \mu + mc_t(i,j) = \mu + y_t + p_t - \frac{1}{\epsilon}a - log(\epsilon) \\
&\quad + \frac{1-\epsilon}{\epsilon}\left[-\widetilde{\eta}\left(p_t(i,j) - p_t(i)\right) - \eta\left(p_t(i) - p_t\right) + c_t + (\eta - 1)\,\theta_t(i)\right] \\
&= -\frac{1-\epsilon}{\epsilon}\widetilde{\eta} p_t(i,j) + \frac{1-\epsilon}{\epsilon}\left(\widetilde{\eta} - \eta\right) p_t(i) + \left(1 + \frac{1-\epsilon}{\epsilon}\eta\right) p_t \\
&\quad + (\mu - \frac{1}{\epsilon}a - log(\epsilon)) + \left(1 + \frac{1-\epsilon}{\epsilon}\right) y_t + \frac{1-\epsilon}{\epsilon}(\eta - 1)\,\theta_t(i) \\
&= -\frac{1-\epsilon}{\epsilon}\widetilde{\eta} p_t(i,j) + \frac{1-\epsilon}{\epsilon}\left(\widetilde{\eta} - \eta\right) p_t(i) + (\mu - \frac{1}{\epsilon}a - log(\epsilon)) \\
&\quad + \left(1 + \frac{1-\epsilon}{\epsilon}\right) q_t + \frac{1-\epsilon}{\epsilon}(\eta - 1)\, p_t + \frac{1-\epsilon}{\epsilon}(\eta - 1)\,\theta_t(i) \\
&= \frac{\frac{1-\epsilon}{\epsilon}\left(\widetilde{\eta} - \eta\right)}{1 + \frac{1-\epsilon}{\epsilon}\widetilde{\eta}} p_t(i) + \frac{1}{1 + \frac{1-\epsilon}{\epsilon}\widetilde{\eta}}(\mu - \frac{1}{\epsilon}a - log(\epsilon)) \\
&\quad + \frac{1 + \frac{1-\epsilon}{\epsilon}}{1 + \frac{1-\epsilon}{\epsilon}\widetilde{\eta}} q_t + \frac{\frac{1-\epsilon}{\epsilon}(\eta - 1)}{1 + \frac{1-\epsilon}{\epsilon}\widetilde{\eta}} p_t + \frac{\frac{1-\epsilon}{\epsilon}(\eta - 1)}{1 + \frac{1-\epsilon}{\epsilon}\widetilde{\eta}} \theta_t(i) \\
&= \frac{\left(\widetilde{\eta} - \eta\right)(1-\epsilon)}{\epsilon + \widetilde{\eta}\,(1-\epsilon)} p_t(i) + \frac{\epsilon}{\epsilon + \widetilde{\eta}\,(1-\epsilon)}(\mu - \frac{1}{\epsilon}a - log(\epsilon)) \\
&\quad + \frac{1}{\epsilon + \widetilde{\eta}\,(1-\epsilon)} q_t + \frac{(1-\epsilon)(\eta - 1)}{\epsilon + \widetilde{\eta}\,(1-\epsilon)} p_t + \frac{(1-\epsilon)(\eta - 1)}{\epsilon + \widetilde{\eta}\,(1-\epsilon)} \theta_t(i).
\end{aligned}$$

E Numerical Solution to the Model

The model is calibrated on a quarterly frequency while the (first-order) auto-correlation of the aggregate and idiosyncratic components of demand in survey data is in an annual frequency. To map the empirical persistence of shocks in an annual frequency into the model with a quarterly frequency, we set the first-order auto correlation of aggregate components of demand as $\rho_u = 0.58$ so that correlation of the fluctuation of the aggregate component of demand four quarters (i.e., one year) ago and current fluctuation of aggregate components of demand ($Corr\left(u_t, u_{t-4}\right) = \rho_u^4 \approx 0.11$) matches the empirical auto-correlation on a yearly basis observed in Table 6. Note that, the shock process by equation (2 indicates the following equation:

$$u_t = \rho_u u_{t-1} + e_t = \rho_u^4 u_{t-4} + \rho_u^3 e_{t-3} + \rho_u^2 e_{t-2} + \rho_u e_{t-1} + e_t,$$

and thus $Corr\left(u_t, u_{t-4}\right) = \rho_u^4$ holds in our model. Similarly, we set the first-order auto correlation of sector-specific components of demand as $\rho_v = 0.30$ so that correlation of the fluctuation of the sector-specific component of demand four quarters (i.e., one year) ago and current fluctuation of sector-specific components of demand ($Corr\left(\widehat{v}_t, \widehat{v}_{t-4}\right) = \frac{\rho_v^3(1-\rho_v)(\rho_v+1-\rho_v^2)}{2} \approx 0.01$) takes a lower value than that of aggregate component of demand as is consistent to the empirical persistence of sector-specific component of demand in Table 2. Note that the shock process by equations (3) and (5) indicate the following equation

$$\widehat{v}_t = \left(\rho_v - 1\right) v_{t-1}(i) + \epsilon_t(i),$$

and thus $Corr\left(\widehat{v}_t, \widehat{v}_{t-4}\right) = \frac{\rho_v^3(1-\rho_v)(\rho_v+1-\rho_v^2)}{2}$ holds in our model.

F Proofs of Propositions

F.1 Proof of Proposition 1

The terms $\mathbb{E}_t\left[u_t\right]$ and $\mathbb{E}_t\left[v_t(i)\right]$ are equal to:

$$\begin{aligned}
\mathbb{E}_t\left[u_t\right] &= \frac{\tau^2}{\sigma^2+\tau^2}\left(q_{t-1}+\rho_u u_{t-1}\right) + \frac{\sigma^2}{\sigma^2+\tau^2}\left[x_t(i) - \rho_v v_{t-1}(i)\right] - q_{t-1} \\
&= \rho_u u_{t-1} + \frac{\sigma^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right] \\
&= \rho_u u_{t-1} + \frac{\sigma^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right] \\
\mathbb{E}_t\left[v_t(i)\right] &= \frac{\sigma^2}{\sigma^2+\tau^2}\rho_v v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1}\right] \\
&= \rho_v v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right] \\
&= \rho_v v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right]
\end{aligned}$$

Thus, $\mathbb{E}_t\left[\tilde{v}_t\right]$ is given by,

$$\begin{aligned}
\mathbb{E}_t\left[\tilde{v}_t(i)\right] &= \rho_v v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right] - v_{t-1}(i) \\
&= (\rho_v - 1) v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[e_t + \epsilon_t(i)\right]. \square
\end{aligned}$$

F.2 Proof of Proposition 2

$$\mathbb{C}(\mathbb{E}_t\left[u_t\right], \mathbb{E}_t\left[\tilde{v}_t\right]) = \frac{\sigma^2}{\sigma^2+\tau^2}\frac{\tau^2}{\sigma^2+\tau^2}\mathbb{V}[e_t + \epsilon_t(i)] = \frac{\sigma^2\tau^2}{\sigma^2+\tau^2} > 0. \square$$

F.3 Proof of Proposition 3

The terms $\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right]$ and $\mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]$ are equal to:

$$\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right] = \frac{1-{\rho_u}^{k+1}}{1-\rho_u}\mathbb{E}_t\left[u_t\right],$$

$$\mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right] = \frac{1-{\rho_v}^{k+1}}{1-\rho_v}\mathbb{E}_t\left[\tilde{v}_t\right],$$

respectively. It follows that:

$$\mathbb{C}\left(\mathbb{E}_t\left[\sum_{h=1}^{k} u_{t+h}\right]\mathbb{E}_t\left[\sum_{h=1}^{k} \widetilde{v}_{t+h}(i)\right]\right) = \frac{1-{\rho_u}^{k+1}}{1-\rho_u}\frac{1-{\rho_v}^{k+1}}{1-\rho_v}\mathbb{C}\left(\mathbb{E}_t\left[u_t\right]\mathbb{E}_t,\left[\tilde{v}_t\right]\right) > 0\Box.$$

F.4 Proof of Proposition 4

First, we guess that $p_t^*(i)$ takes the following form:

$$p_t^*(i) = a_1 p_{t-1} + a_2 x_t(i) + a_3 q_{t-1} + a_4 u_{t-1} + a_5 v_{t-1}(i).$$

Given the guess, and since only a randomly selected fraction $1-\theta$ of firms adjusts prices in any given period, we infer that the aggregate price level must satisfy:

$$\begin{aligned} p_t &= \theta p_{t-1} + (1-\theta)\int_0^1 p_t^*(i)di \\ &= \left[\theta + (1-\theta)\, a_1\right] p_{t-1} + (1-\theta)\, a_2 q_t + (1-\theta)\, a_3 q_{t-1} + (1-\theta)\, a_4 u_{t-1}. \end{aligned}$$

Therefore, $p_t^*(i)$ is obtained as:

$$\begin{aligned} p_t^*(i) &= (1-\beta\theta)\left[(1-r)x_t(i) + r\mathbb{E}_t\left[p_t\right]\right] \ + \beta\theta\mathbb{E}_t[p_{t+1}^*(i)] \\ &= (1-\beta\theta)(1-r)x_t(i) + (1-\beta\theta)r\mathbb{E}_t\left[p_t\right] + \beta\theta\mathbb{E}_t[p_{t+1}^*(i)] \\ &= (1-\beta\theta)(1-r)x_t(i) + (1-\beta\theta)r\mathbb{E}_t\left[p_t\right] \\ &\quad + \beta\theta\mathbb{E}_t\left[a_1 p_t + a_2 x_{t+1}(i) + a_3 q_t + a_4 u_t + a_5 v_t(i)\right] \\ &= (1-\beta\theta)(1-r)x_t(i) + \left[(1-\beta\theta)r + \beta\theta a_1\right]\mathbb{E}_t\left[p_t\right] \\ &\quad + \beta\theta a_2\mathbb{E}_t\left[x_{t+1}(i)\right] + \beta\theta a_3\mathbb{E}_t\left[q_t\right] + \beta\theta a_4\mathbb{E}_t\left[u_t\right] + \beta\theta a_5\mathbb{E}_t\left[v_t(i)\right] \\ &= (1-\beta\theta)(1-r)x_t(i) + \left[(1-\beta\theta)r + \beta\theta a_1\right]\mathbb{E}_t\left[p_t\right] \\ &\quad + \beta\theta a_2\mathbb{E}_t\left[q_t + u_{t+1} + v_{t+1}(i)\right] + \beta\theta a_3\mathbb{E}_t\left[q_t\right] + \beta\theta a_4\mathbb{E}_t\left[u_t\right] + \beta\theta a_5\mathbb{E}_t\left[v_t(i)\right] \\ &= (1-\beta\theta)(1-r)x_t(i) + \left[(1-\beta\theta)r + \beta\theta a_1\right]\mathbb{E}_t\left[p_t\right] \\ &\quad + \beta\theta\left(a_2 + a_3\right)\mathbb{E}_t\left[q_t\right] + \beta\theta\left(a_2\rho_u + a_4\right)\mathbb{E}_t\left[u_t\right] + \beta\theta\left(a_2\rho_v + a_5\right)\mathbb{E}_t\left[v_t(i)\right]. \end{aligned}$$

The term $\mathbb{E}_t[p_t]$ is given by:

$$\mathbb{E}_t[p_t] = [\theta + (1-\theta)a_1]p_{t-1} + (1-\theta)a_2\mathbb{E}_t[q_t] + (1-\theta)a_3q_{t-1} + (1-\theta)a_4u_{t-1},$$

which yields:

$$\begin{aligned}
p_t^*(i) &= (1-\beta\theta)(1-r)x_t(i) + [(1-\beta\theta)r + \beta\theta a_1][\theta + (1-\theta)a_1]p_{t-1} \\
&\quad + [[(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_2 + \beta\theta(a_2+a_3)]\mathbb{E}_t[q_t] \\
&\quad + [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_3q_{t-1} \\
&\quad + [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_4u_{t-1} \\
&\quad + \beta\theta(a_2\rho_u + a_4)\mathbb{E}_t[u_t] + \beta\theta(a_2\rho_v + a_5)\mathbb{E}_t[v_t(i)] \\
&= (1-\beta\theta)(1-r)x_t(i) + [(1-\beta\theta)r + \beta\theta a_1][\theta + (1-\theta)a_1]p_{t-1} \\
&\quad + [[[(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_2 + \beta\theta(a_2+a_3)] + [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_3]q_{t-1} \\
&\quad + [[[(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_2 + \beta\theta(a_2+a_3)] + \beta\theta(a_2\rho_u + a_4)]\mathbb{E}_t[u_t] \\
&\quad + \beta\theta(a_2\rho_v + a_5)\mathbb{E}_t[v_t(i)] \\
&\quad + [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_4u_{t-1} \\
&= (1-\beta\theta)(1-r)x_t(i) + [(1-\beta\theta)r + \beta\theta a_1][\theta + (1-\theta)a_1]p_{t-1} \\
&\quad + b_1q_{t-1} + b_2\mathbb{E}_t[u_t] + b_3\mathbb{E}_t[v_t(i)] + b_4u_{t-1}.
\end{aligned}$$

where

$$\begin{aligned}
b_1 &= [[(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_2 + \beta\theta(a_2+a_3)] + [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_3, \\
b_2 &= [[(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_2 + \beta\theta(a_2+a_3)] + \beta\theta(a_2\rho_u + a_4), \\
b_3 &= \beta\theta(a_2\rho_v + a_5), \\
b_4 &= [(1-\beta\theta)r + \beta\theta a_1](1-\theta)a_4.
\end{aligned}$$

Since

$$\begin{aligned}
x_t(i) &= q_{t-1} + \rho_u u_{t-1} + e_t + \rho_v v_{t-1}(i) + \epsilon_t(i) \\
&\Leftrightarrow e_t = x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i) - \epsilon_t(i), \\
&\Leftrightarrow \epsilon_t(i) = x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i) - e_t,
\end{aligned}$$

The terms $\mathbb{E}_t[u_t]$ and $\mathbb{E}_t[v_t(i)]$ are equal to:

$$\begin{aligned}
\mathbb{E}_t[u_t] &= \rho_u u_{t-1} + \mathbb{E}_t[e_t] \\
&= \rho_u u_{t-1} + \frac{\sigma^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right] \\
\mathbb{E}_t[v_t(i)] &= \rho_v v_{t-1}(i) + \frac{\tau^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right].
\end{aligned}$$

It follows that:

$$\begin{aligned}
p_t^*(i) &= (1-\beta\theta)(1-r)x_t(i) + \left[(1-\beta\theta)r + \beta\theta a_1\right]\left[\theta + (1-\theta)a_1\right]p_{t-1} \\
&\quad + b_1 q_{t-1} + b_2\mathbb{E}_t[u_t] + b_3\mathbb{E}_t[v_t(i)] + b_4 u_{t-1} \\
&= (1-\beta\theta)(1-r)x_t(i) + \left[(1-\beta\theta)r + \beta\theta a_1\right]\left[\theta + (1-\theta)a_1\right]p_{t-1} \\
&\quad + b_2\rho_u u_{t-1} + b_2\frac{\sigma^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right] \\
&\quad + b_3\rho_v v_{t-1}(i) + b_3\frac{\tau^2}{\sigma^2+\tau^2}\left[x_t(i) - q_{t-1} - \rho_u u_{t-1} - \rho_v v_{t-1}(i)\right] \\
&\quad + b_4 u_{t-1} + b_1 q_{t-1} \\
&= \left[(1-\beta\theta)r + \beta\theta a_1\right]\left[\theta + (1-\theta)a_1\right]p_{t-1} \\
&\quad + \left[(1-\beta\theta)(1-r) + b_2\frac{\sigma^2}{\sigma^2+\tau^2} + b_3\frac{\tau^2}{\sigma^2+\tau^2}\right]x_t(i) \\
&\quad + \left[b_1 - b_2\frac{\sigma^2}{\sigma^2+\tau^2} - b_3\frac{\tau^2}{\sigma^2+\tau^2}\right]q_{t-1} \\
&\quad + \left[b_4 + (b_2 - b_3)\frac{\tau^2}{\sigma^2+\tau^2}\rho_u\right]u_{t-1} + \left[b_3 - b_2\right]\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v v_{t-1}(i),
\end{aligned}$$

and thus the equilibrium conditions are:

$$\begin{aligned}
a_1 &= \left[(1-\beta\theta)r + \beta\theta a_1\right]\left[\theta + (1-\theta)a_1\right], \\
a_2 &= (1-\beta\theta)(1-r) + b_2\frac{\sigma^2}{\sigma^2+\tau^2} + b_3\frac{\tau^2}{\sigma^2+\tau^2}, \\
a_3 &= b_1 - b_2\frac{\sigma^2}{\sigma^2+\tau^2} - b_3\frac{\tau^2}{\sigma^2+\tau^2}, \\
a_4 &= b_4 + (b_2 - b_3)\frac{\tau^2}{\sigma^2+\tau^2}\rho_u, \\
a_5 &= \left[b_3 - b_2\right]\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v,
\end{aligned}$$

By simplifying the conditions, we obtain:

$$a_1 = \left[(1-\beta\theta)r + \beta\theta a_1\right]\left[\theta + (1-\theta)a_1\right],$$

$$
\begin{aligned}
a_2 &= (1-\beta\theta)(1-r) \\
&\quad + \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_2 + \beta\theta\left(a_2 + a_3\right)\right] \frac{\sigma^2}{\sigma^2+\tau^2} \\
&\quad + \beta\theta\left(a_2\rho_u + a_4\right)\frac{\sigma^2}{\sigma^2+\tau^2} + \beta\theta\left(a_2\rho_v + a_5\right)\frac{\tau^2}{\sigma^2+\tau^2} \\
&= (1-\beta\theta)(1-r) \\
&\quad + \left[\left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta) + \beta\theta\right]\frac{\sigma^2}{\sigma^2+\tau^2} + \beta\theta\left[\rho_u\frac{\sigma^2}{\sigma^2+\tau^2} + \rho_v\frac{\tau^2}{\sigma^2+\tau^2}\right]\right] a_2 \\
&\quad + \beta\theta\frac{\sigma^2}{\sigma^2+\tau^2}a_3 + \beta\theta\frac{\sigma^2}{\sigma^2+\tau^2}a_4 + \beta\theta\frac{\tau^2}{\sigma^2+\tau^2}a_5,
\end{aligned}
$$

$$
\begin{aligned}
a_3 &= \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_2 + \beta\theta\left(a_2 + a_3\right)\right]\frac{\tau^2}{\sigma^2+\tau^2} \\
&\quad + \left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_3 - \frac{\sigma^2}{\sigma^2+\tau^2}\beta\theta\left(a_2\rho_u + a_4\right) \\
&\quad - \frac{\tau^2}{\sigma^2+\tau^2}\beta\theta\left(a_2\rho_v + a_5\right) \\
&= \left[\left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta) + \beta\theta\right]\frac{\tau^2}{\sigma^2+\tau^2} - \frac{\sigma^2}{\sigma^2+\tau^2}\beta\theta\rho_u - \frac{\tau^2}{\sigma^2+\tau^2}\beta\theta\rho_v\right] a_2 \\
&\quad + \left[\beta\theta\frac{\tau^2}{\sigma^2+\tau^2} + \left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\right] a_3 \\
&\quad - \frac{\sigma^2}{\sigma^2+\tau^2}\beta\theta a_4 - \frac{\tau^2}{\sigma^2+\tau^2}\beta\theta a_5,
\end{aligned}
$$

$$
\begin{aligned}
a_4 &= \left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_4 \\
&\quad + \left[\begin{array}{c} \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_2 + \beta\theta\left(a_2 + a_3\right)\right] \\ + \beta\theta\left(a_2\rho_u + a_4\right) - \beta\theta\left(a_2\rho_v + a_5\right) \end{array}\right]\frac{\tau^2}{\sigma^2+\tau^2}\rho_u \\
&= \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta) + \beta\theta + \beta\theta\rho_u - \beta\theta\rho_v\right]\frac{\tau^2}{\sigma^2+\tau^2}\rho_u a_2 + \beta\theta\frac{\tau^2}{\sigma^2+\tau^2}\rho_u a_3 \\
&\quad + \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta) + \beta\theta\frac{\tau^2}{\sigma^2+\tau^2}\rho_u\right] a_4 - \beta\theta\frac{\tau^2}{\sigma^2+\tau^2}\rho_u a_5,
\end{aligned}
$$

$$
\begin{aligned}
a_5 &= -\left[\begin{array}{c} \left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta)\, a_2 + \beta\theta\left(a_2 + a_3\right)\right] \\ + \beta\theta\left(a_2\rho_u + a_4\right) - \beta\theta\left(a_2\rho_v + a_5\right) \end{array}\right]\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v \\
&= -\left[\left[(1-\beta\theta)r + \beta\theta a_1\right](1-\theta) + \beta\theta + \beta\theta\rho_u - \beta\theta\rho_v\right]\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v a_2 \\
&\quad - \beta\theta\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v a_3 - \beta\theta\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v a_4 + \beta\theta\frac{\sigma^2}{\sigma^2+\tau^2}\rho_v a_5. \square
\end{aligned}
$$

G Survey and National Account Data

G.1 Survey Data

The Annual Survey of Corporate Behavior (ASCB) is administered by the Cabinet Office of Japan across 21 sectors in the economy over the period 2003-2017. The Economic and Social Research Institute in the Cabinet Office of Japan directly surveys approximately 1,000 public-listed Japanese firms on nominal and real growth rates of the Japanese economy as well as nominal and real growth rates of demand in their respective sectors (31 sectors in total).[25] The Cabinet Office of Japan releases the arithmetic averages of the individual firms' expectations within each sector while retaining the data on the expectations of the individual firms confidential.

The industries included in our sample are Foods, Textiles and Apparels, Pulp and Paper, Chemicals, Glass and Ceramics Products, Iron and Steel, Nonferrous Metals, Metal Products, Machinery, Electric Appliances, Transportation Equipment, Precision Instruments, Construction, Wholesale Trade, Retail Trade, Real Estate, Land Transportation, Warehousing and Harbor Transportation Services, Information and Communication, Electric Power and Gas, and Services. We proxy expectations on aggregate demand with survey data on expectations on one-year-ahead GDP growth, and we proxy expectations on total sectoral demand with survey data on expectations on one-year-ahead growth rate in total sectoral demand (industry-level output).

The data provide aggregate responses from surveys for the universe of Japanese firms on expectations within the same enterprise about the one-year-ahead growth rate of total sectoral demand and aggregate demand. Since total sectoral demand compounds aggregate and sector-specific components of demand, we infer expectations on the sector-specific component of demand as the difference between the expectations of total sectoral demand and aggregate demand.

Table 5 provides summary statistics on salient stylized facts on the expectations in the aggregate and sector-specific components of demand. Columns (1) and (2) shows historical averages of the changes in the expectations of one-year-ahead growth rate of aggregate and sector-specific demand, respectively. Entries reveal large differences in the changes of

[25] Sectoral averages are publicly available at: http://www.esri.cao.go.jp/en/stat/ank/ank-e.html. The survey is conducted each January, and questionnaires are available at: http://www.esri.cao.go.jp/en/stat/ank/h28ank/h28ank_questionnaire.pdf.

Table 5: Descriptive statistics about survey data

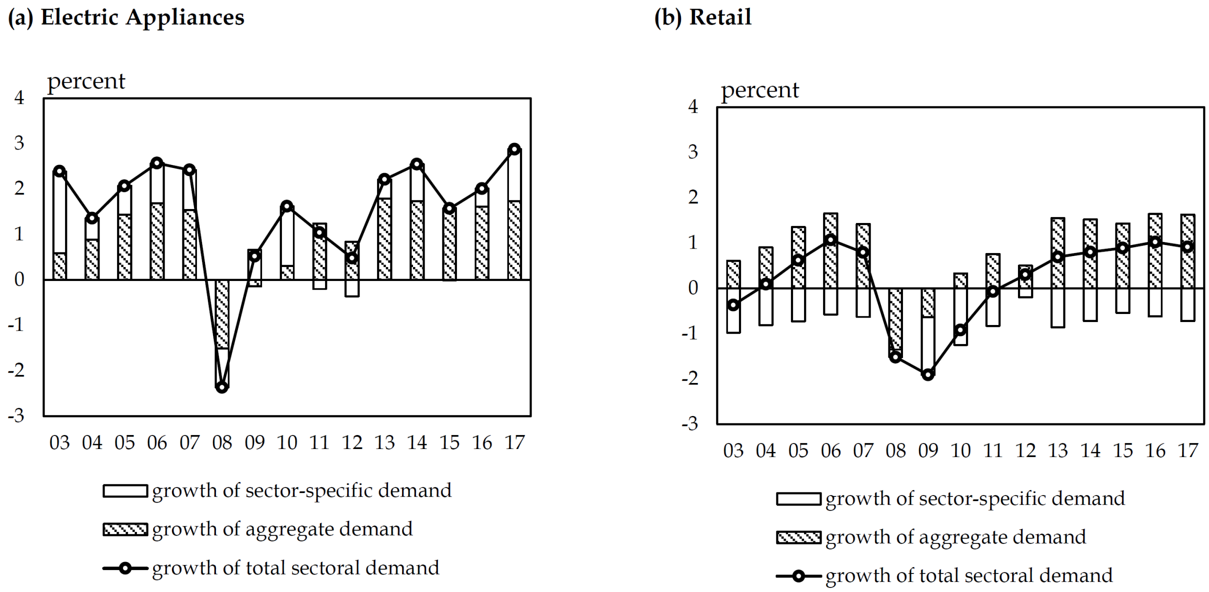
Dataset: Annual survey of corporate behavior; 21 sectors; 2003y-2017y

Sector	*Historical averages*		*Historical standard deviation*		*First-order auto correlation*		*Average sample size*
	(1) Growth of aggregate demand	*(2) Growth of sector-specific demand*	*(3) Growth of aggregate demand*	*(4) Growth of sector-specific demand*	*(5) Growth of aggregate demand*	*(6) Growth of sector-specific demand*	
Foods	1.01	-0.55	0.81	0.51	0.39	0.21	41
Textiles & Apparels	1.02	-0.81	0.84	0.27	0.26	-0.48	28
Pulp & Paper	0.92	-1.12	1.06	1.00	0.33	0.14	11
Chemicals	1.05	-0.03	0.98	0.32	0.25	0.32	73
Glass & Ceramics Products	0.86	-0.54	1.03	0.45	0.24	0.00	20
Iron & Steel	0.92	-0.55	1.03	1.83	0.32	-0.03	23
Nonferrous Metals	1.02	-0.22	1.00	1.64	0.34	0.08	16
Metal Products	0.90	-0.73	0.86	0.85	0.44	0.12	30
Machinery	1.05	0.05	0.97	1.49	0.43	-0.22	78
Electric Appliances	1.02	0.53	0.92	0.68	0.39	-0.10	93
Transportation Equipment	0.98	-0.07	0.99	1.44	0.26	0.17	41
Precision Instruments	1.17	0.18	0.99	0.91	0.62	0.44	13
Construction	1.06	-1.44	0.90	1.17	0.51	0.49	75
Wholesale Trade	1.01	-0.33	0.95	0.37	0.37	0.26	94
Retail Trade	0.89	-0.73	0.90	0.31	0.50	0.02	72
Real Estate	0.96	0.70	0.80	1.35	0.28	0.01	21
Land Transportation	1.02	-0.83	0.78	0.45	0.50	0.31	27
Warehousing & Harbor Transportation Services	1.12	-0.32	0.71	0.29	0.29	0.43	16
Information & Communication	0.95	0.70	0.94	0.91	0.14	0.39	42
Electric Power & Gas	1.19	0.40	1.10	1.03	0.20	0.68	18
Services	0.96	0.32	0.85	0.80	0.44	-0.17	51
Averages across all (31) sectors	1.01	-0.24	0.92	0.81	0.35	0.15	1,019

expectations between the two distinct components of demand. Changes in the expectations of aggregate demand are broadly similar across sectors while changes in the expectations of sector-specific demand differ markedly across sectors. Columns (3) and (4) list historical standard errors of the sectoral average expectations and reveal that both components have sizeable similar volatilities over the sample period. Historical standard deviations are computed as the time-series variation in the sector-level aggregate expectations about the growth of aggregate demand and that of sector-specific demand. Columns (5) and (6) show that the serial correlation of the aggregate component is twice as large as the serial correlation of the sector-specific component.

Figure 4 provides an illustrative example for the electric appliances (panel a) and the retail sectors (panel b), respectively, on the contribution of aggregate and sector-specific component of demand to total secotral demand. The panels show that expectations of the growth of total sectoral demand (black line) are similar across the two sectors. The expectations about sector-specific demand are positive in the early 2000s, they turn negative during 2008 at the time of the global financial crisis, and return positive afterwards. The contribution of the aggregate component of demand (gray bar) is also similar. Moreover, in both sectors, changes in the expectations of sector-specific demand are of similar magnitude to those of aggregate demand. These facts are consistent with the broader evidence in Table

Figure 4: Firms' expectations about their total demand partitioned between aggregate and sector-specific demand



5.

G.2 National Account Data

We compare the statics from survey data with data on aggregate and sector-specific demand in each of the major 21 sectors in the economy from the National Account for Japan (SNA) provided by the Cabinet Office over the period 2004-2018. The data provide statistics of observed changes in aggregate and total sectoral demand that we can compare to those of the equivalent series from the survey data. To equate the measurement between the survey and SNA statistics, we proxy the growth rate of the realized aggregate demand by the growth rate of net nominal output and the growth rate of the realized total sectoral demand by the growth rate of gross nominal output. We then calculate the growth rate of the realized sector-specific demand by subtracting that of realized aggregate demand from that of total sectoral demand. Table 6 provides summary statistics of the data on aggregate and sector-specific components of demand using the same classification in the survey data. There are small differences in the classification between datasets. Columns (1) and (2) show the historical averages, columns (3) and (4) historical standard deviations, and columns (5) and (6) first-order correlation of aggregate and sector-specific components of demand, respectively. Comparison between Tables 5 and 6 shows important differences between the

Table 6: Descriptive statistics about output data

Dataset: SNA statistics; 21 sectors; 2004y-2018y						
	Historical averages		*Historical standard deviation*		*First-order auto correlation*	
Sector	*(1) Growth of aggregate demand*	*(2) Growth of sector-specific demand*	*(3) Growth of aggregate demand*	*(4) Growth of sector-specific demand*	*(5) Growth of aggregate demand*	*(6) Growth of sector-specific demand*
Foods	0.41	0.41	2.27	2.18	0.11	0.27
Textiles & Apparels		-3.19		5.53		-0.01
Pulp & Paper		0.07		4.79		-0.33
Chemicals		1.40		6.43		-0.30
Glass & Ceramics Products		-0.10		7.08		-0.17
Iron & Steel		4.84		14.29		-0.16
Nonferrous Metals		4.84		14.29		-0.16
Metal Products		0.53		5.90		0.14
Machinery		2.43		10.19		-0.04
Electric Appliances		1.55		7.12		-0.09
Transportation Equipment		2.69		10.87		-0.45
Precision Instruments		-0.28		10.37		-0.09
Construction		0.33		4.84		0.57
Wholesale Trade		0.80		3.41		-0.24
Retail Trade		0.80		3.41		-0.24
Real Estate		0.97		0.87		0.76
Land Transportation		0.51		4.35		0.02
Warehousing & Harbor Transportation Services		0.51		4.35		0.02
Information & Communication		0.94		1.46		0.23
Electric Power & Gas		1.17		3.58		0.03
Services		-0.25		2.13		0.41

statistics from the survey data and the observed data, providing further evidence that firms' expectations are not a mere reflection of the underlying observed changes in the different components of demand. For instance, the volatility and auto-correlation of the aggregate and sector-specific components of demand are larger in the survey data.

G.3 Matching the Classification from Survey and National Account Data

The firms and classification of the sectors in the National Account for Japan are matched with those from the survey data in Table 5. Regarding the sample of firms, the survey covers large firms' activities while the SNA conceptually covers the universe of firms' activities. Regarding the classification of the sectors, we match the sectoral series in the SNA (y) to those in the survey (x) as follows (x→ y). (1) Foods → Food products and beverages, (2) Textiles and Apparels → Textile products, (3) Pulp and Paper → Pulp, paper and paper products, (4) Chemicals → Chemicals, (5) Glass and Ceramics Products → Non-metallic mineral products, (6) Iron and Steel → Basic metal, (7) Nonferrous Metals → Basic metal, (8) Metal Products → Fabricated metal products, (9) Machinery → General-purpose, production and business oriented machinery, (10) Electric Appliances → Electrical machinery, equipment and supplies, (11) Transportation Equipment $\rightarrow$ Transport equipment, (12) Precision Instruments $\rightarrow$ Information and communication electronics equipment, (13) Construction $\rightarrow$ Construction, (14) Wholesale Trade $\rightarrow$ Wholesale and retail trade, (15) Retail Trade $\rightarrow$ Wholesale and retail trade, (16) Real Estate $\rightarrow$ Real estate, (17) Land Transportation $\rightarrow$ Transport and postal services, (18) Warehousing and Harbor Transportation Services $\rightarrow$ Transport and postal services, (19) Information and Communication $\rightarrow$ Information and communications, (20) Electric Power and Gas $\rightarrow$ Electricity, gas and water supply, waste management service, and (21) Services $\rightarrow$ Accommodation and food service activities.

H Cross-Sectional Evidence on the Imperfect Information

This section provides the additional evidence on the imperfect information that the firms cannot disentangle the aggregate and sector-specific fluctuations in their total sectoral demand. The dataset is extended to include the small firms in addition to publicly listed large firms. Due to the data limitation of the survey to the small firms, the sample of this regression is cross-sectional dataset by firm size and by industry in 2017 year. We explore whether the sub-group of large firms exhibit higher or lower values in both of the expectations on the growth rate of aggregate and sector-specific demands than small firms.

Table 7 in panel (a) shows that dummy for publicly listed firms is positive and statistically significant, indicating that large firms' expectations on aggregate demand is higher than small firms. The panel (b) also shows that dummy for publicly listed firms is positive and statistically significant, indicating that large firms' expectations on sector-specific demand is higher than small firms. Hence, using the cross-sectional dataset, we confirm the empirical regularities in the main analysis that the firms whose expectations on the growth rate of the aggregate demand are higher tend to hold higher expectations on the growth rate of the sector-specific demand and vice versa (i.e. co-movement between their expectations on the growth rates of aggregate and sector-specific demand).

I Financial Statements Statistics of Corporations Data

We use quarterly data on sector-level sales of Japanese firms from the Financial Statements Statistics of Corporations by Industry, compiled by the Ministry of Finance of Japan. The data cover the period 1975:Q3-2018:Q3 for 29 major sectors in the economy. Specifically,

Table 7: Firms' expectations on aggregate and sector-specific demands by firm size

(a) Aggregate demand

Dataset: Annual survey of corporate behavior; 31 sectors; 2017y

Dependent Variable: firms' expectations on the growth rate of the aggregate demand

	One year ahead expectations
Constant	1.52***
	(0.01)
Dummy for Publicly listed firms	**0.20*****
	(0.04)
Observations	62
Adjusted-R^2	0.03

(b) Sector-specific demand

Dataset: Annual survey of corporate behavior; 31 sectors; 2017y

Dependent Variable: firms' expectations on the growth rate of the sector-specific demand

	One year ahead expectations
Constant	-0.38***
	(0.01)
Dummy for Publicly listed firms	**0.32***
	(0.18)
Observations	62
Adjusted-R^2	0.04

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators.

**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

the following sectors are included in our dataset: Foods, Textiles, Wood Products, Pulp and Paper, Printing, Chemicals, Oil and Coal Products, Glass and Ceramics Products, Iron and Steel, Nonferrous Metals, Metal Products, Machinery, Electric Devices, Cars and Related Products, Other Transportation Equipment, Other Products, Mining, Construction, Electric Power, Gas and Water Supply, Information and Communication, Land Transportation, Water Transportation, Wholesale, Retail, Real Estate, Hotel, Living-Related Service, Other Service. The data is available at http://www.mof.go.jp/english/pri/reference/ssc/index.htm.

Table 8 reports summary statistics for the sector(industry)-level sales data. Column (1) lists the historical averages of the quarter-on-quarter sales growth in each sector, which are all positive. Columns (2) and (3) show the standard deviation and first-order auto correlation of the sales growth in each sector and confirm the high volatility and low persistent of the sectoral sales.

J Extracting the Sequence of Shocks on Aggregate and Sector-Specific Components of Demand

To extract the sequence of shocks on aggregate and sector-specific components of demand $(e_t, \{\epsilon_t(i)\}_{i=1}^{29})$, we decompose fluctuations in aggregate and sector-specific components (i.e.,

Table 8: Descriptive statistics about sales data

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 sectors; 1975/3Q-2018/3Q

Sector	*(1) Historical averages*	*(2) Historical standard deviation*	*(3) First-order auto correlation*
Foods	0.68	3.85	-0.15
Textiles	0.02	7.22	-0.14
Wood Products	0.18	10.73	-0.10
Pulp and Paper	0.42	6.15	0.04
Printing	0.49	7.15	-0.13
Chemicals	0.63	3.96	0.12
Oil and Coal Products	0.12	9.59	0.02
Glass and Ceramics Products	0.37	5.16	-0.08
Iron and Steel	0.32	5.43	0.24
Nonferrous Metals	0.67	6.53	0.34
Metal Product	0.79	6.53	-0.04
Machinery	0.92	4.58	0.13
Electric Device	1.01	4.59	0.26
Cars and Related Products	1.11	5.98	0.13
Other Transportation Equipment	0.25	9.47	-0.23
Other Products	0.87	7.53	-0.23
Mining	0.39	10.98	-0.16
Construction	0.94	3.50	0.01
Electric Power	1.03	3.81	0.11
Gas and Water Supply	1.01	3.83	0.22
Information and Communication	1.82	5.03	-0.02
Land Transportation	1.09	5.14	-0.04
Water Transportation	0.25	6.04	0.10
Whole-sale	0.53	4.26	-0.02
Retail	1.35	3.86	0.04
Real Estate	1.14	9.22	-0.14
Hotel	1.25	9.25	-0.03
Living-Related Service	1.65	10.86	-0.09
Other Service.	1.74	10.23	-0.29

$u_t, \{\widetilde{x}_t(i) - u_t\}_{i=1}^{29}$) into expected component and shocks for firms using the equations (2), (3) and (5). More concretely, we use equation (2 that characterizes the law of motion of aggregate demand as:

$$u_t = \rho_u u_{t-1} + e_t,$$

to decompose aggregate demand into the expected component ($\mathbb{E}_{t-1}[u_t] = \rho_u u_{t-1}$) and shock ($e_t$). We estimate the parameter ρ_u and the unobservable shock e_t using the equation:

$$u_t = c_u + \rho_u u_{t-1} + e_t,$$

where c_u is a constant term that normalizes e_t to have mean zero. We then proxy the shock to aggregate demand as:

$$\widehat{e}_t = u_t - \widehat{c}_u - \widehat{\rho}_u u_{t-1},$$

and the variance of the shock $\sigma_t^2 = \mathbb{V}(e_t) = \mathbb{E}[e_t^2]$ is approximated by $\frac{1}{2k+1}\Sigma_{s=-k}^{k}\widehat{e}_t^2$.

Similarly, we use equation (3) that characterizes the law of motion of sector-specific demand ($\{\widetilde{v}_t(i)\}_{i=1}^{29}$) as:

$$\widetilde{v}_t(i) = v_t(i) - v_{t-1}(i) = \rho_v \left(v_{t-1}(i) - v_{t-2}(i)\right) + \epsilon_t(i) - \epsilon_{t-1}(i) = \rho_v \widetilde{v}_{t-1}(i) + \epsilon_t(i) - \epsilon_{t-1}(i),$$

to decompose sector-specific demand into the expected component ($\mathbb{E}_{t-1}[\widetilde{v}_t(i)] = \rho_v \widetilde{v}_{t-1}(i) - \epsilon_{t-1}(i)$) and shock ($\epsilon_t(i)$). Since ($\rho_v, \epsilon_t(i), \epsilon_{t-1}(i)$) are unobservable for us, we estimate them from following empirical equation to obtain ($\rho_v, \epsilon_t(i) - \epsilon_{t-1}(i)$) :

$$\left(\widetilde{x}_t(i) - u_t\right) = c_v(i) + \rho_v \left(\widetilde{x}_{t-1}(i) - u_{t-1}\right) + \left(\epsilon_t(i) - \epsilon_{t-1}(i)\right),$$

where $c_v(i)$ is a constant term to normalize $\epsilon_t(i) - \epsilon_{t-1}(i)$ as mean zero. We then obtain

$$\widehat{\epsilon}_t(i) - \widehat{\epsilon}_{t-1}(i) = \left(\widetilde{x}_t(i) - u_t\right) - \widehat{c}_v(i) - \rho_v \left(\widetilde{x}_{t-1}(i) - u_{t-1}\right)$$

as the proxy for shock on sector-specific demand ($\epsilon_t(i) - \epsilon_{t-1}(i)$). Using the cross-sectional variation of $\widehat{\epsilon}_t(i) - \widehat{\epsilon}_{t-1}(i)$, we approximate $\tau_t^2 = \mathbb{V}(\epsilon_t(i)) = \mathbb{E}[\epsilon_t^2(i)]$ by $\frac{1}{2k+1}\Sigma_{s=-k}^{k}\left(\frac{1}{29}\Sigma_{i=1}^{29}\frac{(\widehat{\epsilon}_t(i)-\widehat{\epsilon}_{t-1}(i))^2}{2}\right)$.[26]

[26]Note that the following equation holds,

$$\begin{aligned} \mathbb{V}\left(\widehat{\epsilon}_t(i) - \widehat{\epsilon}_{t-1}(i)\right) &= \mathbb{E}\left[\left(\widehat{\epsilon}_t(i) - \widehat{\epsilon}_{t-1}(i)\right)^2\right] = 2\mathbb{V}\left(\epsilon_t(i)\right) \\ &\Leftrightarrow \mathbb{V}\left(\epsilon_t(i)\right) = \frac{1}{2}\mathbb{V}\left(\epsilon_t(i) - \epsilon_{t-1}(i)\right), \end{aligned}$$

and thus the variance of $\epsilon_t(i) - \epsilon_{t-1}(i)$ is monotonically increasing in τ_t^2.

Table 9 reports summary statistics for estimates of the aggregate and sector-specific components of demand $\left(u_t, \{\widetilde{x}_t(i) - u_t\}_{i=1}^{29}\right)$ for the average (columns 1 and 2), standard deviation (columns 3 and 4), and first-order autocorrelation (columns 5 and 6) of the series. Columns (7) and (8) report standard deviation of $\widehat{e}_t$ and $\{\widehat{\epsilon}_t(i)\}_{i=1}^{29}$, respectively.

Table 9: Descriptive statistics about aggregate and sector-specific components of demand

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 sectors; 1975/4Q-2018/3Q

	Historical averages		*Historical standard deviation*		*First-order auto correlation*		*Historical standard deviation*	
Sector	*(1) Growth of aggregate demand*	*(2) Growth of sector-specific demand*	*(3) Growth of aggregate demand*	*(4) Growth of sector-specific demand*	*(5) Growth of aggregate demand*	*(6) Growth of sector-specific demand*	*(7) Aggregate shocks*	*(8) Sector-specific shocks*
Foods		-0.04		4.08		0.06		2.88
Textiles		-0.69		6.68		-0.16		4.67
Wood Products		-0.54		10.48		-0.14		7.35
Pulp and Paper		-0.30		5.91		0.00		4.19
Printing		-0.23		7.08		-0.07		5.00
Chemicals		-0.09		3.10		-0.09		2.19
Oil and Coal Products		-0.60		8.38		-0.15		5.88
Glass and Ceramics Products		-0.35		4.95		-0.16		3.47
Iron and Steel		-0.39		4.06		0.04		2.87
Nonferrous Metals		-0.04		4.93		0.09		3.48
Metal Product		0.07		6.14		-0.16		4.30
Machinery		0.21		3.73		-0.20		2.59
Electric Device		0.29		3.35		-0.03		2.37
Cars and Related Products		0.39		4.67		-0.08		3.30
Other Transportation Equipment		-0.47		9.66		-0.21		6.69
Other Products	0.72	0.16	6.22	6.62	0.45	-0.27	2.54	4.51
Mining		-0.32		9.92		-0.27		6.76
Construction		0.22		4.10		0.09		2.87
Electric Power		0.32		4.24		0.07		2.99
Gas and Water Supply		0.30		4.12		0.12		2.89
Information and Communication		1.11		5.22		-0.01		3.70
Land Transportation		0.37		5.51		-0.07		3.89
Water Transportation		-0.47		5.14		-0.07		3.63
Whole-sale		-0.18		3.11		-0.26		2.13
Retail		0.64		3.90		0.03		2.75
Real Estate		0.43		8.65		-0.12		6.08
Hotel		0.53		9.52		-0.02		6.75
Living-Related Service		0.94		11.30		-0.11		7.97
Other Service.		1.02		10.09		-0.29		6.85

K Aggregate Demand and the Output Gap

To evaluate whether the extracted (unnormalized) changes in aggregate demand ($u_t = \Sigma_{i=1}^{29} \Lambda_i \widetilde{x}_t(i)$) is a plausible measure of aggregate disturbances, and it is consistent with alternative measures, we compare the eight-quarters backward moving averages of the changes in aggregate demand, $\frac{1}{8}\Sigma_{s=0}^{7} u_{t-s}$,[27] with the averages of changes in total sectoral demand across sectors ($u_t = \frac{1}{29}\Sigma_{i=1}^{29} \widetilde{x}_t(i)$) and the output gap published by the Bank of Japa n.[28]

[27]Our measure of the changes in aggregate demand is a flow rather than stock concept. By comparing moving averages of the changes in aggregate demand (i.e., the averages of flow data) with the output gap (i.e. stock data), we ensure that our measure is consistent with conventional measures.

[28]The series is available here. https://www.boj.or.jp/en/research/research_data/gap/index.htm/
The description of the methodology for the estimation is here https://www.boj.or.jp/en/research/brp/ron_2017/ron170531a.htm/.

Figure 5: Changes in aggregate demand and output gap

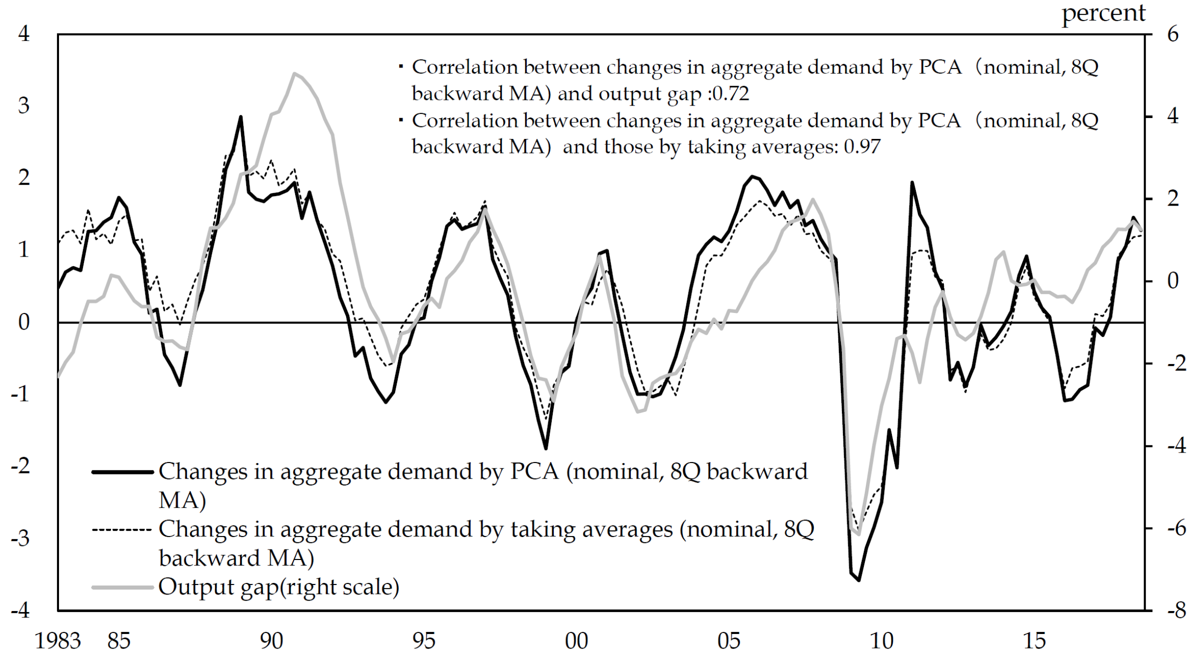


Figure 5 examines the relationship between the dynamics of our estimates for aggregate shocks and the output gaps. It shows that our measure of changes in aggregate demand highly co-moves with the averages of changes in sectoral demand across sectors, with a correlation coefficient equal to 0.97. It also shows that our measure of changes in aggregate demand and the output gap are highly correlated, with a correlation coefficient equal to 0.72, suggesting that our identified measure for the changes in aggregate demand is consistent with alternative measures of the changes in aggregate demand.

L Regressions Based on Changes in Inflation

This section provides the estimation results for the regression based on the changes in regression. Following the equation (31), the empirical equation is as follows:

$$\begin{aligned}\pi_t - \pi_{t-1} =& c_1 + c_2 \left(\pi_{t-1} - \pi_{t-2}\right) + c_3 \mathbf{1}_{\{2000-2018\}} \left(\pi_{t-1} - \pi_{t-2}\right) \\ &+ c_4 \left(\left(\tau_t/\sigma_t\right)\pi_{t-1} - \left(\tau_{t-1}/\sigma_{t-1}\right)\pi_{t-2}\right) + c_5 \left(u_t - u_{t-1}\right) \\ &+ c_6 \mathbf{1}_{\{2000-2018\}} \left(u_t - u_{t-1}\right) + c_7 \left(\left(\tau_t/\sigma_t\right) u_t - \left(\tau_{t-1}/\sigma_{t-1}\right) u_{t-1}\right) \\ &+ c_8 \left(u_{t-1} - u_{t-2}\right) + c_9 \left(u_{t-2} - u_{t-3}\right) + \varepsilon_t^c,\end{aligned} \tag{43}$$

where the coefficients $c_1, \ldots, c_9$ are regression coefficients, and ε_t^c is the error term.

Table 10: Estimation of inflation dynamics (changes in inflation)

Dataset: Financial statement statistics of corporations by industry, consumer price index; 29 sectors; 1976/3Q-2018/3Q				
Dependent Variable: Inflation rate ($\triangle\pi_t$, core consumer price index, seasonally adjusted, QoQ, annualized)				
	2 years trimmed mean	3 years trimmed mean	5 years trimmed mean	10 years trimmed mean
Constant	-0.04	-0.04	-0.04	-0.04
	(0.07)	(0.07)	(0.07)	(0.07)
△Lag of inflation (π_{t-1})	-0.17	-0.23	-0.27	0.38
	(0.14)	(0.19)	(0.14)	(0.36)
△Lag of inflation×time dummy (2000-2018)	-0.24 **	-0.26 *	-0.27 *	-0.22 *
($\pi_{t-1} \times 1_{\{2000-2018\}}$)	(0.12)	(0.13)	(0.14)	(0.11)
△Lag of inflation	-0.00	0.03	-0.06	-0.25 *
×shock heterogeneity ($\pi_{t-1} \times {}^{\tau_t}/_{\sigma_t}$)	(0.05)	(0.07)	(0.10)	(0.14)
△Changes in aggregate demand (u_t)	0.31 ***	0.28 **	0.30 **	0.33
	(0.08	(0.11)	(0.14)	(0.22)
△Changes in aggregate demand ×time	-0.02	-0.01	-0.01	0.03
dummy (2000-2018) ($u_t \times 1_{\{2000-2018\}}$)	(0.07)	(0.08)	(0.08)	(0.08)
△Changes in aggregate demand	**-0.08 *****	**-0.06 ****	**-0.07**	**-0.08**
×shock heterogeneity ($\mathbf{u_t \times {}^{\tau_t}/_{\sigma_t}}$)	(0.03)	(0.03)	(0.04)	(0.08)
Observations	169	169	169	169
Adjusted-R^2	0.21	0.20	0.19	0.19

Note: Estimated by ordinary-least-squares. The standard errors are HAC estimators. First and second lags of differences in changes in aggregate demand are included in estimation as control variables. Data extrapolation using the values in the closest periods is applied for the missing values in the estimates of shock heterogeneity. The series for the core consumer price index is "all items, less fresh food (impact of consumption taxes are adjusted)".
**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

Table 10 shows the estimates for equation (43), using the τ/σ ratio based on time-windows of two year (column 1), three-year (columns 2), five years (column 3) and ten years (column 4), respectively. Important for our analysis, the interaction term between aggregate demand and the degree of shock heterogeneity $((\tau_t/\sigma_t)\,u_t - (\tau_{t-1}/\sigma_{t-1})\,u_{t-1})$ is negative for all entries and significant for columns 1 and 2, implying that a rise in the τ_t/σ_t ratio reduces the positive correlation between inflation and aggregate demand, in accordance with the results of our analysis in the main text.

M Sensitivity of Sectoral Inflation to Movements in Sector-Specific Demand

This section assesses the empirical validity of our model from the perspective of the sectoral inflation dynamics. We derive a measure for sector-specific inflation as the difference between sectoral inflation and aggregate inflation, $\pi_t(i) - \pi_t$, from the theoretical model in Section 3. We first derive a measure of sectoral inflation using the theoretical model by aggregating the optimal price setting equation across firms within each sector, as shown in Appendix F.4. The sectoral inflation rate in sector i $(\pi_t(i))$ is described by the equation:

$$\pi_t(i) = \pi_t + \alpha_2 \widetilde{v}_t(i) + \alpha_5 \widetilde{v}_{t-1}(i) \tag{44}$$

where $\alpha_2 \equiv (1-\theta)a_2$ and $\alpha_5 \equiv a_5(1-\theta)$, as defined in Proposition 4. Equation (44) shows that the sensitivity of the sector-specific component of inflation (i.e., the difference between sectoral inflation and aggregate inflation: $\pi_t(i) - \pi_t$) to changes in current sector-specific demand ($\widetilde{v}_t(i)$) depends on α_2, which we know from our previous analysis in section 4.1 and Figure 2 is negatively related to shock heterogeneity (τ/σ). It is straightforward to see from equation (44) that in our model the sensitivity of the sector-specific component of inflation to changes in current sector-specific demand ($\widetilde{v}_t(i)$) is determined by α_2, which we already know from equation (28) is negatively related to shock heterogeneity (τ/σ). We now investigates whether the model predictions are supported in the data.

To estimate the relationship between the degree of shock heterogeneity and the sensitivity of the sector-specific component of the inflation in each sector to sector-specific demand, we follow the insights from the theoretical model, encapsulated by equation (44), and construct a panel data-set for the sector-specific component of the inflation rates ($\pi_t(i) - \pi_t$), sector-specific demand in each sector ($v_t(i)$), and the measures for shock heterogeneity (τ_t/σ_t) that is common across sectors. We obtain measures for π_t, $v_t(i)$ and τ_t/σ_t from the Financial Statements Statistics of Corporations by Industry, and we measure sectoral inflation $\pi_t(i)$ with the Producer Price index (PPI) in Japan, which is released by the Bank of Japan on a monthly basis.[29] We obtain the series for sector-specific demand ($v_t(i)$) from the PPI dataset. We consider series for 13 manufacturing industries.[30] The empirical specification of sectoral inflation equation is:

$$\pi_t(i) - \pi_t = d_1(i) + (d_2 + d_3 dummy + d_4(\tau_t/\sigma_t))\,\widetilde{v}_t(i) + d_5\widetilde{v}_{t-1}(i) + \varepsilon_t^d, \tag{45}$$

where $d_1(i)$ is fixed effect dummy, parameters d_2-d_5 are regression coefficients, *dummy* is a dummy variable equal to 1 for the period 2000-2018 to control for the years with exogenous fall in price stickiness, as in our benchmark specification, and ε_t^d is the error term.

Table 11 shows the estimates for equation (45) for different measures of shock heterogeneity based on time windows of two years (column 1), three years (columns 2), five years (column 3) and ten years (column 4), respectively. All entries show that the sector-specific component of inflation is positively correlated with current sector-specific demand ($\widetilde{v}_t(i)$). Important for our analysis, the interaction term between sector-specific demand and the de-

[29]For details, see https://www.boj.or.jp/en/statistics/pi/cgpi_release/index.htm/

[30]Specifically, the following sectors are included in our dataset: Foods, Textiles, Wood Products, Pulp and Paper, Chemicals, Oil and Coal Products, Glass and Ceramics Products, Iron and Steel, Nonferrous Metals, Metal Products, Machinery, Electric Devices, Cars and Related Products.

Table 11: Estimation of the sectoral inflation dynamics

Dataset: Financial statement statistics of corporations by industry, producer price index; 13 sectors; 1976/1Q-2018/3Q				
Dependent Variable: sector-specific component of inflation rate ($\pi_t(i) - \pi_t$, seasonally adjusted, QoQ, annualized)				
	2 years trimmed mean	*3 years trimmed mean*	*5 years trimmed mean*	*10 years trimmed mean*
Changes in sector-specific demand	0.58 ***	0.54 ***	0.59 ***	0.54 **
	(0.16)	(0.15)	(0.17)	(0.25)
Sector-specific demand ×time	-0.08	-0.10	-0.12	-0.11
dummy (2000-2018)	(0.13)	(0.13)	(0.13)	(0.13)
Sector-specific demand	**-0.11 ****	**-0.08 ***	**-0.10 ****	**-0.08**
×shock heterogeneity	(0.04)	(0.04)	(0.05)	(0.08)
Observations	1,779	1,779	1,779	1,779
Adjusted-R^2	0.03	0.02	0.02	0.02

Note: Estimated by ordinary-least-squares with fixed effect models. The standard errors are HAC estimators. First lag of sector-specific demand is included in estimation as control variables. Data extrapolation using the values in the closest periods is applied for the missing values in the estimates of shock heterogeneity.
**** Significant at the 1 percent level. ** Significant at the 5 percent level.* Significant at the 10 percent level.*

gree of shock heterogeneity ($\widetilde{v}_t(i) \times \tau_t/\sigma_t$) is negative in all entries and significant for most of the measures of shock heterogeneity, with the exception of the ten-year window. Our results show that the data supports a decrease in the sensitivity of the sector-specific component of inflation in response to a raise in shock heterogeneity, consistent with the prediction in our theoretical model.

N Monte Carlo Experiment

Our discussion in Section 4 about the reduced sensitivity of inflation to aggregate demand due to imperfect information and demand shock heterogeneity can be relevant to the discussion regarding the flattening of Philips curve in Japan. To redirect our result to the Philips curve, we conduct a Monte Carlo experiment. We use the theoretical model as the data-generating process and feed the system with aggregate shocks, u_t, to generate data series for inflation, π_t, for 1,000,000 periods. We allow for different degrees of information heterogeneity, as represented by the ratio, τ/σ, within the range of values $[0, 1]$ and for degrees of nominal price rigidities, represented by the parameter θ in the wide range of values $\{0.2, 0.4, 0.6, 0.8\}$. To make results consistent with widely used specifications of the Phillips curve, we estimate the slope coefficient that captures the sensitivity of prices to real activity for two representative versions of the Phillips curve. First, a New Keynesian Phillips curve that features forward-looking expectations on inflation and second, a hybrid Phillips curve with backward- and forward-looking expectations on inflation:

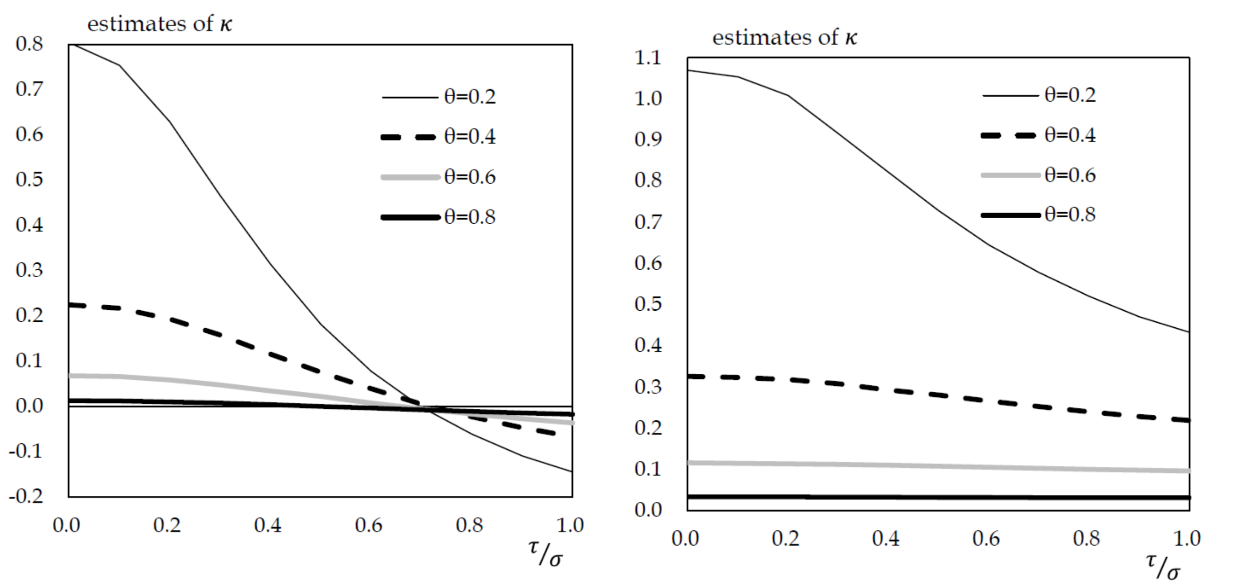
$$\pi_t = \beta \mathbb{E}[\pi_{t+1}|\mathcal{H}_t(i)] + \kappa \tilde{y}_t,$$
$$\pi_t = (1-\gamma)\mathbb{E}[\pi_{t+1}|\mathcal{H}_t(i)] + \kappa \tilde{y}_t + \gamma \pi_{t-1},$$

where the proxy of output gap $\tilde{y}_t$ is defined as cumulative changes in output from three period before $\tilde{y}_t \equiv y_t - y_{t-3}$. In our model, $Y_t = Q_t/P_t$, and thus $\tilde{y}_t = (y_t - y_{t-1}) + (y_{t-1} - y_{t-2}) + (y_{t-2} - y_{t-3}) = (q_t - q_{t-1}) + (q_{t-1} - q_{t-2}) + (q_{t-2} - q_{t-3}) - (p_t - p_{t-1}) - (p_{t-1} - p_{t-2}) - (p_{t-2} - p_{t-3}) = \Sigma_{j=0}^{2}(u_{t-j} - \pi_{t-j})$.[31]

Figure 6: Estimates for the slope coefficient in the New Keynesian and the hybrid Phillips Curve

(a) Estimates for the slope coefficient (κ) in the New Keynesian Phillips Curve

(b) Estimates for the slope coefficient (κ) in the hybrid Phillips Curve



Notes: Parameters are $r = 0.5$, $\beta = 0.99, \rho_u = 0.58$, $\rho_v = 0.30$.

Panels (a) and (b) in Figure 6 show estimates for the coefficient κ in the New Keynesian and hybrid Phillips curve, respectively, for values of τ/σ within the range $[0, 1]$ (on the x-axes) and different degrees of nominal price rigidity (θ, different lines). For both specifications, the slope coefficient κ is monotonically decreasing in θ and τ/σ, indicating that the empirical estimation correctly attributes the increase in information heterogeneity to a reduction in the sensitivity of inflation to real activity, irrespective of the degree of nominal price rigidity, as predicted by the theoretical model.

[31] In the estimation, we set $\beta = 0.99$ and estimate parameters γ and κ using GMM with lagged inflation. Although not the main focus of this study, γ changes only slightly along with τ/σ and θ.