Kyoto University,
Graduate School of Economics
Research Project Center Discussion Paper Series

How Well Do the Sticky Price Models Explain the Disaggregated Price Responses to Aggregate Technology and Monetary Policy Shocks?

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Discussion Paper No. E-10-007

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October, 2010

How well do the sticky price models explain the disaggregated price responses to aggregate technology and monetary policy shocks?*

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This version: October, 2010

Abstract

This paper documents empirically and analyzes theoretically the responses of disaggregated prices to aggregate technology and monetary policy shocks. Based on the price data of US personal consumption expenditure, we find that disaggregated price responses have features across shocks and across sectors that are difficult to explain using standard multi-sector sticky price models. In terms of shocks, a substantial fraction of disaggregated prices initially rise in response to a contractionary monetary policy shock, while most prices fall immediately in response to an aggregate technological improvement. In terms of sectors, the disaggregated price responses are correlated weakly with the frequency of price changes. We extend the standard model to reconcile these observations. We find that the cost channel of monetary policy and cross-sectional heterogeneity in real rigidity could pave the way for explaining these facts.

*We thank Kosuke Aoki, Jing Han, Tsutomu Watanabe, and seminar participants at the Bank of Japan and Kansai University for helpful discussions and comments. We also acknowledge Miles S. Kimball and John G. Fernald for supplying the updated data on total factor productivity. Takayuki Tsuruga gratefully acknowledges the financial support of a Grant-in-aid for Scientific Research. Views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

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Keywords: Sticky prices; Disaggregated inflation; Vector autoregressions; Monetary policy; Total factor productivity

JEL classification: E31; E32; E52

1 Introduction

Recent empirical studies on structural vector autoregressions (SVAR) have shown that aggregate prices respond differently, depending on the type of shock. While the difference in the responses may be explained by the difference in the exogenous stochastic processes across shocks per se, some argue that the difference occurs in a theoretically inconsistent way. This was pointed out originally by Altig, Christiano, Eichenbaum and Evans (2005, ACEL). They show that aggregate inflation responds rapidly to an aggregate technology shock compared with a monetary policy shock. Later, Dupor, Han, and Tsai (2009) find that the estimated degree of price stickiness changes substantially when they match the theoretical impulse response functions to each shock with the data. Also, recent studies have argued that disaggregated prices respond differently across sectors. With the stylized fact of significant cross-sectional heterogeneity in the frequency of price changes in the micro data, recent empirical studies examine the cross-sectional relationship between the price dynamics and the degree of nominal price rigidity.[1] Along this line of research, however, little attention has been paid to the question of how differently disaggregated prices respond to aggregate technology and monetary policy shocks and of how disaggregated price responses are related with the frequency of price changes.[2]

In this paper, we study empirically and theoretically the disaggregated price responses across shocks and across sectors. We estimate the responses of highly disaggregated prices

[1] Examples of recent papers include: Blis and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008), who measured the frequency of price changes using micro-price data; and Balke and Wynne (2007), Bils, Klenow, and Kryvtsov (2003), Boivin, Giannoni, and Mihov (2009), and Mackowiak, Moench, and Wiederholt (2009), who used VAR analysis to investigate sector-specific impulse response functions.

[2] Bils, Klenow, and Kryvtsov (2003) studied disaggregated inflation responses to two aggregate shocks. Using a two-sector model consisting of a sticky price sector and a flexible price sector, they evaluated their sticky price model by examining the price response of sticky price goods relative to that of flexible price goods to the two shocks. In contrast, we evaluate multi-sector models with much more disaggregated prices by comparing simulated responses with the data.

of personal consumption expenditure (PCE) items to a positive shock to the aggregate technological growth rate and to a contractionary shock to the monetary policy rule. The estimated disaggregated price responses indicate qualitative differences between shocks and large variations across sectors. We show that a standard multi-sector Calvo-type sticky price model cannot replicate these features for disaggregated price responses. We then explore possible explanations for the difference across shocks and across sectors by extending the model.

Using a standard SVAR, we estimate the impulse response functions of disaggregated prices to the two types of shocks. A comparison across shocks suggests that the bulk of disaggregated prices show a quicker decline to a positive shock to technological growth rate than to a contractionary monetary policy shock. In particular, nearly all of the disaggregated prices fall immediately in response to technological improvement, whereas a substantial number of disaggregated prices initially rise and then decline in response to a contractionary monetary policy shock. On the other hand, a comparison across sectors indicates that cross-sectional variations in nominal price rigidity play a limited role in accounting for the variations in the disaggregated price responses. In particular, we observe statistically significant negative correlations between the disaggregated price response and frequency of price changes, in most periods after the shocks, but we also observe that the cross-sectional link is weak quantitatively, regardless of the length of the period after the shocks.

We find that these features in the data cannot be explained well by a standard multi-sector Calvo-type sticky price model à la Carvalho (2006) with heterogeneous price stickiness across sectors. In the model, disaggregated prices exhibit qualitatively symmetric responses to both shocks. That is, they fall immediately in response to both shocks. Furthermore, the cross-sectional variation in price responses is strongly correlated with the frequency of price adjustment.

To reconcile our findings with the data, we extend the multi-sector sticky price model by introducing: (i) a cost channel of monetary policy; and (ii) heterogeneity of real rigidity across sectors. The first helps generate the asymmetric responses of disaggregated prices to the two shocks. The second helps weaken the cross-sectional correlation between the disaggregated price response and the frequency of price adjustment.

When there is a cost channel of monetary policy, nominal marginal cost depends on the nominal interest rate. In response to an unexpected rise in the federal funds rate, nominal marginal cost increases initially. Consequently, disaggregated prices rise temporarily. In contrast, in response to a positive technology shock, nominal marginal cost decreases substantially, because the federal funds rate is lowered by the monetary policy. As a result, disaggregated prices fall more quickly in response to a positive technology shock than to a monetary policy shock.

Heterogeneity in real rigidity weakens the effect of nominal price rigidity on variations in disaggregated price responses. However, it is not necessarily the case that any real rigidities can produce this outcome. We consider two types of real rigidity discussed by Chari, Kehoe and McGrattan (2000): (i) sector-specific fixed factor in the production function; and (ii) sector-specific kinked demand curve à la Kimball (1995). Our simulation exercise suggests that the former is successful in explaining the data while the latter is not. This implies that distinguishing real rigidities is important for understanding prices.

The rest of the paper is as follows. Section 2 describes our data and econometric methodology. Section 3 presents our empirical results. Section 4 discusses the predictions of the standard multi-sector sticky price model and its extensions and argues for the importance of heterogeneity in real rigidity. Section 5 concludes.

2 Econometric Methodology and Data

In this section, we estimate the effect of aggregate technology and monetary policy shocks on disaggregated prices. To this end, we first use macroeconomic variables to identify shocks to technological growth rate and monetary policy by SVAR similar to ACEL. We then regress disaggregated inflation on its own lags and macroeconomic variables to estimate the impulse response functions of disaggregated prices to the aggregate shocks.[3]

[3] This approach is essentially the same as Balke and Wynne (2007).

2.1 Identifying aggregate technology and monetary policy shocks

In the macro VAR, we formulate a 10-variable VAR with four lags. Let Y_t be a vector of macroeconomic variables that includes Δlog (Relative price of investment$_t$), Δlog(GDP$_t$/Hours$_t$), Δ log(GDP deflator$_t$), Capacity utilization$_t$, log(Hours$_t$), log(GDP$_t$/Hours$_t$) - log(Real wages$_t$), log(Consumption$_t$/GDP$_t$), log(Investment$_t$/GDP$_t$), Δ log(Commodity price index$_t$) and Federal funds rate$_t$.[4] We use the same set of macroeconomic variables as ACEL except that (i) we add the commodity price index into the system of equations; and (ii) we omit the velocity of circulation from the system.[5] The sample period is 1959:Q3– 2008:Q3.

We identify aggregate technology shocks using long-run restrictions and monetary policy shocks using short-run restrictions in the same spirit as ACEL. In particular, we identify the aggregate technology shock by assuming that only innovations to the growth of total factor productivity (and capital embodied technology) affect the long-run level of labor productivity. When imposing this long-run restriction, we use the instrumental variable method of Shapiro and Watson (1988). Furthermore, we identify the monetary policy shock using the block recursive restrictions of Christiano, Eichenbaum, and Evans (1999): monetary policy shocks do not contemporaneously affect the first nine variables in Y_t.

2.2 Disaggregated inflation equation

Let $\pi_{j,t}$ be the quarterly change in the (log) price index for sector j. Our estimation equation is designed to assess the dynamic effects of the macroeconomic variables in Y_t on $\pi_{j,t}$

$$\pi_{j,t} = \sum_{\ell=1}^{4} \rho_{j,\ell}\pi_{j,t-\ell} + \sum_{\ell=0}^{4} Y'_{t-\ell}\gamma_{j,\ell} + \varepsilon_{j,t}, \tag{1}$$

[4] While ACEL employed the price of investment used in Fisher (2006), we construct the price series of investment, using the price deflators and weights for durables, structures, equipment and software, residential investment, and government investment in the National Income and Product Accounts. Furthermore, we use the commodity price index from the three-month average of the monthly CRB spot index, published by the Commodity Research Bureau.

[5] We choose this particular set of macroeconomic variables for two practical reasons. First, a number of empirical studies have included a commodity price index in a VAR to identify the monetary policy shock, following the suggestion by Sims (1992). Second, when we include the velocity of circulation, the subsample analysis using the period 1984:Q1–2008:Q3 reveals that the VAR system becomes explosive.

where $\varepsilon_{j,t}$ is a regression error, which can be interpreted as an idiosyncratic shock. Furthermore, $\rho_{j,\ell}$ denotes the ℓ-th autoregressive parameter of disaggregated inflation, and $\gamma_{j,\ell}$ is a (10×1) parameter vector for the macroeconomic variables $Y_{t-\ell}$. The constant term is suppressed for expositional purposes. In this regression, we allow for the possibility that disaggregated inflation responds to shocks at the impact period. Furthermore, we assume that the effect of disaggregated inflation on the macroeconomic variables is negligible.[6]

The disaggregated price data used in our estimation are the PCE price series for 1959:Q3–2008:Q3, which are published by the Bureau of Economic Analysis (BEA). Because our macro VAR is based on quarterly data, we use the quarterly price series, which is the three-month average of the monthly price series that the BEA releases every month. Among the 363 price series from the BEA's underlying table for PCE prices, we choose highly disaggregated price series to the extent possible. We thus remove price indices that overlap categories as a result of aggregation (e.g., durables, nondurables, and services).

Because we are interested in the relationship between the disaggregated price responses and the degree of nominal price rigidity, we also drop some price series to match PCE price series with the entry-level items (ELIs) in the Consumer Price Index. We use the frequencies of price changes excluding sales and product substitutions measured by Nakamura and Steinsson (2008). They measure the good-specific frequency of price changes from the CPI Research Database gathered by the Bureau of Labor Statistics over 1988–1997 and 1998–2005. In matching their frequencies over 1998–2005 with the PCE price series, we take the weighted average of frequencies based on the expenditure weights when a price in the PCE data set corresponds to more than one ELI in their data set of frequency of price changes. When a price in the PCE data set does not correspond to any ELI in their data set, we drop the price series. Using this sample selection process, we obtain 134 price series for estimation.

[6] Note that the endogeneity problem arises if disaggregated prices have a nonnegligible effect on the macroeconomic variables. However, the price series we use are highly disaggregated so that it would be reasonable to assume that they barely affect aggregate variables.

3 Empirical Results

In this section, we aim to establish that aggregate technology and monetary policy shocks have qualitatively asymmetric dynamic effects on disaggregated prices and that disaggregated price responses have a weak relationship to heterogeneity in nominal price stickiness.

3.1 Response of disaggregated prices

Figure 1 plots the impulse response functions to aggregate technology and monetary policy shocks. The upper left panel shows the (unweighted) mean and median responses of disaggregated prices to a one percent increase in the aggregate technology growth rate, and the lower left panel shows those to a one percent increase in the federal funds rate. The dashed lines represent cross-sectional variability in disaggregated price responses using the 10th–90th percentile ranges. The right panels plot the aggregated price responses to the two shocks for comparisons.

The figure has two notable features. First, while a shock to aggregate technology growth leads to an immediate decline in most disaggregated prices, a monetary policy shock appears to have the delayed effect on the disaggregated prices. In particular, unlike the response to the aggregate technology shock, a large number of prices are above zero after the contractionary monetary policy shock. Second, the 10th–90th percentile ranges appear to be wide, which suggests considerable cross-sectional differences in the disaggregated price responses. We now look at these features in more detail.

3.1.1 How different are disaggregated prices across shocks?

Focusing on the first feature of the disaggregated price responses, we compute the shares of the positive price responses to the total number of price responses for each of the shocks. The shares are the white bars in Figure 2, while the shares of the significantly positive responses at the five percent significance level are shown by the shaded bars. Here, the horizontal axis measures the quarters after each of the shocks. The upper panel is for a positive aggregate technology shock, whereas the lower panel is for a contractionary monetary policy shock.

In response to the technology shock, about 9.7–20.2 percent are positive for the first four quarters, evaluated at the point estimate, but none of the responses is significantly positive at the five percent significance level. In contrast, in response to the monetary policy shock, about 45.5–55.2 percent of the 134 price series are positive for the first four quarters, while only 1.5–9.7 percent of the 134 price series are significantly positive at the five percent significance level.

This asymmetry across shocks observed at the sector level has an implication for the asymmetry of the aggregated price responses between the two shocks, discussed in ACEL, Dupor, Han, and Tsai (2009) and Paciello (2009a,b). In particular, the fact that most disaggregated prices fall at once in response to a positive aggregate technology shock and a large number of prices increases in response to a contractionary monetary policy shock implies that the asymmetry of aggregated price responses stems from responses at the disaggregated level and is not an artifact of the weights used for aggregating prices. Thus, the asymmetry should be explained in the multi-sector sticky price model at the disaggregated level as well as the aggregate level.

3.1.2 How different are disaggregated prices across sectors?

We next evaluate variations in the disaggregated price responses across sectors, the second feature of our impulse response analysis. The multi-sector sticky price model predicts that frequently adjusted prices should respond more quickly to any shock than infrequently adjusted prices. Motivated by this prediction, we examine to what extent the frequency of price changes can be cross-sectionally associated with the disaggregated price responses. In other words, we examine the correlations between the disaggregated price responses estimated from our SVAR and frequencies of regular price changes reported by Nakamura and Steinsson (2008).

Let $\Psi_j^k(\tau)$ be the impulse response of the disaggregated price of sector j in τ quarters after a price-reducing shock k. Using the monthly frequency of price changes fr_j, we calculate the sample correlation coefficients between $\Psi_j^k(\tau)$ and fr_j across sectors, denoted by $Corr_j\left[\Psi_j^k(\tau), fr_j\right]$, where we have 134 sectors for sector index j, and shock index k corresponds to a positive shock to aggregate technology growth or a positive shock to the federal funds rate. Furthermore, we consider quarters after shock τ up to 24 quarters (i.e.,

$\tau = 0, 1, 2, ..., 24$). Note that the correlation should be negative because more frequently adjusted prices decrease by a larger amount in response to shock k. Thus, we examine whether the signs of the correlation coefficients are negative and see how the correlation coefficients evolve over τ for each k.[7]

Overall, the correlation coefficients are negative for both shocks, which is consistent with the prediction of the standard sticky price model in terms of direction. The circular markers in Figure 3 present the correlation coefficients for various periods of τ for each shock. Here the length of each bar attached to a circular marker represents the 95 percent confidence intervals of $Corr_j\left[\Psi_j^k(\tau), fr_j\right]$. As shown in the upper panel of the figure, the correlation coefficients take negative values over all periods of τ, when the shock is a positive technology shock. Moreover, these are significantly negative in all quarters except for the first two quarters. In contrast, the lower panel of the figure shows that the correlation coefficients for a positive federal fund rate shock are negative in most periods although they are positive in the first four quarters. These are significantly different from zero only for $\tau \geq 9$.

However, the correlations are weak over the entire period after the shocks. The correlation coefficients for the technology shock range between -0.32 for $\tau = 6$ and -0.13 for $\tau = 0$, and the average over the entire period is -.029. For the monetary policy shock, the correlation coefficients range between -0.31 for $\tau = 24$ and 0.08 for $\tau = 2$ and the average over the entire period is -0.19.

The weak correlation might come from the fact that we do not consider broad categorizations in the PCE items such as durables, nondurables and services. To explore this possibility, we regress the disaggregated responses for each τ on fr_j together with a constant and dummy variables for durables and services. The R-squareds for technology and monetary policy shocks are 15.1 and 7.1 percent, respectively, when the average is taken across τ. Without dummies for durables and services, the average of the R-squareds over 24 quarters is only 8.7 percent for the technology shock and 5.0 percent for the monetary policy shock, implying that the increments in R-squared are marginal. Therefore, the role of the frequency of price changes in accounting for variations in disaggregated price responses is limited, and

[7] As a robustness check, we also use the frequency of price changes including sales reported in Nakamura and Steinsson (2008). We find that the results are unaltered qualitatively even if we change the frequency of price changes.

most variations remain unexplained even after consideration of broad categorizations in the PCE items.

3.2 Robustness

This subsection conducts sensitivity analysis based on different identification schemes of aggregate shocks and subsample analysis.

3.2.1 Identification schemes

Our empirical results are obtained based on an SVAR. However, some argue that the SVAR approach is problematic because identifying assumptions may not hold. Thus, we employ the measure of aggregate shocks obtained under alternative identification schemes: the monetary policy shock developed by Romer and Romer (2004) and the quarterly version of the purified total factor productivity series in Basu, Fernald, and Kimball (2006).[8] These aggregate shocks are convenient because the use of these "exogenous" shocks allows us to avoid the difficult task of finding what identification assumptions in the SVAR are plausible. Moreover, we also use the factor-augmented VAR by Boivin, Giannoni, and Mihov (2009) to identify the monetary policy shock.

To obtain the impulse responses of disaggregated prices based on the first two shocks, we follow Romer and Romer's (2004) approach. We regress disaggregated inflation on its own lags and contemporaneous and lagged values of the identified aggregate shock. Our regression is given by

$$\pi_{j,t} = \sum_{\ell=1}^{8} \rho_{j,\ell}^{k} \pi_{j,t-\ell} + \sum_{\ell=0}^{16} \gamma_{j,\ell}^{k} S_{t-\ell}^{k} + \varepsilon_{j,t}^{k}, \tag{2}$$

where $\rho_{j,\ell}^{k}$ denotes the coefficient of lagged disaggregated inflation, $\gamma_{j,\ell}^{k}$ is the coefficient of the shock series and $\varepsilon_{j,t}^{k}$ is the error term. Again, the constant term is suppressed. The number of lags ℓ is chosen according to Romer and Romer (2004). Here, S_t^k is either the monetary policy shock measure by Romer and Romer (2004) or the quarterly measure of

[8] These quarterly data of the purified total productivity series were kindly provided by Miles S. Kimball. This data set is produced by John Fernald and roughly matches the original annual data set in Basu, Fernald, and Kimball (2006) when converted from quarterly to annual data.

purified technology growth of Basu, Fernald and Kimball (2006). The former measure is originally monthly data between January 1969 and December 1996. In running the above regression, we convert the monthly series into a quarterly series by taking the sum of the three monthly values of the original series. This results in confining the sample period to the period over 1969:Q1 to 1996:Q4 to obtain the impulse responses of disaggregated inflation. The sample period of the purified total factor productivity series is from 1959:Q3 to 2008:Q3, which is the same as that of disaggregated inflation.

Overall, the results are robust qualitatively to the use of the two aggregate shocks mentioned above. First, in terms of the difference between shocks, the shares of the positive responses to the total price responses for the monetary policy shock are quite similar to the results based on the SVAR. The share of positive responses for the technology shock is somewhat larger than the baseline empirical results. For example, the share increases to 23.1–38.1 percent from the benchmark SVAR results of 9.7–20.2 percent in the fourth quarter after the shock. However, only a few of the responses are significantly positive at the five percent significance level.

Second, the role of the frequency of price changes in explaining variations in price responses across sectors is also limited when we use the alternative measure of aggregate shocks. Figure 5 indicates that the correlation coefficients are negative for the technology shock, but the absolute value of the correlation coefficient is again low. The correlation coefficients for the price responses to the monetary policy shock are not significantly different from zero up to three years after the shock and then turn out to be significantly negative.

Lastly, we report the estimation results when the factor-augmented VAR of Boivin, Giannoni, and Mihov (2009) is used for identifying the monetary policy shock. To make comparison easier with our previous results, we use the disaggregated price responses estimated by Boivin, Giannoni, and Mihov (2009) and select the 134 price responses out of their 191 price responses. The price data are monthly from January 1976 to June 2005. Figure 6 displays the share of positive price responses in the 134 price responses to a contractionary monetary policy shock (the upper panel) and correlation coefficients with the frequency of price changes (the lower panel). The upper panel shows that the shares of positive price responses range between 16.4 and 68.7 percent for the first year after the shock and that the shares of significantly positive price responses at the five percent significance level range between 1.5 and 14.2 percent. Again, a large number of disaggregated prices rise temporarily after a monetary tightening shock, consistent with the results based on the SVAR. Turning to the correlation coefficients, the point estimates are negative from the impact period, but the absolute values remain small.

3.2.2 Subsample analysis

Up to this point, our results have been based on the period from 1959:Q3. However, recent studies have pointed out changes in the time series properties of inflation and the effectiveness of monetary policy since the early 1980s.[9] To see the effect of a change in the sample period on our results, we reestimate (1) using data from 1984:Q1 to 2008:Q3.

The difference across shocks in terms of the share is less clear than the full sample estimation as shown in Figure 7. However, when we focus on the share of significantly positive price responses, the asymmetry across shocks is still observable. The share ranges between 5.2 and 22.4 percent for the first year after the monetary policy shock while almost no prices show a significantly positive response after the technology shock.

The correlation coefficients shown in Figure 8 again suggest that the cross-sectional link is weak between the disaggregated price response and the frequency of price change. Furthermore, compared with the full sample analysis, the correlation coefficients display clearer asymmetry across shocks. While the coefficients under the technology shock are significantly negative, ranging between -0.54 and -0.33, the coefficients under the monetary policy shock are not significantly different from zero for all τ.

4 Multi-sector Sticky Price Models

In this section, we examine sticky price models for the two empirical features of the disaggregated price responses. We first study the baseline multi-sector sticky price model. In the baseline model, firms in the economy are identical except that the degree of price stickiness

[9] See, for example, Boivin and Giannoni (2006) and Stock and Watson (2002) for evidence on the reduction in the volatility of inflation. Clark (2006) also documented the structural break in the disaggregate inflation series in the early 1980s.

differs across sectors. The simulation exercises suggest that the baseline model needs to be modified in accounting for the two empirical features of the disaggregated prices. We then discuss some extensions to make the model fit the data better.

4.1 The baseline model

4.1.1 Households

Consider a continuum of households, indexed by $h \in [0,1]$. The infinitely lived households are monopolistic suppliers of differentiated labor services and set their nominal wage rates in a staggered manner as in Erceg, Henderson, and Levin (2000). Their preferences are over the aggregate consumption C_t, differentiated labor service $L_t(h)$, and real money balances M_t/P_t, as described in the following expected utility function

$$\max \ E_t \sum_{t=0}^{\infty} \beta^t \left[\log(C_t) - \phi_L \frac{L_t(h)^{1+\eta}}{1+\eta} + \phi_m \log\left(\frac{M_t}{P_t}\right)\right], \tag{3}$$

where β denotes the discount factor of households satisfying $\beta \in (0,1)$, $\eta \geq 0$ denotes the inverse of the Frisch labor-supply elasticity, and $\phi_L \geq 0$ and $\phi_m \geq 0$ are utility weights on labor disutility and the utility of real money balances, respectively. Aggregate consumption is a composite aggregated over N goods

$$C_t \equiv \prod_{j=1}^{N} C_{j,t}^{\frac{1}{N}},$$

where aggregation weights are the same across sectors and $C_{j,t}$ is the household's consumption of goods produced in sector j. The aggregate price index P_t is given by

$$P_t = \prod_{j=1}^{N} P_{j,t}^{\frac{1}{N}},$$

where $P_{j,t}$ is the disaggregated price of good j.

The budget constraint for household h is

$$\sum_{j=1}^{N} P_{j,t}C_{j,t} + \frac{B_t}{R_t} + M_t \leq W_t(h)\, L_t(h) + B_{t-1} + M_{t-1} + \Pi_t + T_t. \tag{4}$$

In the right-hand side of the equation, the household earns the nominal wage rate $W_t(h)$ per unit of labor supply $L_t(h)$ and carries the nominal one-period bond B_{t-1} and the nominal money balances M_{t-1} from the previous period to the current period. Households also receive the total profits of firms Π_t and transfers T_t from the monetary authority. In the left-hand side of (4), households purchase N consumption goods and hold the nominal bond discounted by the gross nominal interest rate on one-period bonds and cash for the next period. We assume complete state-contingent markets and identical initial conditions for all households so that we can drop the household index h from variables except for $W_t(h)$ and $L_t(h)$.

Let L_t be the composite of differentiated labor service : $L_t = \left[\int_0^1 L_t(h)^{(\theta_w-1)/\theta_w} dh\right]^{\theta_w/(\theta_w-1)}$, where $\theta_w > 1$ is the elasticity of substitution. The demand curve for differentiated labor services $L_t(h)$ is $L_t(h) = \left[W_t(h)/W_t\right]^{-\theta_w} L_t$, where W_t denotes the aggregate wage index defined as $W_t = \left[\int_0^1 W_t(h)^{1-\theta_w} dh\right]^{1/(1-\theta_w)}$.

In each period, the household can choose its nominal wage optimally with probability $1-\lambda_w$ to maximize expected lifetime utility. When the household is allowed to reset its nominal wage, its optimal wage rate W_t^* satisfies

$$W_t^* = \frac{\theta_w}{\theta_w - 1} \frac{E_t \sum_{s=0}^{\infty} (\beta\lambda_w)^s \left\{\phi_L \left[\frac{W_t^*}{W_{t+s}}\right]^{-\theta_w} L_{t+s}^{1+\eta}\right\}}{E_t \sum_{s=0}^{\infty} (\beta\lambda_w)^s \left[\frac{W_t^*}{W_{t+s}}\right]^{-\theta_w} L_{t+s}}.$$

Under Calvo-type wage stickiness, the law of motion for the nominal aggregate wage index is given by

$$W_t = \left[\lambda_w W_{t-1}^{1-\theta_w} + (1-\lambda_w) W_t^{*1-\theta_w}\right]^{\frac{1}{1-\theta_w}} . \tag{5}$$

4.1.2 Firms

The economy has N sectors. In each sector, there is a continuum of firms indexed by $f \in [0,1]$, each of which produces differentiated products $Y_{j,t}(f)$. Let $Y_{j,t}$ be a composite of differentiated goods produced in sector j, for $j = 1, ...N$, that is defined as

$$Y_{j,t} = \left[\int_0^1 Y_{j,t}(f)^{\frac{\theta_p - 1}{\theta_p}} df\right]^{\frac{\theta_p}{\theta_p - 1}}, \tag{6}$$

where $\theta_p > 1$ denotes the elasticity of substitution between differentiated products in each sector. The demand function for differentiated product $Y_{j,t}(f)$ is given by

$$Y_{j,t}(f) = \left[\frac{P_{j,t}(f)}{P_{j,t}}\right]^{-\theta_p} Y_{j,t}. \tag{7}$$

The disaggregated price index $P_{j,t}$ is defined as $P_{j,t} = \left[\int_0^1 P_{j,t}(f)^{1-\theta_p}\, df\right]^{1/(1-\theta_p)}$.

Each firm in sector j produces output using the following technology:

$$Y_{j,t}(f) = Z_t L_{j,t}(f) - F Z_t. \tag{8}$$

Here Z_t represents the aggregate technology that is common to all firms in the economy.[10] Furthermore, $L_{j,t}(f)$ is the labor demand used to produce output $Y_{j,t}(f)$, and F is the fixed cost calibrated to guarantee the zero profits of all firms at the steady state. Given the production function (8), the nominal marginal cost function MC_t is

$$MC_t = \frac{W_t}{Z_t}, \tag{9}$$

which is common across all firms and sectors.

In each period, firms are allowed to reset prices optimally with the probability of $1 - \lambda_j$ under monopolistic competition in the product market and their prices remain fixed otherwise. Given the demand function (7), the optimal reset price $P^*_{j,t}$ solves the maximization problem:

$$\max_{P_{j,t}(f)} E_t \sum_{s=0}^{\infty} (\beta\lambda_j)^s \frac{\Lambda_{t+s}}{\Lambda_t} \frac{D_{j,t,t+s}(f)}{P_{j,t+s}}, \tag{10}$$

$$s.t.\ D_{j,t,t+s}(f) = P_{j,t+s}(f)\, Y_{j,t,t+s}(f) - W_{t+s} L_{j,t,t+s}(f), \tag{11}$$

where $D_{j,t,t+s}(f)$, $Y_{j,t,t+s}(f)$, and $L_{j,t,t+s}(f)$ are the current period profits of the firm, the output, and labor demand, conditional on the optimal reset price $P^*_{j,t}$, respectively. Λ_{t+s} is the Lagrange multiplier associated with the household's budget constraint (4). The optimal

[10] Here we do not introduce sector-specific technology and firm-specific technology in the production function because our interest is in the disaggregated price responses to aggregate shocks.

reset price $P^*_{j,t}$ satisfies

$$P^*_{j,t} = \frac{\theta_p}{\theta_p - 1} \frac{E_t \sum_{s=0}^{\infty} (\beta\lambda_j)^s \left(\frac{\Lambda_{t+s}}{\Lambda_t}\right) Y_{j,t,t+s}(f)\, MC_{t+s}/P_{j,t+s}}{E_t \sum_{s=0}^{\infty} (\beta\lambda_j)^s \left(\frac{\Lambda_{t+s}}{\Lambda_t}\right) Y_{j,t,t+s}(f)\, /P_{j,t+s}}. \tag{12}$$

Under Calvo-type price stickiness, the price index of the goods j evolves according to

$$P_{j,t} = \left[\lambda_j P_{j,t-1}^{1-\theta_p} + (1-\lambda_j)\, P^{*\,1-\theta_p}_{j,t}\right]^{\frac{1}{1-\theta_p}} . \tag{13}$$

4.1.3 Aggregate technology and monetary policy rule

We assume that the growth rate of the aggregate technology follows an AR(1) process of the form

$$\frac{Z_t}{Z_{t-1}} = \left(\frac{Z_{t-1}}{Z_{t-2}}\right)^{\rho_z} \exp(e_{z,t}), \tag{14}$$

where $e_{z,t}$ is i.i.d. and $\rho_z \in [0,1)$.

The nominal interest rate R_t is determined by the lagged nominal interest rate and the aggregate inflation rate

$$R_t = R_{t-1}^{\rho_r} \left(\frac{P_t}{P_{t-1}}\right)^{(1-\rho_r)\psi} \exp(e_{r,t}), \tag{15}$$

where ρ_r is the autoregressive parameter of the policy rate, $\psi > 1$ is a policy weight on inflation and $e_{r,t}$ is an i.i.d. monetary policy shock.

4.1.4 Equilibrium and market clearing conditions

The market clearing conditions for good $j = 1, ..., N$ are given by

$$C_{j,t} = Y_{j,t} = \left[\int_0^1 Y_{j,t}(f)^{\frac{\theta_p - 1}{\theta_p}} df\right]^{\frac{\theta_p}{\theta_p - 1}} \text{ for } j = 1, ...N. \tag{16}$$

The labor market clearing condition is

$$L_t = \left[\int_0^1 L_t(h)^{\frac{\theta_w - 1}{\theta_w}} dh\right]^{\frac{\theta_w}{\theta_w - 1}} = \sum_{j=1}^{N} \int_0^1 L_{j,t}(f)\, df. \tag{17}$$

The bond market clearing condition implies $B_t = 0$ at all dates and states. Finally, the profits of firms and transfers from the government are specified as $\Pi_t = \sum_{j=1}^{N} \int_0^1 D_{j,t}(f)df$ and $T_t = M_t - M_{t-1}$, respectively.

An equilibrium of the economy is a collection of allocations and prices, $\{C_{j,t}, Y_{j,t}, Y_{j,t}(f), L_t(h), L_{j,t}(f), P_{j,t}, P_{j,t}(f), W_t, B_t\}_{t=0}^{\infty}$, for $j = 1, ...N$, which satisfy the following conditions: (i) the households' allocations and wages solve the utility-maximization problem; (ii) producers' allocations and prices solve the profit-maximization problem; (iii) markets for the composite goods, composite labor, and bonds all clear; and (iv) monetary policy and profits are as specified above.

4.1.5 Calibration

We calibrate the parameters based on existing studies. We set the discount factor of households β to $1.04^{-1/4}$ and the Frisch labor supply η to unity. The weight for labor disutility ϕ_L is calibrated so that the labor services supplied by households are equal to 0.3 in the steady state. We set the weight for utility from real money balances ϕ_m to 0.05.

The elasticity of demand among differentiated labor services θ_w is 21, which is borrowed from Christiano, Eichenbaum, and Evans (2005). We follow the literature in setting θ_p to 11. Regarding the aggregate technology shock, we set $\rho_z = 0.9$, consistent with ACEL, who estimate this parameter over the sample period between 1959:Q2 and 2001:Q4. We parameterize the Taylor rule (15) as $\rho_r = 0.9$ and $\psi = 1.1$. We set the degree of nominal wages stickiness λ_w to 0.85, according to Barattieri, Basu, Gottschalk (2009), who estimate the probability of nominal wage adjustment to be approximately 14–16 percent per quarter.[11]

To calibrate the frequency of price changes $1 - \lambda_j$ in each sector j, we use the frequency of regular price changes reported by Nakamura and Steinsson (2008). The number of sectors N is set to 134 for comparison purpose. Because Nakamura and Steinsson (2008) report the monthly frequency of price changes, we transform them to obtain the quarterly frequency as follows: $\lambda_j = (1 - fr_j)^3$.[12]

[11] They also found little heterogeneity in the probability of nominal wage adjustment across industries as well as across occupations. This fact provides a rationale to not introduce heterogeneity in wage settings across sectors into the model.

[12] In evaluating the model, we calculate the weighted average of the monthly frequency of price changes

4.2 Simulation results

4.2.1 The baseline model

In this subsection, we evaluate the baseline model in replicating the features of the disaggregated price responses using the impulse response functions to a positive shock to the aggregate technology $e_{z,t}$ and contractionary shock to the monetary policy rule $e_{r,t}$.

The rectangular markers in Figure 9 show the share of positive price responses to the two shocks. The share is zero over the entire period after the shocks, because all disaggregated prices fall immediately after both shocks. In this sense, the disaggregated price responses are symmetric across shocks. This symmetry comes from (9) and (12). Because both unexpected technological improvement and contractionary monetary policy shocks lead to a decline in the nominal marginal cost common to all sectors, there is no reason that some of the disaggregated prices increase, resulting in a zero share of positive price responses to both shocks.

The model predicts a negative correlation between the disaggregated price responses and the frequency of price changes, but the cross-sectional link in the model is quantitatively much stronger than the data suggest. The rectangular markers in Figure 10 compare the correlation coefficients in the model with those in the data. The correlation coefficients amount to -0.75 at the impact period under both shocks, which suggests a stronger link than the data (-0.13 for the technology shock and 0.05 for the monetary policy shock). The correlation coefficient increases to -0.43 for both shocks until six years after the shock and becomes close to the data (-0.31 for the technology shock and -0.28 for the monetary policy shock). However, the magnitude is inconsistent with the data because almost all correlation coefficients are lower than what the 95 percent confidence intervals suggest. Because the nominal marginal cost is equal in all sectors in the baseline model, all cross-sectional variations in disaggregated price responses originate only from heterogeneity in nominal price stickiness. As a consequence, the cross-sectional link is very strong.[13]

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based on the ELIs to match the PCE item price indices. Using the weighted average of frequencies might influence our simulation results for the disaggregated price dynamics. As a sensitivity analysis, we also simulate a model consisting of a larger number of sectors than the baseline model, where the frequency of price changes is calibrated at the level of ELIs. The simulation results on the disaggregated price responses to the two shocks is qualitatively unaltered.

[13] This result can be obtained under various parameterizations. For example, we simulate the model under

4.2.2 Cost channel of monetary policy

We now modify the baseline model to account for the asymmetric disaggregated price responses by introducing a cost channel of monetary policy. Some existing studies have argued that a cost channel explains the temporary increase in the aggregate prices after a monetary tightening shock.[14] A cost channel may be useful in breaking the symmetry in disaggregated price responses because marginal cost temporarily increases in response to a contractionary monetary policy shock but not to a positive technology shock.

Suppose that firms must borrow the wage bill from financial intermediaries in advance at the interest rate R_t. We replace the nominal marginal cost (9) with

$$MC_t = R_t \frac{W_t}{z_t}. \tag{18}$$

As a result, the nominal marginal cost depends on the nominal interest rate.[15]

Figure 9 shows that the cost channel helps generate asymmetric price responses across shocks. The share of positive price responses is zero over the entire period after the technology shock (shown by the triangular markers in the upper panel). In contrast, the share of positive disaggregated price responses ranges between 23.9 and 66.4 percent over the first year after the contractionary monetary policy shock (shown in the lower panel). Although the theoretical share is somewhat larger than the empirical share of 45.5–55.2 percent, the cost channel successfully produces asymmetric responses of disaggregated prices across shocks.

To see the intuition behind the asymmetry across shocks, note that the nominal interest rate responds to the two shocks in opposite directions. For a positive technology growth shock, the improved technology negatively affects nominal marginal cost immediately. This direct effect on marginal cost tends to dominate the indirect effect of sticky nominal wage

a wide range of degrees of nominal wage stickiness λ_w or of values of the persistence of the monetary policy rule ρ_r. Our result is also robust even when the expenditure share of $1/N$ for each good or elasticity of substitution among goods θ_p varies across sectors.

[14] For instance, Christiano, Eichenbaum and Evans (2005) suggested that when a cost channel exists along with sticky wages, the aggregate prices can initially rise in response to a contractionary monetary policy shock. Empirically, several papers argue for the presence of a cost channel (Barth and Ramey, 2001; Ravenna and Walsh, 2006; Chowdhury, Hoffmann, and Schabert, 2006; and Tillmann, 2008). One exception is Rabanal (2007), who estimated a medium-sized New Keynesian model by Bayesian estimation.

[15] In addition to the replacement of the marginal cost function, we also modify the households' budget constraint (4) because they have deposits with the financial intermediaries.

increases coming from the increased labor demand. Hence, on average, disaggregated prices should decrease, implying decreased aggregate inflation. Because of the decreased aggregate inflation, the nominal interest rate is lowered according to the monetary policy rule (15), which leads to a further fall in nominal marginal cost and disaggregated prices.

In contrast, the contractionary monetary policy shock directly increases the nominal interest rate. Thus, it temporarily increases, rather than decreases, the nominal marginal cost because of (18) together with a gradual decrease in wages. Firms that produce goods with a low frequency of price changes decrease their current prices because they put a large weight on the future decreased marginal cost in determining current prices. However, firms producing goods with a high frequency of price changes increase their current prices based on the temporary increase in marginal cost because they have plenty of opportunities to reset prices in the future. For this reason, about a half of the disaggregated prices show positive responses to a contractionary monetary policy shock.

A by-product of this mechanism is a positive relationship between the disaggregated price responses and the frequency of price changes for the monetary policy shock. When the monetary tightening shock occurs, the responses of frequently adjusted prices should be larger than those of infrequently adjusted prices, implying a positive correlation between responses and frequencies. Triangular markers in the lower panel of Figure 10 confirm this conjecture. Unfortunately, the theoretical correlation coefficients are significantly larger than the empirical correlation coefficients for the absolute values and lie outside the 95 percent confidence intervals obtained from the empirical analysis. This result suggests that a further modification is required to account for cross-sectional variations in disaggregated price responses.

4.2.3 Heterogeneous real rigidities

To weaken the correlation between price responses and the frequency of price changes, we introduce heterogeneous real rigidities into the model with the cost channel from the view point of strategic complementarity. Carvalho (2006) argues that strategic complementarity matters for aggregate price dynamics using a multi-sector sticky price model. We also adopt strategic complementarity, but assume that its degree varies across sectors, because such real rigidities may work as an additional factor that causes variations in disaggregated price responses compared with the case of no real rigidities. In what follows, we consider two forms of real rigidities: (i) a sector-specific fixed factor in the production function and (ii) a sector-specific kinked demand curve.

Sector-specific fixed factor of production We first discuss the role of a sector-specific factor in the production function. Suppose that the production function for sector j is given by

$$Y_{j,t}(f) = Z_t L_{j,t}(f)^{\phi_j} \bar{H}_j^{1-\phi_j} - F_j Z_t, \tag{19}$$

rather than (8), where ϕ_j is a sector-specific parameter for returns to labor satisfying $0 < \phi_j \leq 1$. Here $\bar{H}_j$ denotes a sector-specific factor, and F_j is a sector-specific fixed cost that ensures the long-run zero profit condition. Chari, Kehoe, and McGrattan (2000) assume that goods are produced with a fixed factor in addition to labor and capital. Here we follow Chari, Kehoe and McGrattan (2000) to interpret $\bar{H}_j$ as an inelastically supplied factor, such as land. The sector-specific factor generates real rigidities because of decreasing-returns-to-scale technology, but the degrees of real rigidities are different across sectors because of ϕ_j.

By normalizing $\bar{H}_j$ to unity for all sectors for simplicity, we obtain the marginal cost function

$$MC_{j,t}(f) = \left[\frac{1}{\phi_j} L_{j,t}\left(f\right)^{1-\phi_j}\right] R_t \frac{W_t}{Z_t}. \tag{20}$$

Because ϕ_j varies across sectors, marginal cost fluctuates heterogeneously.

To simulate the model with heterogeneous real rigidity, we assign ϕ_j to the production function in each sector j by targeting the moments from the data. Because there seems no comprehensive micro evidence on ϕ_j, we randomly draw $\left\{\phi_j\right\}_{j=1}^{N}$ from a distribution and evaluate the model. Here, the moments simulated from a particular set of ϕ_j critically depend on the combination of the observed λ_j and the generated ϕ_j. Hence, we evaluate the model by taking the average of the theoretical moments obtained from 100 repeated simulations. Evaluating the model with the moments averaged over simulations permits us to see, from the distribution of ϕ_j, how much heterogeneity the model requires in the degree of real rigidities but not to see how the model should assign the value of ϕ_j to each λ_j.

While we leave the detail of computations to the appendix of the paper, the simulation method is as follows. First, we draw ϕ_j from a linear function of $\phi_j = \underline{\phi} + (1-\underline{\phi})x_j$, where x_j is a random variable that follows a beta distribution with a probability density of $f_x(x_j; \alpha_x, \beta_x)$ and $\underline{\phi}$ is a lower bound for ϕ_j.[16] Second, we choose α_x and β_x by minimizing the quadratic form of the distance between the simulated and actual moments from the data. Here our target moments are the averages of correlation coefficients $Corr_j\left[\Psi_j^k(\tau), fr_j\right]$ over different $\tau = 0, 1, ..., 24$ for a positive shock to the technology growth rate and a positive shock to the federal funds rate. The resulting parameters imply that $E(\phi_j) = 0.90$, $std(\phi_j) = 0.18$, and skewness of -1.87. Thus, ϕ_j is highly diverse but is highly concentrated on a range of values near unity. Indeed, approximately 70.5 percent of ϕ_j is more than 0.95.

The circular markers in Figure 11 show the simulated share of positive price responses for each shock. Because of the cost channel of monetary policy, the simulated shares of price responses in the lower panel are positive up to one year after the monetary policy shock. Nevertheless, the heterogeneity in real rigidities improves the fit of the model to the data. In comparison with the lower panel of Figure 9, the shares for the first year after the shock shift downward from the range of 23.9–66.4 percent to a range of 9.0–44.8 percent, falling in the range of the data expressed by the white bars. Moreover, the upper panel of Figure 11 shows that the share of positive price responses is no longer equal to zero for several quarters after the positive technology shock. The simulated shares of positive price responses are 1.5–4.5 percent for the first year after the shock, which remains comparable to the data.

Turning to the correlation coefficients, the model with heterogeneity in ϕ_j fares much better in weakening the correlation between the disaggregated price response and the frequency of price changes than the models previously discussed. The correlation coefficients depicted by circular markers in Figure 12 are now much closer to the data for both shocks. Almost all correlation coefficients now lie inside the 95 percent confidence intervals for each

[16] We set the lower value of $\underline{\phi}$ to 1/3 in the simulations. Without this lower bound, the beta distribution may generate ϕ_j close to zero and may make the computation impossible because of the infinitely large steady-state value of marginal cost (See (20).)

period and each shock.

To see the role of heterogeneity in ϕ_j in the production function, note that the New Keynesian Phillips curve at the sector level is given by

$$\pi_{j,t} = \kappa_j D_j mc^R_{j,t} - \kappa_j D_j q_{j,t} + \beta E_t \pi_{j,t+1}, \tag{21}$$

where $mc^R_{j,t}$ denotes the log-deviation of the average sectoral real marginal cost from the steady state, and $q_{j,t}$ is the log-deviation of the relative price $(P_{j,t}/P_t)$ from the steady state. Furthermore, $\kappa_j \equiv (1-\lambda_j)(1-\lambda_j\beta)/\lambda_j$ and $D_j \equiv \phi_j/(\phi_j + (1-\phi_j)\theta_p)$. The heterogeneity in the nominal price stickiness affects $\pi_{j,t}$ through the slope parameter κ_j. In contrast, the heterogeneity in real rigidities affects $\pi_{j,t}$ through the other slope parameter D_j and the movements in the sector-specific real marginal cost $mc^R_{j,t}$.

This heterogeneity in real rigidities results in breaking a strong cross-sectional link between the disaggregated price responses and the frequency of price changes. Therefore, the portion of variations in disaggregated price responses attributed to heterogeneity in the frequency of price changes is reduced significantly.

Sector-specific kinked demand curve The reason that the model with the above heterogeneous real rigidities can replicate the weak correlation between the disaggregated price responses and the frequency of price changes comes from two sources: the sector-specific slope coefficient D_j and the sector-specific fluctuations of real marginal cost $mc^R_{j,t}$. We argue that the latter is much more important than the former.

To illustrate this, we next consider the kinked demand curve of Kimball (1995), another type of strategic complementarity. As the existing literature emphasizes, the kinked demand curve is another useful device in generating real rigidities.[17] However, an important difference from the sector-specific factor in the production function is that this type of real rigidity can produce the heterogeneity in real rigidity from the demand function. As a result, the sector-specific kinked demand curve affects the slope parameter in the New Keynesian Phillips curve but does not affect the marginal cost fluctuations.

[17] A few examples are: Chari, Kehoe, and McGrattan (2000), Dotsey and King (2005), Eichenbaum and Fisher (2007) and Coenen, Levin, and Christoffel (2007).

We assume that the elasticity and curvature of the demand function for differentiated goods vary across sectors. Here, we use (18) rather than (20) to isolate the role of the sector-specific kinked demand curve. The aggregator of differentiated products in sector j is defined as

$$\int_0^1 G_j\left(\frac{Y_{j,t}(f)}{Y_{j,t}}\right) df = 1,$$

where $G_j(\cdot)$ satisfies $G_j'(\cdot) > 0$, $G_j''(\cdot) < 1$, and $G_j(1) = 1$.[18] Here, the standard CES aggregator (6) corresponds to the special case where $G_j\left(Y_{j,t}(f)/Y_{j,t}\right) = \left(Y_{j,t}(f)/Y_{j,t}\right)^{(\theta_p-1)/\theta_p}$. Denoting the elasticity of demand for goods $Y_j(f)$ around the steady state by Δ_j, the slope of the sector-specific elasticity of demand ξ_j is given by

$$\xi_j \equiv \left[\frac{P_j(f)/P_j}{\Delta_j}\frac{\partial\Delta_j}{\partial\left(P_j(f)/P_j\right)}\right]_{Y_j(f)/Y_j=1} = \Delta_j\left[\frac{G_j'''(1)}{G_j''(1)}\right] + \Delta_j + 1.$$

Firms' pricing behavior is influenced by the parameter ξ_j. For a higher value of ξ_j, the firm's profit in sector j is more likely to decline when its price increases. As a result, the pass-through of marginal cost to the price becomes moderate.[19]

Under the production function of (8) and the sector-specific kinked demand curve, the New Keynesian Phillips curve for sector j is

$$\pi_{j,t} = \kappa_j A_j mc_t^R - \kappa_j A_j q_{j,t} + \beta E_t \pi_{j,t+1}, \tag{22}$$

where the coefficient A_j is given by

$$A_j \equiv \frac{\theta_p - 1}{\theta_p + \xi_j - 1}.$$

Here, mc_t^R is the log-deviation of real marginal cost that is *common* to all sectors. The coefficient A_j decreases with ξ_j, reducing the pass-through from marginal cost to inflation.

[18] Here we follow Eichenbaum and Fisher's (2007) specification for the nonconstant elasticity of demand.

[19] Note that the CES aggregator with heterogeneous elasticity of demand alone is incapable of weakening the correlation. To see this, under linear technology, the elasticity of demand θ_p does not enter the coefficients for real marginal cost in the New Keynesian Phillips curve and thus it has no effect on disaggregated inflation dynamics.

To evaluate the model with the sector-specific kinked demand curve, we assign randomly drawn $\{\xi_j\}_{j=1}^N$ to each sector j. Here, we parameterize ξ_j randomly from the gamma distribution. We again choose parameters of the gamma distribution to match the averages of correlation coefficients $Corr_j\left[\Psi_j^k(\tau), fr_j\right]$ over $\tau = 0, 1, ..., 24$ for the two shocks. The resulting gamma distribution has $E(\xi_j) = 79$ and $std(\xi_j) = 333$.[20]

The triangular markers in Figure 11 depict the simulated results under the model with the sector-specific kinked demand curve. The upper panel of the figure shows that the model generates no positive price response to a positive shock to the aggregate technology growth as in the model without heterogeneous real rigidities. For the monetary tightening shock shown in the lower panel, the share of positive price responses for the first year after the shocks ranges between 20.8 and 54.5 percent, which is close to the 9.0– 44.8 percent range in the model with the sector-specific factor of production. Hence, the model of the sector-specific kinked demand curve is as good as the model with a sector-specific fixed factor of production in accounting for the positive disaggregated price responses to a monetary tightening shock. In contrast, even though we freely choose the parameters for the gamma distribution to match the target moments, the effects of introducing the sector-specific kinked demand curve on the weak correlation are rather limited as suggested by Figure 12. The correlation coefficients depicted by the triangular markers in Figure 12 show that most of them lie outside the 95 percent confidence intervals, regardless of shock k.

To summarize, the sector-specific marginal cost responses are more important in generating the weak correlations than the sector-specific slope coefficient. Our analysis suggests that the difference between these two models with heterogeneous real rigidities stems from the marginal cost responses. Therefore, heterogeneous fluctuations in the marginal cost seems to be a key to understanding heterogeneity in the disaggregated price responses to shocks.

[20] The calibrated mean for our heterogeneous ξ_j is not directly comparable to the values of homogeneous ξ used in the one-sector models, but roughly consistent with the values in the previous studies. For example, while Eichenbaum and Fisher (2007) and Coenen, Levin, and Christoffel (2007) set homogeneous ξ to 10 and 33, respectively, Kimball (1995) sets ξ to 471 and Chari, Kehoe, and McGrattan (2000) set ξ to 385.

5 Concluding Remarks

In the light of growing interest in highly disaggregated price dynamics in recent research, this paper studied the responses of disaggregated prices to aggregate technology shocks compared with monetary policy shocks, focusing on the difference across both shocks and sectors. Using the disaggregated price data in the US, we empirically found two features related to the disaggregated price responses. First, a substantial number of disaggregated prices tend to rise temporarily in response to a contractionary monetary policy shock, but such a pattern is not observed in response to an aggregate technological improvement. Second, the disaggregated price responses are weakly correlated with the frequency of price changes.

The standard multi-sector sticky price model fails to replicate these two features. Namely, the model generates symmetric price responses across shocks and stronger correlation with the frequency of price changes than the data. We extended the model and found that the model with a cost channel of monetary policy and heterogeneous real rigidities in the form of a sector-specific fixed factor of production can explain these features. The introduction of the cost channel allows marginal cost to depend on the nominal interest rate that responds in the opposite direction, resulting in asymmetric responses across shocks. The heterogeneous real rigidity that stems from the sector-specific fixed factor of production generates a large cross-sectional variation in the marginal cost, weakening the correlation between the frequency of price changes and disaggregated price responses. Thus, we conclude that modeling the marginal cost structure and its fluctuations that change across sectors is important for understanding disaggregated prices.

Extending the standard multi-sector model to other dimensions is possible and could be explored to overcome the shortcomings of the standard model. For example, heterogeneity in financial market imperfection and in households' preferences, and heterogeneous beliefs of economic agents about shocks might be a possible explanation. Furthermore, our finding on the differences in the disaggregated price responses across shocks may be explained by the rational inattention model in a sticky price environment.[21] These lines of research would be promising avenues for future research.

[21] For a discussion of the rational inattention model, see Mackowiak and Wiederholt (2009), Paciello (2009b) and Sims (2003).

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A Appendix

A.1 Calibrating heterogeneous real rigidities

In this appendix, we explain how to calibrate ϕ_j in the production function and ξ_j in the kinked demand curve. Let us consider the case of calibrating ϕ_j. Our parameterization takes several steps similar to the indirect inference. First, we draw a random variable $x_j \in [0,1]$ from a beta distribution $f(x;\alpha_x,\beta_x)$ for each sector j. We randomly assign ϕ_j to each sector j by $\phi_j = (1-\underline{\phi})x_j + \underline{\phi}$ where $\underline{\phi} \in [0,1]$ is a lower bound for ϕ_j. The lower bound for ϕ_j is required to avoid having the infinitely large steady-state marginal cost. The upper bound for ϕ_j is unity to rule out the possibility of increasing returns to labor. Thus, the support for ϕ_j is $[\underline{\phi}, 1]$. Second, we compute the simulated moments that are of interest. Because the simulated moments depend critically on the particular combination of λ_j and the randomly drawn value of ϕ_j, we mitigate the effect on the simulation results by taking S sets of random parameterization. In particular, we compute the vector of the simulated moments $m_s(\Phi;\alpha_x,\beta_x)$ for $s = 1, 2, ..., S$, where Φ is a vector of calibrated parameters including λ_j and $\underline{\phi}$. Here we set $S = 30$. Third, we choose the parameters for the beta distribution α_x and β_x to minimize

$$\left(m_{data} - \frac{1}{S}\sum_{s=1}^{\infty} m_s(\Phi;\alpha_x,\beta_x)\right)' \Omega \left(m_{data} - \frac{1}{S}\sum_{s=1}^{\infty} m_s(\Phi;\alpha_x,\beta_x)\right),$$

where m_{data} is the moment from the data.

We pick the two averages of correlation coefficients over τ as the moment from the data. Namely, the moment from the data is

$$m_{data} = \frac{1}{25}\sum_{\tau=0}^{24} \begin{bmatrix} Corr_j(\Psi_j^{Tech}(\tau), \lambda_j) \\ Corr_j(\Psi_j^{MP}(\tau), \lambda_j) \end{bmatrix},$$

where $Tech$ refers to a positive shock to the technology growth rate and MP refers to a positive shock to the federal funds rate. We set Ω to a (2×2) identity matrix.

Next consider the case of the sector-specific kinked demand curve. The parameter ξ_j is generated from the gamma distribution. Let $g_\xi(\xi_j;k_\xi,\theta_\xi)$ be the probability density of ξ_j. We choose the parameters k_ξ and θ_ξ to match the simulated moments $m_s(\Phi;k_\xi,\theta_\xi)$ in the same way as the case of the sector-specific fixed factor of production. Because the mean and the standard deviation of ξ_j have a one-to-one relationship to the parameters k_ξ and θ_ξ, we report the mean and the standard deviation in the main text.

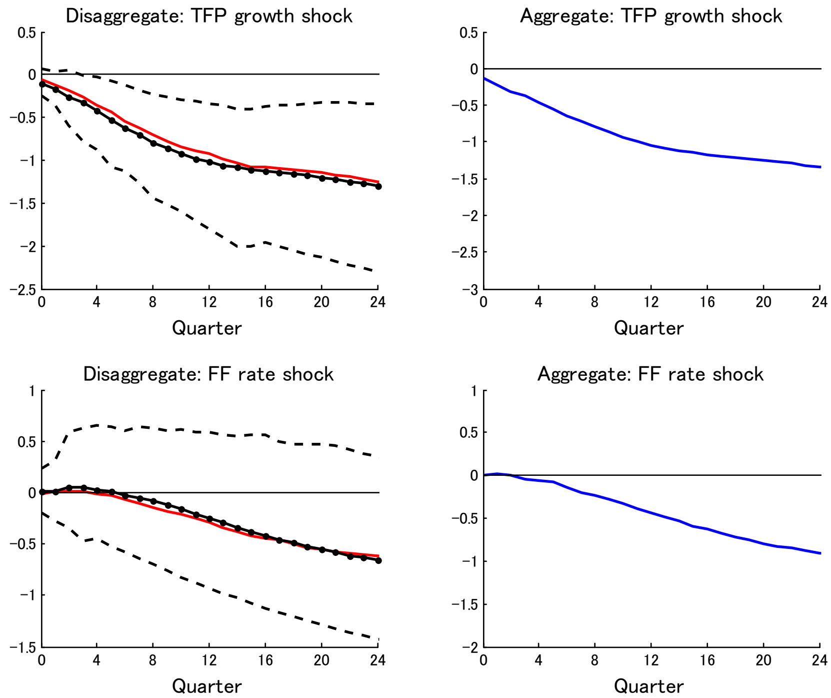


Figure 1: Impulse response functions of disaggregated and aggregate prices to different shocks

Notes: The upper panels plot the impulse response functions to a one percent increase in the total factor productivity estimated from the SVAR. The lower panels plot the impulse response function to a one percent increase in the federal funds rate (expressed as an annual rate). In the left panels, a dotted line denotes the mean response of disaggregated prices (cumulative sum of inflation), a solid line denotes the median response of disaggregated prices and a dashed line defines the 10th–90th percentile range of responses to express the variability. A solid line in the right panels is the aggregate price response obtained from the SVAR.

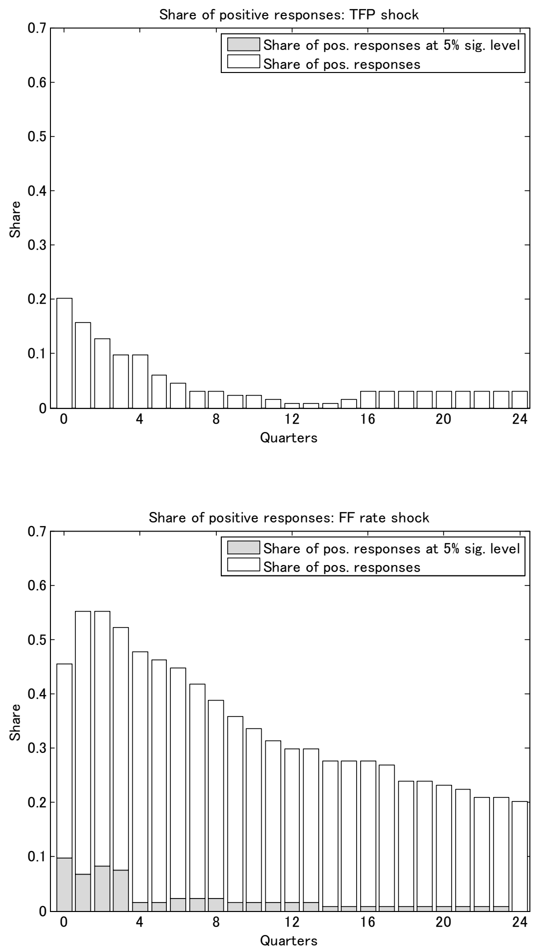


Figure 2: Shares of positive price responses after aggregate shocks that lower prices

Notes: The upper panel shows the share of positive disaggregated price responses to all price responses to a one percent increase in aggregate technology growth. The lower panel is the share of positive disaggregated price responses to all price responses for a contractionary shock to the federal fund rate. The two shocks are identified using the SVAR. The height of the shaded bar measures the share of positive price responses that are significantly positive at the five percent significance level.

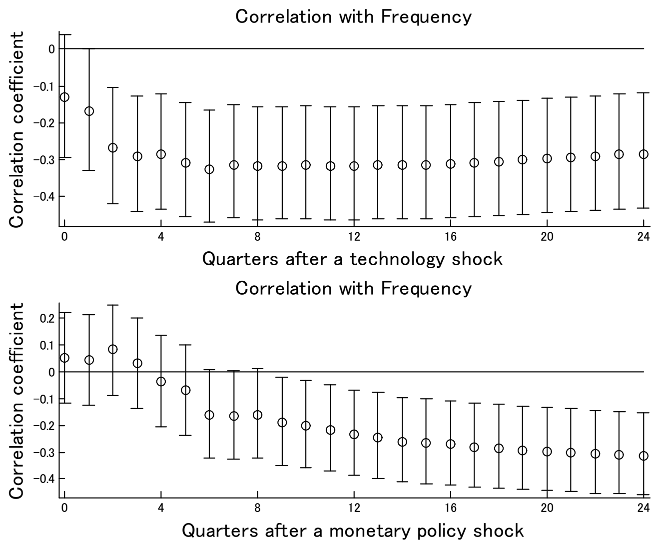


Figure 3: Correlation coefficients between disaggregated price responses and the frequency of price changes

Notes: The circular markers indicate the point estimate of the correlation coefficients between the disaggregated price responses after a shock and the frequency of price changes measured by Nakamura and Steinsson (2008). The length of each bar indicates the 95 percent confidence intervals of the correlation coefficients. The upper panel is the case of the responses to a one percent increase in aggregated technology growth, while the lower panel is the case of the responses to a one percent increase in the federal funds rate.

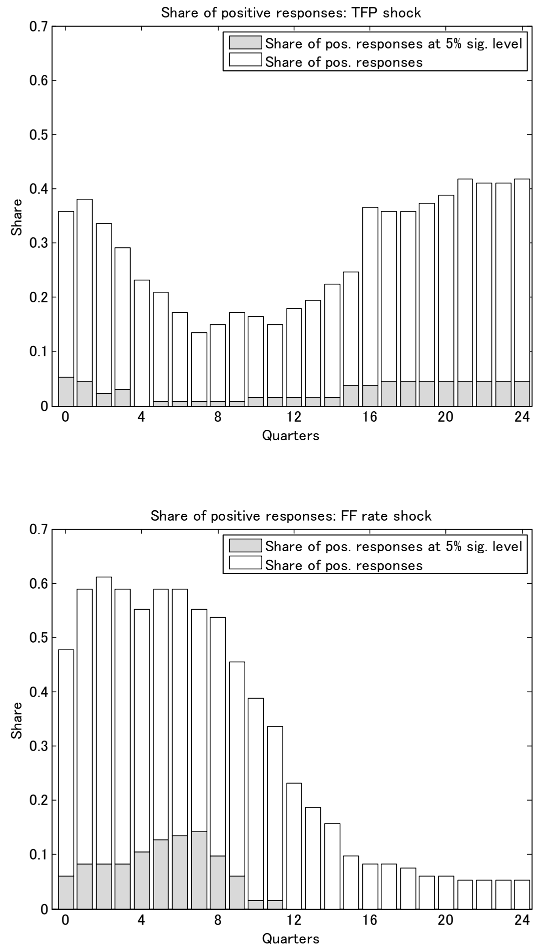


Figure 4: Shares of positive price responses to a shock to technology growth identified by Basu, Fernald, and Kimball (2006) and to a contractionary monetary policy shock identified by Romer and Romer (2004)

Notes: The shares are calculated based on the impulse response functions estimated by (2). The shock series used here are the quarterly version of the purified total factor productivity growth by Basu, Fernald and Kimball (2006) over the period 1959:Q3–2008: Q3 and the monetary policy shock measure by Romer and Romer (2004) over the period 1969:Q1–1996:Q4. The height of the shaded bar measures the share of positive price responses that are significantly positive at the five percent significance level.

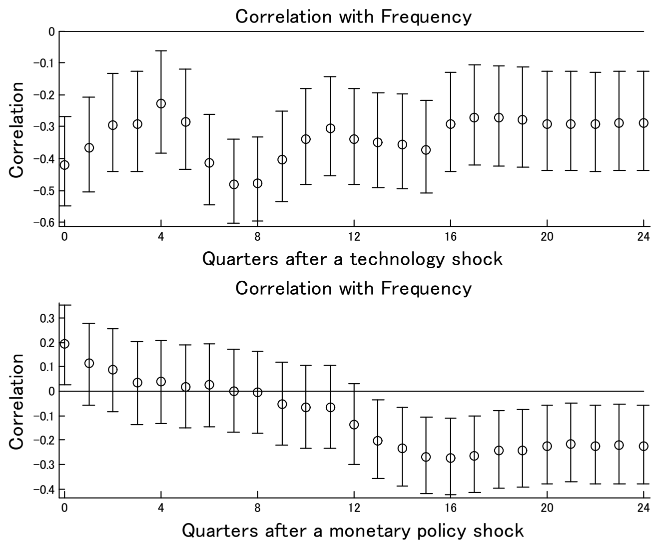


Figure 5: Correlation coefficients between the disaggregated price responses and the frequency of price changes based on aggregate shocks by Basu, Fernald, and Kimball (2006) and Romer and Romer (2004)

Notes: The disaggregated price responses are estimated from (2). The upper panel is based on the shock series identified by Basu, Fernald, and Kimball (2006) and the lower panel is based on the shock series based on Romer and Romer (2004). See the notes of Figure 3 for further details.

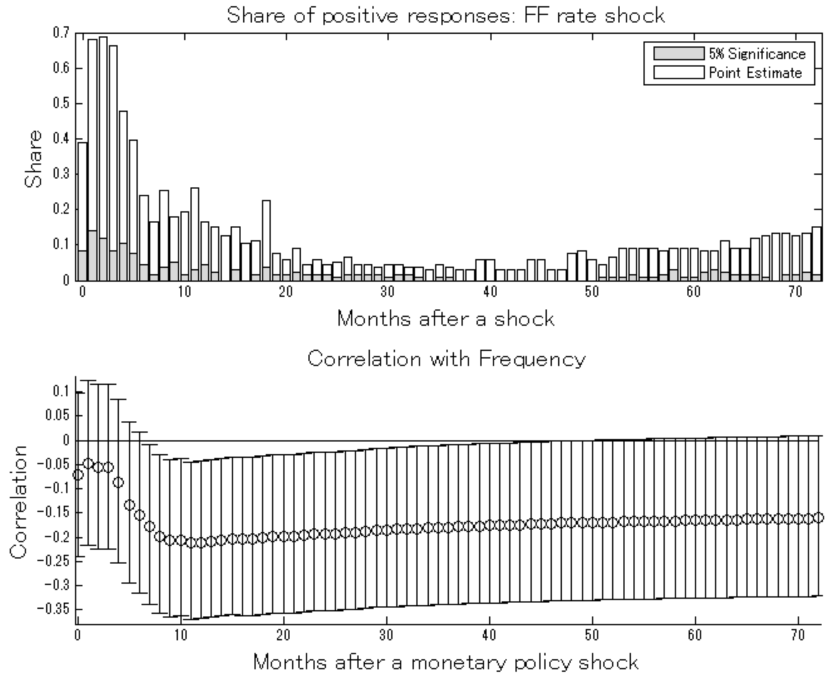


Figure 6: Shares of positive price responses to a contractionary shock to the federal fund rate and correlation coefficients between the disaggregated price and the frequency of price changes, based on by the factor-augmented VAR in Boivin, Giannoni, and Mihov (2009)

Notes: For both panels, the impulse response functions of the disaggregated prices are obtained from the estimates of Boivin, Giannoni, and Mihov's (2009) factor-augmented VAR. The shaded bars in the upper panel represent the share of significantly positive price responses at the five percent significance level. The lower panel is the correlation coefficient (circular markers) between the disaggregated price responses to a monetary policy shock and the frequency of price changes. The length of the bars attached to circular markers in the lower panel measures the 95 percent confidence intervals.

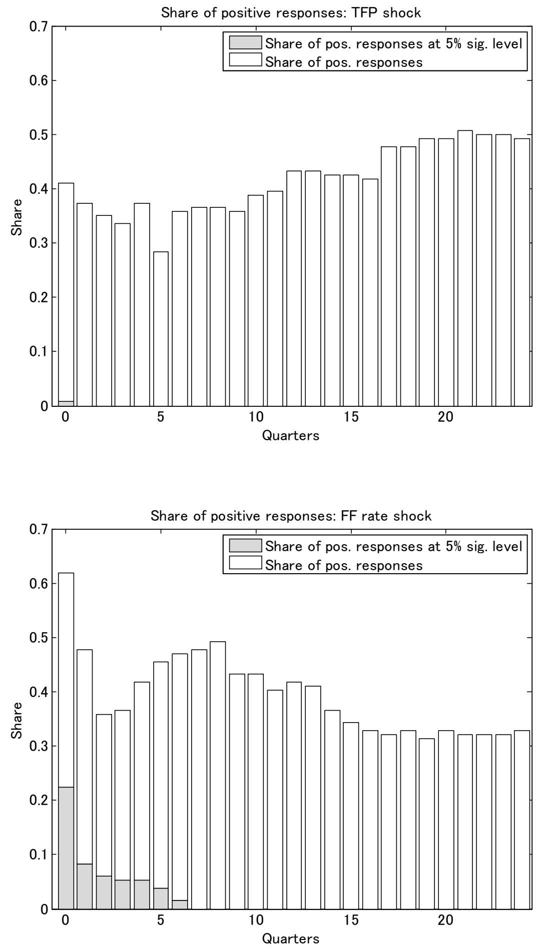


Figure 7: Shares of positive price responses to aggregate shocks that lower prices: Based on the subsample period from 1981:Q1 - 2008:Q3

Notes: The shares are calculated from the impulse response functions estimated over the period 1984:Q1–2008:Q3. See the notes of Figure 2 for further detail.

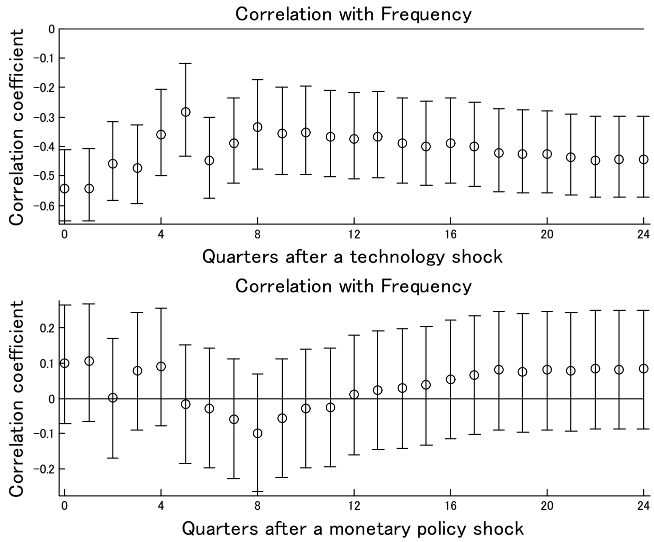


Figure 8: Correlation coefficients between the disaggregated price responses and the frequency of price changes: Post 1984 samples

Notes: The correlation coefficients are calculated based on the impulse response functions estimated using the subsample periods after 1984:Q1. See the notes of Figure 3 for further detail.

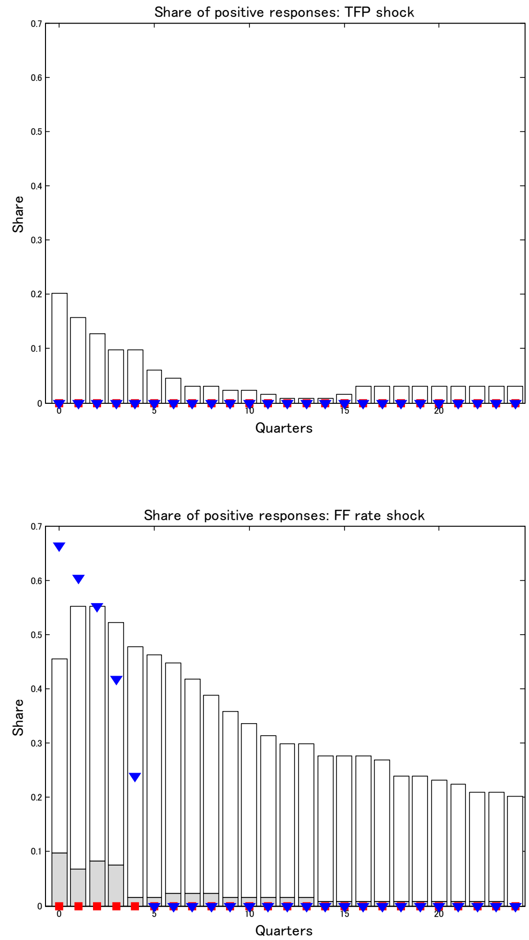


Figure 9: The simulated shares of positive price responses to all price responses to a one percent increase in aggregate technology and a contractionary shock in the federal fund rate

Notes: The rectangular markers in both panels indicate the shares of positive disaggregated price responses to all disaggregated price responses under the baseline model. The triangular markers are the corresponding share under the model with the cost channel of monetary policy. The figure repeats the estimation results shown in Figure 2 for comparisons.

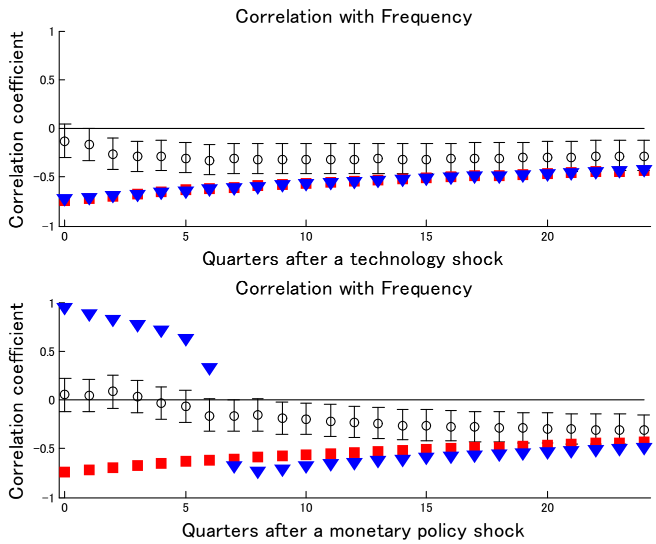
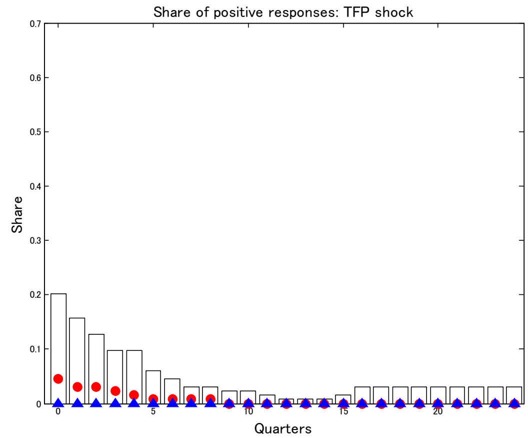


Figure 10: The simulated correlation coefficients between the disaggregated price responses and the frequency of price changes based on the baseline model and the model with a cost channel of monetary policy

Notes: The rectangular markers are the correlation coefficients between the disaggregated price responses and the frequency of price changes under the baseline model. The triangular markers are the correlation coefficients under the model with the cost channel of monetary policy. The figure repeats the estimation results shown in Figure 3 for comparisons.



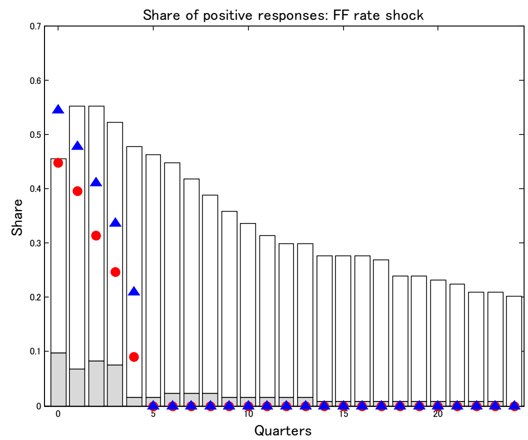


Figure 11: The average of the simulated shares of positive price responses to all disaggregated price responses to different shocks: The model with heterogeneous real rigidity

Notes: The circular markers represent the average of the simulated shares of positive disaggregated price responses to all disaggregated price responses to a positive technology shock and a contractionary monetary policy shock under the sector-specific factor of production (19). The triangular markers are the average of the simulated shares under the sector-specific kinked demand curve. Each simulation is based on a randomly drawn parameterization of ϕ_j or ξ_j. The number of simulations is 100.

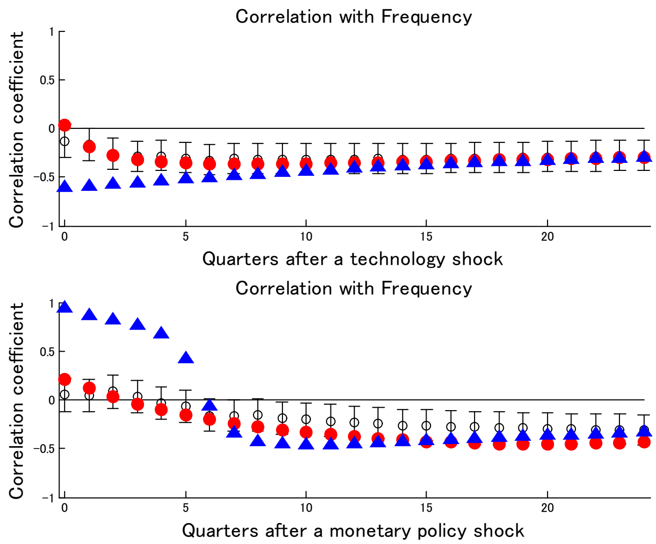


Figure 12: The average of the simulated correlation coefficients between the disaggregated price responses and the frequency of price changes: The model with the sector-specific factor of production and the model with the sector-specific kinked demand curve

Notes: The circular markers show the averages of the simulated correlation coefficients between the disaggregated price and the frequency of price changes based on the model with heterogeneous real rigidities coming from the sector-specific factor of production. The triangular markers are based on the model with heterogeneous real rigidities coming from the sector-specific kinked demand curve. The average of the correlation coefficients are taken over a randomized parameterization of ϕ_j or ξ_j. Both models incorporate the cost channel of monetary policy. The figure repeats the estimation results shown in Figure 3 for comparison. The number of simulations is 100.