Sectoral Price Facts in a Sticky-Price Model*

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Abstract

We develop a multisector sticky-price DSGE model that can endogenously deliver differential responses of prices to aggregate and sectoral shocks. Input-output production linkages and a (standard) monetary policy rule induce across-sector pricing interactions that contribute to a slow response of prices to aggregate shocks. In turn, labor market segmentation at the sectoral level induces within-sector pricing substitutability, which helps the model deliver a fast response of prices to sector-specific shocks. We estimate the model using aggregate and sectoral price and quantity data for the U.S., and find that it accounts well for a range of sectoral price facts.

JEL classification codes: E30, E31, E32

Keywords: heterogeneity, price stickiness, sectoral data, FAVAR, aggregate shocks, sectoral shocks

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1 Introduction

The increasing availability of very disaggregated price data has renewed interest in models of price setting. In particular, there is interest in taking fully-specified models that have arguably been successful in accounting for aggregate dynamics and confronting their implications for the behavior of prices at more disaggregated levels with the new empirical evidence (for surveys of the literature, see Klenow and Malin 2011 and Nakamura and Steinsson 2013).

This is an important area for research in macroeconomics. Assumptions about the nature of price setting are key determinants of the conclusions that can be drawn from the vast majority of fully-specified macroeconomic models that have been brought to bear on actual policy questions, and are regularly used by central banks as an input to the monetary policy decision-making process. Knowledge of how these models fare when confronted with more disaggregated price data can shed light on whether their ability to match aggregate dynamics comes at the expense of poor performance or implausible implications in other dimensions. In turn, this may provide guidance for the development of alternative models that perform well along those dimensions, and hence are arguably more reliable for policy analysis.

While most of the available empirical evidence in the literature is based on micro data on prices of individual goods and services (Bils and Klenow 2004, and many subsequent papers), a growing literature has produced novel empirical facts about the behavior of sectoral prices. In this paper we assess the ability of sticky-price models of the kind that are now routinely used for policy analysis to account for those facts.

A prominent paper in this growing literature is Boivin et al. (2009) (henceforth BGM).[1] The authors employ a Factor Augmented Vector Autoregression (FAVAR) framework to analyze the response of quite disaggregated price indices to different shocks, considering the natural partition of shocks into common and series-specific that is inherent in their empirical methodology. Among their findings, one seems to be particularly challenging to standard models of price setting, and has thus caught the attention of researchers in the field: sectoral prices respond faster to "idiosyncratic" (series-specific) shocks than to "aggregate" (common) shocks.

At a first pass, intuition suggests that this pattern is hard to square with most available models of price setting. Consider, for example, a menu-cost model in which firms optimally choose when to incur a fixed cost to change prices, and are subject to aggregate and sector-specific shocks. Since paying the menu cost allows a firm to choose whichever price it desires, it should take the opportunity to respond to all relevant shocks. Alternatively, consider the Calvo (1983) model of price setting. Since firms'

[1]Other recent empirical papers on sectoral price dynamics are Clark (2006), Balke and Wynne (2007), Altissimo et al. (2009), Maćkowiak et al. (2009), Reis and Watson (2010), Beck et al. (2016), De Graeve and Walentin (2015), and Andrade and Zachariadis (2016).

infrequent opportunities to change prices arrive exogenously, they should again take the occasion to respond to all shocks. This line of reasoning suggests that these models of price setting – and other models in which firms change prices infrequently, for that matter – should have difficulty generating price responses with different speeds to different shocks.[2]

We investigate whether standard multisector New Keynesian models can account for the new empirical evidence – in particular for the differential speed of price responses to different shocks. In order to establish a benchmark for comparisons and build intuition, we start our analysis by finding restrictions on parameter values under which our model conforms with the "first-pass intuition" laid out previously, and delivers the exact same response of sectoral prices to aggregate and sector-specific shocks. The specification that produces this result features perfect wage equalization across sectors and no intermediate inputs in production, coupled with the commonly used assumption of exogenous nominal aggregate demand. Under these restrictions, nominal marginal costs become a combination of exogenous driving processes, exhibiting what we refer to as "strategic neutrality in price setting," as each firm's pricing decision is independent from other firms' – both within and across sectors. In that case, if aggregate and sector-specific shocks exhibit the same dynamics, the model delivers the same response of sectoral prices irrespective of the nature of the shock. In what follows we refer to this case as the "first-pass specification."

Three departures from the aforementioned first-pass specification deliver endogenous differential responses of prices to aggregate and sector-specific shocks in our model. The reason is that, when departing from this specification, a firm's nominal marginal cost depends also on endogenous variables – in particular, on other prices. In our model, the resulting pricing interactions slow down the response of prices to aggregate shocks and speed up the responses to sector-specific shocks – despite the frequency of price changes being exogenous and independent of the nature of the shock.

The first departure is an input-output production structure, borrowed from Basu (1995). It renders firms' pricing decisions strategic complements in response to aggregate shocks, while price adjustments after sector-specific shocks continue to be (almost) strategically neutral. Firms use other goods as production inputs, and this creates a direct dependence of their marginal costs on the aggregate price level. In this context, whenever a shock affects the aggregate price level, adjusting firms change their prices less – since nominal marginal costs are "held back" by prices that have not yet adjusted. This is what happens when the economy is hit with an aggregate shock. In contrast, the aggregate price level is essentially exogenous with respect to sector-specific shocks – because the latter has only a small effect on the former –, which renders that pricing complementarity unimportant. Sectoral prices

[2] Similar points have been made elsewhere in the literature. For example, when writing about the Calvo (1983) model of price setting, Maćkowiak and Smets (2009) conjecture that "If the frequency of price changes were decisive for impulse responses, one would expect prices to respond with roughly equal speed to both kinds of shocks". Regarding menu-cost models, Maćkowiak et al. (2009) argue that "when firms respond quickly to sector-specific shocks and sector-specific shocks hit frequently, then firms also respond quickly to aggregate shocks."

therefore respond to sector-specific shocks (almost) as fast as in the first-pass specification.

The second departure is due to our assumption that the markets for a second factor of production are sector-specific. This segmentation creates a direct (negative) dependence of a firm's marginal cost on its sectoral relative price – the sectoral price level relative to the aggregate price level – because of an "expenditure switching effect." A higher sectoral relative price implies less demand for the sector's output, which induces lower demand for the sector-specific factor, reducing its price and thus lowering marginal costs. This positive dependence of a firm's marginal cost on the aggregate price level, and negative dependence on its own sectoral price level, produce *two* types of pricing interdependence: a strategic complementarity in price setting across sectors, and a strategic substitutability within sectors. The former slows down price responses to aggregate shocks for the same reason as the input-output production structure. In turn, because a sectoral shock does affect prices in the sector, the within-sector strategic substitutability works to speed up price responses to that shock: the presence of non-adjusting firms in that sector induces adjusting firms to change their prices more than they would in the absence of such a strategic substitutability. This pattern of *two-way* pricing interactions is impossible to replicate with a version of the model that features an economy-wide factor market, and requires an unrealistic parameterization of the model with firm-specific factor markets. In order to allow for an easy comparison between our model and the most commonly used sticky-price models, we introduce this second ingredient by assuming that labor is the sector-specific input.

The third departure from the first-pass specification is the (standard) assumption that monetary policy responds to endogenous variables – in particular, it takes the form of an interest rate rule (Taylor 1993). This departure turns the nominal wage, an important component of firms' marginal costs, from an exogenous variable (under the first-pass specification) into an endogenous one. It induces a differential response of prices to aggregate and sector-specific shocks through a mechanism similar to the one arising with the input-output production structure. A sectoral shock has little effect on aggregate variables, and thus assuming that monetary policy responds to these variables makes little difference relative to the first-pass specification. In contrast, endogenous monetary policy leads aggregate shocks to have an impact on the (now endogenous) nominal wage, thus differentiating the price response relative to the first-pass specification.

We then move to a quantitative assessment of our model. Our approach is to look at model and data through the lens of an identical FAVAR framework. To that end, we follow BGM and first present various stylized facts on sectoral prices based on the impulse responses from a FAVAR estimated with aggregate and sectoral price and quantity data for the U.S. economy. Another FAVAR with the same specification is estimated on *artificial* time series – obtained by simulating our (estimated) structural model – on the same variables. We then compare the sectoral price facts to the corresponding moments obtained from the model-implied FAVAR.[3]

From the FAVAR analysis, we find that the model has the ability to match the differential speed of responses of sectoral prices to aggregate and sector-specific shocks. Moreover, all of the three aforementioned features play a non-trivial role quantitatively: the model is less successful in matching the sectoral price facts with any combinations of two features. As the model predicts, all three are responsible for the observed slow price responses to aggregate shocks; "endogenous" monetary policy in particular plays a key role. This reflects the fact that assumptions on monetary policy are consequential for conclusions about the extent of monetary non-neutrality in price-setting models. Labor market segmentation, on the other hand, plays a relatively smaller role in slowing down the responses of prices to aggregate shocks. However, it provides the only mechanism that speeds up the responses of prices to sector-specific shocks. The model therefore does not match the observed fast responses of prices to sector-specific shocks without such segmentation.

We also find that the model can match additional sectoral price facts. The estimated model implies that: i) there is relatively smaller cross-sectional variation in the speed of price responses to aggregate shocks than to sector-specific shocks; ii) a sectoral price tends to adjust more to shocks in the short-run when firms in that sector change their prices more frequently; iii) sectors that respond quickly to sector-specific shocks also respond quickly to aggregate shocks; and iv) supply-type shocks are relatively more important drivers of fluctuations in prices and quantities. These implications are consistent with the empirical evidence from the FAVAR estimated on the actual data.

Because of the "ingredients" that we use in the model, our paper is related to different lines of research. These include papers that follow Basu (1995) in explicitly modeling input-output production structures as a source of real rigidity (Blanchard 1987; Hornstein and Praschnik 1997; Bergin and Feenstra 2000; Huang et al. 2004; Huang and Liu 2004; Huang 2006; Dotsey and King 2006; Nakamura and Steinsson 2010). This paper is also related to the growing literature that incorporates heterogeneity in price setting behavior in dynamic macroeconomic models.[4] Our assumption of labor market segmentation is motivated by empirical studies showing that factor reallocation is more flexible within sectors than across sectors or industries (Davis and Haltiwanger 1992; Parent 2000; Hobijn 2012).[5] Our labor market specification therefore falls between the two (extreme) assumptions often made in the business cycle literature: firm-specific factor markets (e.g. Woodford 2003; Altig et al. 2011) and economy-wide factor markets (e.g. Gali 2008; Chari et al. 2000).[6] Finally, our use

[3]See Consolo et al.(2009) and Kryshko (2011) on the mapping between structural models and dynamic factor models.

[4]Bils and Klenow (2004) and Nakamura and Steinsson (2008) provide evidence of heterogeneity in price rigidity. For an overview of this literature, see Klenow and Malin (2011) and Nakamura and Steinsson (2013).

[5]Ramey and Shapiro (1998, 2001), Autor et al. (2014), and Dix-Carneiro (2014) also report related results.

[6]Our assumption regarding the labor market is the same as in, e.g., Carlstrom et al. (2006). However, to our knowledge the existing papers that assume labor market segmentation at the sectoral level do not explore its implications for the pattern of interdependence among firms' pricing decisions.

of sectoral data in the estimation of the structural model connects our paper with Lee (2007) and Bouakez et al. (2009).

Turning to the questions that we address in the paper, Maćkowiak et al. (2009) provide a first assessment of the ability of models with Calvo (1983) pricing to match the sectoral price facts that they document with their statistical model – in particular the "random-walk-type" response of sectoral price to series-specific shocks. They conclude that such models require extreme assumptions to match the latter fact – more specifically, assumptions that produce implausible dynamics for firms' frictionless optimal prices.

In contrast to Maćkowiak et al. (2009), we focus on the ability of our model to match a series of sectoral price facts derived from BGM's FAVAR (and variations thereof that we estimate). These facts differ in some dimensions from the empirical findings of Maćkowiak et al. (2009). Because of our focus, we discuss in detail the mechanisms that allow our model to match BGM's sectoral price facts without the need for extreme assumptions.

Shamloo (2010) is closest to our paper. She studies a sticky-price DSGE model with a heterogeneous input-output structure, heterogeneity in price rigidity, and a monetary policy that follows a Taylor rule. She emphasizes a novel implication of her model: heterogeneous responses of prices to aggregate shocks that are due to differences across sectors in the importance of intermediate goods as production inputs – which she relates empirically to the location of the sectors along the "production chain." In contrast, she also points out that all sectoral prices respond to their own sector-specific shocks quickly in her model.

While the pattern of price responses produced by Shamloo's model is consistent with the finding of Maćkowiak et al. (2009) – who emphasize that the distribution of the speed of price responses to sector-specific shocks is tighter than the distribution of the speed of responses to aggregate shocks – it is in fact opposite to what we find using BGM's FAVAR framework. We show that in BGM's FAVAR – and in alternative specifications that we estimate – the tighter distribution of the speed of responses of sectoral prices is the one obtained in response to common shocks. Our estimated structural model matches the finding that we document with BGM's FAVAR, rather than the opposite finding of Maćkowiak et al. (2009).[7] We later discuss how the two statistical methods may lead to opposite results, thereby producing a tangential contribution to the literature on factor analysis.

[7]This implication of our estimated structural model is not "hard-wired" into it. Under a suitable parameterization it is also capable of producing the opposite result regarding the cross-sectional dispersion of the speeds of price responses to aggregate and sectoral shocks.

2 Empirical sectoral price facts

We first present the sectoral price facts of interest, derived from a FAVAR. While the framework is essentially the same as BGM's FAVAR, for computational reasons we use a lower level of disaggregation of the personal consumption expenditures (PCE) data.[8] Our baseline FAVAR and structural model have 27 sectors. The sectors and the corresponding data are constructed by partially combining 50 subcategories of the third-level disaggregation of PCE. In particular, to construct a sector we combine such subcategories, that i) belong to a same (second-level) category of PCE *and* ii) share a similar degree of nominal rigidities[9]. These sectors are presented in Table 8 in the appendix.

We estimate the FAVAR on the same dataset used in our structural model estimation to allow a direct comparison between our structural and reduced-form empirical results. The observables are the nominal interest rate, consumption growth rate, inflation as well as their sectoral counterparts. We use the effective federal funds rate as a measure of the nominal interest rate. Consumption, as mentioned, is given by PCE, with the corresponding price deflators as the measure of prices. The data are quarterly, and the sample period is 1983:Q1 to 2008:Q2.[10]

Since the dataset used here is different from BGM's, we accordingly adjust the number of common factors and lags; they are two and four respectively. Results are robust with respect to not only the FAVAR specification but also the level of disaggregation, the frequency of the data (i.e. monthly or quarterly), and the inclusion of other aggregate observables such as labor hours. The *online* appendix provides details of the data as well as the results of those robustness exercises, one of which uses the exact same specification and data as BGM.

2.1 Facts on the speed of price adjustments

Figure 1 presents the impulse response functions (IRFs) from the FAVAR. Panel (a) shows the responses of sectoral PCE prices to an innovation to the common component, and the corresponding unweighted average of the IRFs. Panel (b) shows the responses of sectoral PCE prices to an innovation to their respective sector-specific components, and the corresponding unweighted average of the IRFs. The responses are scaled so that the initial impact equals minus one for all series.[11]

From these IRFs we compute measures of the speed of the price responses to each type of shock, following Maćkowiak et al. (2009). Given an impulse response function denoted by IRF_t, the speed of

[8]We thank the authors for making their code and data available on their websites. For brevity we refer the reader to BGM for details on the FAVAR model that they employ.

[9]Sectoral frequencies of price changes are constructed by aggregating up from the ELI-level price-setting statistics reported by Nakamura and Steinsson (2008), using time-averaged consumption expenditures shares as weights.

[10]We focus on the period of the "great moderation," because i) our paper highlights the role of Taylor-type interest rate rules (as opposed to unconventional monetary policy) and ii) the great moderation era is largely consistent with our assumption that the model parameters, especially the coefficients in the Taylor rule and covariances of the shocks, are stable.

[11]We apply the same normalization to all IRFs presented subsequently.

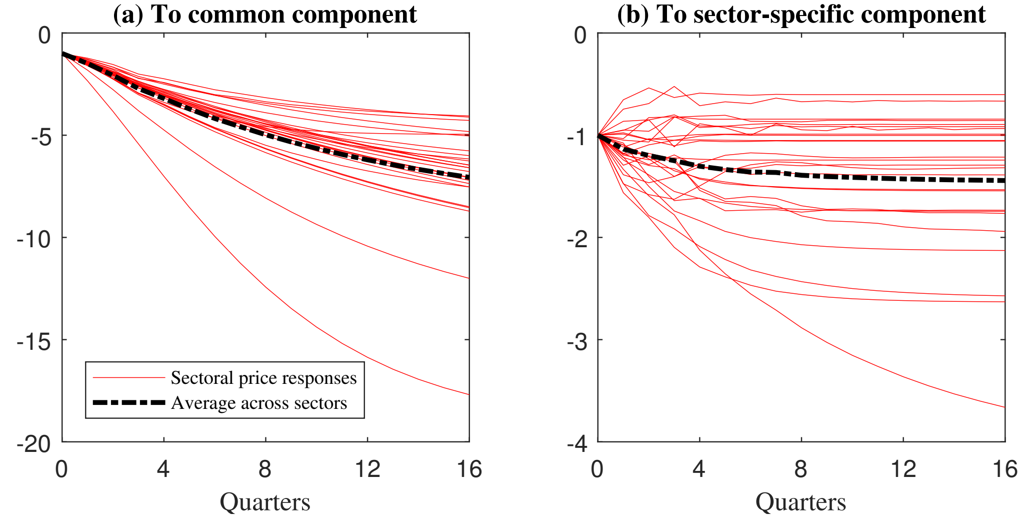

Figure 1: Impulse response of PCE price series

the response is given by the ratio of the average "short-run" response (first 2 quarters) to the average "long-run" response (last 2 quarters in the two-year horizon):

$$\text{speed of response} = \frac{\sum_{t=0}^{1} |IRF_t|}{\sum_{t=7}^{8} |IRF_t|}. \tag{1}$$

Figure 2 shows the distribution of the speed of the responses of sectoral prices to an innovation to the common component (panel (a)), and to their respective sector-specific components (panel (b)). Table 1 reports some descriptive statistics based on these two distributions.

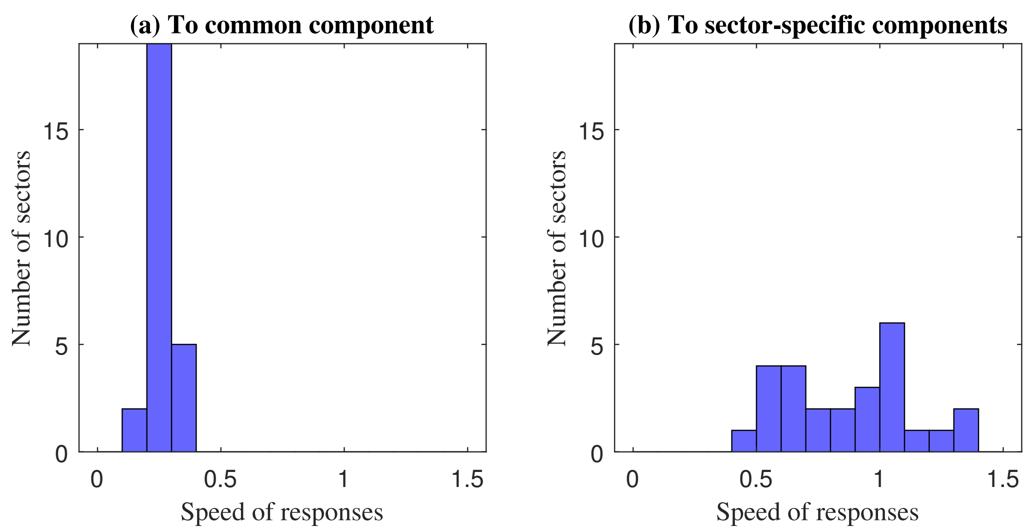

Figure 2: Cross-sectional distribution of speed of responses

The figure and table indicate that the median (and average) speed of response of sectoral prices to sector-specific components is substantially higher than to common shocks – by more than a factor of 3. This conclusion is common to BGM and Maćkowiak et al. (2009). In addition, there is relatively

Table 1: Statistics on the speed of responses to shocks

	Speed of sectoral price responses		
	to common component		to specific components
Mean	0.276		0.875
Median	0.275		0.912
Std. deviation	0.049		0.265
Corr. with sectoral frequency	0.439		0.390
Correlation	–	0.382	–

Note: Sectoral frequencies are constructed by aggregating price-setting statistics reported by Nakamura and Steinsson (2008).

larger cross-sectional variation in the speed of responses to sector-specific shocks than to common shocks. The cross-sectional standard deviations are 0.265 and 0.049, respectively. This implies that sectoral prices tend to respond at more similar speeds when the economy is hit by aggregate shocks.[12]

We also find that the speed of price responses and the frequency of price adjustments are related. The correlation between the sectoral speeds of responses and the sectoral frequencies of price changes is positive for both the common (0.439) and sector-specific components (0.390), indicating sectoral prices tend to respond faster to shocks in sectors where firms change their prices more frequently. Furthermore, the correlation between the speed of responses to both types of shocks is positive: sectors that respond quickly to sector-specific shocks also respond quickly to common shocks. In our FAVAR this correlation is 0.382. These results are largely insensitive whether we use sectoral frequency of price changes from Nakamura and Steinsson (2008) or from our own estimates using the structural model (Section 5).

2.2 Additional facts on the correlations between prices and quantities

Although our prime focus is on the speed of price responses, this subsection reports complementary findings from the FAVAR. Specifically, we revisit BGM's results on the cross-section of correlations between the sector-specific component of PCE inflation rates and the corresponding sector-specific component of quantities (in growth rates), and on the cross-section of correlations between the component of PCE inflation rates and growth rate of quantities that are driven by the common components. These are depicted in Figure 3. Table 2 provides summary statistics. The main finding is that most correlations are negative. This led BGM to conclude that supply-type shocks are relatively more important drivers of fluctuations in prices and quantities. This is a conjecture we verify below.

Table 2: Statistics on the correlations between components of prices and quantities

	Correlation between inflation and growth of quantities	
	Common component	Specific components
Mean	−0.224	−0.285
Median	−0.163	−0.290
Max.	0.483	0.116
Min.	−0.869	−0.978

[12] Our findings on the cross-sectional dispersion of the speed of responses differ from the results of Maćkowiak et al. (2009). The differences are discussed in detail in Section 7.

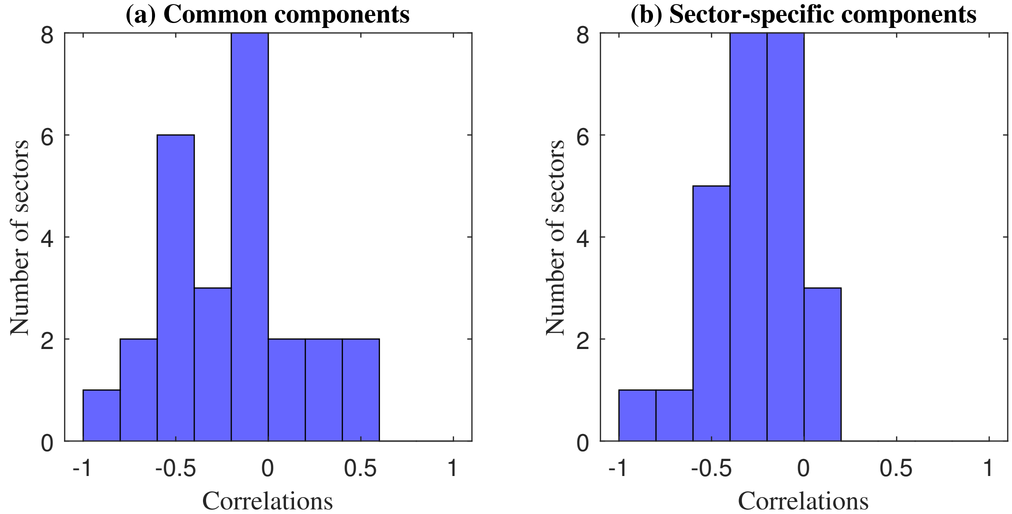

Figure 3: Cross-sectional distributions of correlations between price- and quantity-components of PCE.

2.3 Summary

We conclude the section with a summary of our findings:

1. The average speed of response of sectoral prices to sector-specific shocks is higher than the average speed of response to shocks to the common component (by more than a factor of 3).

2. The cross-sectional standard deviation of the sectoral speeds of responses to shocks to the common component is smaller than the corresponding standard deviation for the responses to sector-specific shocks.

3. The correlation between the sectoral speeds of responses and the sectoral frequencies of price changes is positive for both the common and sector-specific components.

4. The correlation between the speed of responses to both types of shocks is positive.

5. The correlation between the sector-specific component of PCE inflation rates and the corresponding sector-specific component of the growth rate in quantities is on average negative – the same applies to the fluctuations that are driven by the common component.

We confront our model with these sectoral price facts. In particular, special attention is paid to the *first* fact, because it is not obvious that such price dynamics would emerge naturally from a standard New Keynesian model as outlined in the introduction.

3 The model

The model is a variant of the standard New Keynesian model, from which we make the following departures: i) add multiple sectors that are subject to idiosyncratic demand and supply shocks, and that differ in the degree of price stickiness; ii) assume that firms' varieties are also used as intermediate inputs in production; and iii) assume that labor markets are sector-specific.

The economy is divided into a finite number of sectors indexed by $k \in \{1, 2, ..., K\}$. There is a continuum of firms indexed by $i \in [0, 1]$. Each firm belongs to one of the K sectors and produces a differentiated good that is used for consumption and as an intermediate input. We refer to firm i that belongs to sector k as "firm ik." We use $\mathcal{I}_k$ to denote the set that contains the indices of firms that belong to sector k (so that $\bigcup_{k=1}^{K} \mathcal{I}_k = [0, 1]$). Its measure, n_k, represents the size of the sector.

3.1 Representative household

The representative consumer derives utility from a composite consumption good, supplies different types of labor to firms in different sectors, and has access to a complete set of state-contingent claims. Subject to the budget constraint presented below, she maximizes

$$E_0 \left[\sum_{t=0}^{\infty} \beta^t \Gamma_t \left(\log (C_t) - \sum_{k=1}^{K} \omega_k \frac{H_{k,t}^{1+\varphi}}{1+\varphi} \right) \right],$$

where C_t denotes the household's consumption of the composite good, and $H_{k,t}$ denotes the hours of labor services supplied to sector k. Labor is fully mobile within each sector, but immobile across sectors. The parameters β, φ, and $\{\omega_k\}_{k=1}^{K}$ are, respectively, the discount factor, the inverse of the (Frisch) elasticity of labor supply, and the relative disutilities of supplying hours to sector k. Lastly, Γ_t denotes the aggregate preference shock.

The flow budget constraint of the household is given by

$$P_t C_t + E_t [Q_{t,t+1} B_{t+1}] = B_t + \sum_{k=1}^{K} W_{k,t} H_{k,t} + \sum_{k=1}^{K} \int_{\mathcal{I}_k} \Pi_{k,t}(i) di,$$

where P_t denotes the aggregate price level to be defined below, $W_{k,t}$ is the wage rate in sector k, and $\Pi_{k,t}(i)$ denotes profits of firm ik. Households can trade nominal securities with arbitrary patterns of state-contingent payoffs: B_{t+1} denotes household's holding of one-period state-contingent nominal securities and $Q_{t,t+1}$ is the nominal stochastic discount factor.

The aggregate consumption composite is:

$$C_t = \left(\sum_{k=1}^{K} (n_k D_{k,t})^{1/\eta} C_{k,t}{}^{(\eta-1)/\eta} \right)^{\eta/(\eta-1)},$$

where η is the elasticity of substitution between the sectoral consumption composites to be defined below, and $D_{k,t} > 0$ is a relative demand shock satisfying $\sum_{k=1}^{K} n_k D_{k,t} = 1$. The underlying aggregate price index is

$$P_t = \left(\sum_{k=1}^{K} (n_k D_{k,t}) P_{k,t}^{1-\eta} \right)^{1/(1-\eta)},$$

where $P_{k,t}$ is the sectoral price index associated with the sectoral consumption composite $C_{k,t}$. Given aggregate consumption C_t, and the price levels $P_{k,t}$ and P_t, the optimal demand for the sectoral composite goods is given by

$$C_{k,t} = n_k D_{k,t} \left(\frac{P_{k,t}}{P_t}\right)^{-\eta} C_t. \tag{2}$$

Sectoral consumption composites are given by

$$C_{k,t} = \left(\left(\frac{1}{n_k}\right)^{1/\theta} \int_{\mathcal{I}_k} C_{k,t}(i)^{(\theta-1)/\theta} di\right)^{\theta/(\theta-1)},$$

with corresponding sectoral price indices

$$P_{k,t} = \left(\frac{1}{n_k} \int_{\mathcal{I}_k} P_{k,t}(i)^{1-\theta} di\right)^{1/(1-\theta)},$$

where θ denotes the within-sector elasticity of substitution between consumption varieties. The optimal demand for firm ik's good, $C_{k,t}(i)$, is:

$$C_{k,t}(i) = \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} C_{k,t} = D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} \left(\frac{P_{k,t}}{P_t}\right)^{-\eta} C_t. \tag{3}$$

The two remaining first-order conditions for the household's problem are:

$$Q_{t,t+1} = \beta \left(\frac{\Gamma_{t+1}}{\Gamma_t}\right) \left(\frac{C_t}{C_{t+1}}\right) \left(\frac{P_t}{P_{t+1}}\right),$$

$$\frac{W_{k,t}}{P_t} = \omega_k H_{k,t}^{\varphi} C_t.$$

3.2 Firms

Firms use sector-specific labor and other (intermediate) goods to produce according to the following technology:

$$Y_{k,t}(i) = A_t A_{k,t} H_{k,t}(i)^{1-\delta} Z_{k,t}(i)^{\delta},$$

where $Y_{k,t}(i)$ is the production of firm ik, A_t is economy-wide productivity, $A_{k,t}$ is sector-specific productivity, $H_{k,t}(i)$ denotes hours of labor that firm ik employs, $Z_{k,t}(i)$ is firm ik's usage of other goods as intermediate inputs, and δ is the elasticity of output with respect to intermediate inputs.

Firms combine the varieties of goods to form composites of sectoral intermediate inputs through a Dixit-Stiglitz aggregator. The sectoral intermediate inputs are further assembled into the composite intermediate input that can be used for production. The total quantity of intermediate inputs employed by firm ik is a Dixit-Stiglitz aggregator of sectoral intermediate inputs with the same across-sector elasticity of substitution as the one between consumption varieties:

$$Z_{k,t}(i) = \left(\sum_{k'=1}^{K} \left(n_{k'} D_{k',t}\right)^{1/\eta} Z_{k,k',t}(i)^{(\eta-1)/\eta}\right)^{\eta/(\eta-1)},$$

where the sectoral intermediate input, $Z_{k,k',t}(i)$, denotes the amount of firm ik's usage of sector-k'

goods as intermediate inputs, and is given by

$$Z_{k,k',t}(i) = \left(\left(\frac{1}{n_{k'}} \right)^{1/\theta} \int_{\mathcal{I}_{k'}} Z_{k,k',t}(i,i')^{(\theta-1)/\theta} di' \right)^{\theta/(\theta-1)}.$$

$Z_{k,k',t}(i,i')$ denotes the quantity of goods that firm ik purchases from firm $i'k'$.

Taking prices P_t, $P_{k',t}$, $P_{k',t}(i')$, and $W_{k,t}$ as given, firm ik decides how much of each input to employ in production. The cost-minimization problem yields the following optimality conditions:

$$Z_{k,t}(i) = \frac{\delta}{1-\delta} \frac{W_{k,t}}{P_t} H_{k,t}(i), \tag{4}$$

$$Z_{k,k',t}(i) = n_{k'} D_{k',t} \left(\frac{P_{k',t}}{P_t} \right)^{-\eta} Z_{k,t}(i),$$

$$Z_{k,k',t}(i,i') = \frac{1}{n_{k'}} \left(\frac{P_{k',t}(i')}{P_{k',t}} \right)^{-\theta} Z_{k,k',t}(i).$$

Prices are sticky as in Calvo (1983). A firm in sector k adjusts its price with probability $1-\alpha_k$ each period. Thus, the sectoral price level $P_{k,t}$ evolves according to

$$\begin{aligned} P_{k,t} &= \left[\frac{1}{n_k} \int_{\mathcal{I}^*_{k,t}} {P^*_{k,t}}^{1-\theta} di + \frac{1}{n_k} \int_{\mathcal{I}_k - \mathcal{I}^*_{k,t}} P_{k,t-1}(i)^{1-\theta} di \right]^{\frac{1}{1-\theta}} \\ &= \left[(1-\alpha_k) {P^*_{k,t}}^{1-\theta} + \alpha_k P_{k,t-1}^{1-\theta} \right]^{\frac{1}{1-\theta}}, \end{aligned} \tag{5}$$

where $P^*_{k,t}$ is the common price chosen by the firms that adjust at time t. These firms are grouped into set $\mathcal{I}^*_{k,t} \subset \mathcal{I}_k$, which is a randomly chosen subset with measure $n_k (1-\alpha_k)$.

Firms that adjust their prices at time t maximize expected discounted profits:

$$\max_{P_{k,t}(i)} E_t \sum_{s=0}^{\infty} \alpha_k^s Q_{t,t+s} \Pi_{k,t+s}(i),$$

where $Q_{t,t+s}$ and $\Pi_{k,t+s}(i)$ are respectively the stochastic discount factor between time t and $t+s$ and firm ik's nominal profit at time $t+s$ given that the price chosen at time t is still being charged:

$$Q_{t,t+s} = \beta^s \left(\frac{\Gamma_{t+s}}{\Gamma_t} \right) \left(\frac{C_t}{C_{t+s}} \right) \left(\frac{P_t}{P_{t+s}} \right),$$

$$\Pi_{k,t+s}(i) = P_{k,t}(i) Y_{k,t+s}(i) - W_{k,t+s} H_{k,t+s}(i) - P_{t+s} Z_{k,t+s}(i).$$

The first-order condition that determines price setting is:

$$E_t \sum_{s=0}^{\infty} \alpha_k^s Q_{t,t+s} \left(\frac{P^*_{k,t}}{P_{k,t+s}} \right)^{-\theta} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\eta} Y_{t+s} \left[P^*_{k,t} - \left(\frac{\theta}{\theta-1} \right) MC_{k,t+s} \right] = 0,$$

where

$$MC_{k,t+s} = A_{t+s}^{-1} A_{k,t+s}^{-1} \frac{1}{1-\delta} \left(\frac{\delta}{1-\delta} \right)^{-\delta} P_{t+s}^{\delta} W_{k,t+s}^{1-\delta} \tag{6}$$

is the nominal marginal cost of firm ik at time $t+s$. Together with (5), optimal price setting determines equilibrium dynamics of sectoral prices. The aggregate price dynamics are then determined by aggregation of such sectoral prices.

3.3 Policy

For simplicity we abstract from any influence of fiscal policy on equilibrium. We assume that the government does not collect taxes or purchase goods. To close the model, we consider two assumptions for monetary policy: i) that it is explicitly characterized by a Taylor-type interest rate rule; or ii) that policy is such that nominal aggregate consumption follows a given exogenous stochastic process.

Under the explicit interest rate rule the gross nominal interest rate I_t is set according to

$$\frac{I_t}{I} = \left(\frac{I_{t-1}}{I} \right)^{\rho_i} \left[\left(\frac{P_t}{P_{t-1}} \right)^{\phi_\pi} \left(\frac{C_t}{C} \right)^{\frac{\phi_c}{4}} \right]^{1-\rho_i} \exp(\mu_t),$$

where μ_t is a monetary policy shock, and C and I are the zero-inflation-steady-state levels of consumption and interest rate, respectively.

Under the alternative assumption for monetary policy, we impose an exogenous stochastic process for nominal aggregate consumption, denoted by $M_t \equiv P_t C_t$. As usual, this can be rationalized by introducing an exogenous money supply and a cash-in-advance constraint on consumption.

3.4 Equilibrium

Equilibrium is characterized by an allocation of quantities and prices that satisfy the households' optimality conditions and budget constraint, the firms' optimality conditions, the monetary policy rule, and finally the market-clearing conditions:

$$\begin{aligned} B_t &= 0, \\ H_{k,t} &= \int_{\mathcal{I}_k} H_{k,t}(i) di \quad \forall k, \\ Y_{k,t}(i) &= C_{k,t}(i) + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i', i) di' \quad \forall i, k. \end{aligned}$$

The first equation is the asset market clearing condition.[13] The second is the labor market clearing condition for each sector. The last condition equates supply and demand for each good, and indicates that firm $ik's$ output can be either consumed by the household, $C_{k,t}(i)$, or employed as inputs by other firms, $\sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i', i) di'$.

[13] For a discussion of alternative ways to think about bond-market clearing and interest-rate determination in a cashless-limit economy see Woodford (2003).

We solve the model by log-linearizing the equilibrium conditions around the deterministic zero-inflation steady state. The online appendix provides a detailed derivation of the steady-state equilibrium as well as the full set of log-linearized equations. In what follows, lowercase letters denote log-deviation from their steady state counterparts.

4 Inspecting the mechanisms

In this section we analyze the mechanisms through which our model delivers a differential response of prices to aggregate and sectoral shocks. In our model, there are three sources that generate such the mechanisms: i) pricing interactions produced by intermediate inputs; ii) pricing interactions produced by labor market segmentation; and iii) monetary policy responses to endogenous variables.

To develop intuition, we follow the literature on pricing interactions and analyze how firms would set their prices if they could reoptimize frictionlessly every period. Our discussion starts from a special case in which the first-pass intuition that the Calvo model cannot produce price responses with different speeds depending on the type of the shocks indeed holds true. We then depart from this case to highlight the three sources of endogenous differential responses one-by-one, and thus illustrate why the first-pass intuition does not hold more generally.

4.1 Identical responses

To get the model to produce the same response of sectoral prices to aggregate and sector-specific shocks, we start by abstracting from intermediate inputs ($\delta = 0$). In addition, we assume perfectly elastic labor supply ($\varphi = 0$). This eliminates the effects of labor market segmentation, equalizing wages across sectors. Lastly, nominal consumption (m_t) evolves exogenously.

Under these assumptions, the model exhibits what we refer to as "strategic neutrality" – as opposed to strategic complementarity or substitutability – in price setting. A clear way to see the neutrality result is by looking at firm ik's *frictionless optimal price* $p_{k,t}^{**}(i)$, which is given by:

$$p_{k,t}^{**}(i) = m_t - a_t - a_{k,t}, \tag{7}$$

where the right hand side is firm ik's nominal marginal cost.[14] As shown in (6), a key determinant of the marginal cost is the wage rate, which we have substituted out to obtain equation (7), using the household's intra-temporal optimality condition (i.e. labor supply schedule) and the production function.

Under this "first-pass specification," marginal costs are simply a linear combination of exogenous stochastic processes ($m_t - a_t - a_{k,t}$), thereby making a firm's pricing decisions completely insulated from other firms'. This leads firms to respond in exactly the same way to the various shocks, provided they have the same dynamics.[15]

[14] This is the price that firm ik would choose if it could change prices continuously. The derivations of frictionless optimal prices are presented in the online appendix.

[15] Note that in this case demand shocks have no effect on pricing decisions. This is so because wage equalization implies that pure relative-demand shifts have no effect on marginal costs.

4.2 Differential responses

From the result in the last subsection, it follows trivially that one source of differential dynamics in the response of sectoral prices to shocks are differential dynamics of the shocks themselves. To isolate this factor from the mechanisms that endogenously deliver a differential price response to shocks, in the remainder of this section we assume that all exogenous stochastic processes exhibit the same dynamics. We relax this assumption when we move to our quantitative analysis.

Away from the particular parameterization of the previous subsection, in general, a firm's nominal marginal cost depends on endogenous variables – in particular, on other prices. As we show below, pricing interdependence tends to generate different price responses depending on the nature of shocks.

4.2.1 The effect of intermediate inputs ($\delta > 0$, $\varphi = 0$, m_t exogenous)

We continue to neutralize the effect of labor market segmentation by setting $\varphi = 0$, and maintain the assumption of exogenous nominal consumption. This yields the following expression for firm ik's frictionless optimal price $p_{k,t}^{**}(i)$:

$$p_{k,t}^{**}(i) = (1 - \delta)\, m_t - a_t - a_{k,t} + \delta p_t. \tag{8}$$

The first three terms on the right hand side of (8) are exogenous processes. The last term, however, involves the aggregate price level p_t, which renders firms' pricing decisions strategic complements. This complementarity follows directly from the fact that goods are inputs to production, and thus their prices affect marginal costs.

Unlike aggregate shocks, sector-specific shocks ($a_{k,t}$) have only a small effect on the aggregate price level – which for expositional purposes we take to be zero; that is, the price level is (almost) exogenous with respect to sector-specific shocks. Hence, when analyzing the effects of such shocks, the presence of p_t in equation (8) becomes immaterial, and thus firms adjust their prices in response to sectoral shocks essentially in the same way as in the case of strategic neutrality in pricing decisions.[16]

In contrast, an aggregate shock does move the aggregate price level, and thus how the latter responds matters. Strategic complementarity in pricing decisions – i.e., a positive coefficient on the aggregate price level – implies that firms in a given sector would like to keep their prices in line with other firms' – including those in other sectors (i.e. an *across-sector* strategic complementarity). In this context, in the presence of nominal rigidities and staggered price setting, adjusting firms do not change their prices by as much in response to aggregate shocks, since nominal marginal costs are "held back" by prices that have yet to adjust.

In sum, input-output linkages generate across-sector complementarities in response to aggregate shocks and (almost) no pricing interactions in response to sector-specific shocks. This mechanism implies slower price responses to aggregate shocks than to sector-specific shocks.[17]

[16] The "strategic neutrality" result does not hold exactly, because sectors are small, yet not of zero measure. Hence, input-output linkages still generate pricing interactions with respect to sector-specific shocks. The quantitative effect of such pricing interactions, however, is negligible, as shown in Section 6.

[17] Since frictionless optimal prices are independent from the sources of price rigidities, the mechanisms considered here are also likely to be operative in other price setting models in which firms' price adjustments are not completely synchronized. Nakamura and Steinsson (2010), in particular, have shown that the introduction of intermediate inputs

4.2.2 The effect of labor market segmentation ($\delta = 0$, $\varphi > 0$, m_t exogenous)

Labor market segmentation at the sectoral level produces a different type of pricing interaction. To highlight this feature, we continue to assume exogenous nominal output, but we now abstract from intermediate inputs ($\delta = 0$) and make labor market segmentation relevant by assuming a finite Frisch elasticity ($\varphi > 0$). This produces the following expression for firm ik's frictionless optimal price:

$$p_{k,t}^{**}(i) = (1+\varphi)\, m_t + \varphi d_{k,t} - (1+\varphi)\, a_t - (1+\varphi)\, a_{k,t} - \varphi p_t \\ + \varphi\eta p_t - \varphi\eta p_{k,t}. \tag{9}$$

The first four terms on the right-hand-side of (9) involve exogenous processes, while the fifth term ($-\varphi p_t$) is reminiscent of models with an economy-wide labor market. It implies a strategic substitutability in price setting.[18]

The two terms in the second row ($\varphi\eta p_t$ and $-\varphi\eta p_{k,t}$) arise because sectoral labor market segmentation creates a direct dependence of a firm's marginal cost on its sectoral *relative* price, due to an "expenditure switching effect." A higher sectoral relative price implies lower demand for the sector's output and labor hours, which translates into a lower sectoral wage and thus lower marginal costs. This dependence of a firm's marginal cost on the aggregate price level and on its own sectoral price level induces *two* types of strategic interaction in pricing decisions: strategic complementarity in price setting *across sectors* ($\varphi\eta p_t$ term), and strategic substitutability *within sectors* ($-\varphi\eta p_{k,t}$ term). The strength of these pricing interactions depends on the degree of substitutability between varieties in different sectors, and on the Frisch elasticity of sectoral labor supply. Jointly, these parameters determine to what extent changes in sectoral relative prices affect sectoral wages.

The intuition for how across-sector strategic complementarity contributes to a slower response of prices to aggregate versus sectoral shocks is similar to the one developed in Section 4.2.1. We therefore focus on the intuition for how within-sector strategic substitutability leads prices to respond faster to sector-specific shocks than in the case with strategic neutrality.

To fix ideas, consider how a negative sector-specific productivity shock affects adjusting firms' pricing decisions.[19] As can be seen from equation (6), the direct effect of the shock is to increase marginal costs in that sector. On top of that, for a given sectoral price level, lower productivity generates the need for additional labor input to compensate for the lower marginal product of labor and produce enough to satisfy demand. With labor market segmentation, this implies a higher sectoral wage. As a result, all else equal, marginal costs in the sector hit by the adverse productivity shock tend to increase by more than the direct effect of lower productivity. Hence, in the presence of nominal rigidities and staggered price setting, a negative productivity shock leads adjusting firms to increase their prices by more than they would otherwise. This example illustrates the workings of within-sector

in a multisector state-dependent model generates a large amount of strategic complementarity conditional on aggregate shocks, which magnifies monetary non-neutrality – without dampening price responses to idiosyncratic shocks.

[18] Woodford (2003) provides an extensive discussion on how an economy-wide labor market, as often assumed in standard business cycle models, generates strategic substitutability in price setting. Since this result is well known, for brevity we refer the interested reader to Woodford (2003, chapter 3).

[19] Once again, for expositional reasons we take each sector to be negligible, so that sectoral shocks have essentially no aggregate effects.

strategic substitutability, which manifests itself through the term, $-\varphi\eta p_{k,t}$, in equation (9).

The aforementioned mechanism is absent in a version of the model with an economy-wide labor market, in which wage rates are equalized across sectors and thus sectoral relative prices do not appear in firm's marginal costs. In this environment, a sectoral shock and the presence of non-adjusting firms in that sector would have a negligible effect on the *aggregate* wage rate and hence no meaningful indirect effect on firms' pricing decisions.

A version of the model with firm-specific labor markets, under reasonable assumptions, also fails to generate distinct strategic interactions as in the model with sectoral labor. With firm-specific labor markets, the frictionless optimal price is given by:

$$\begin{aligned}(1+\varphi\theta)\,p_{k,t}^{**}(i) &= (1+\varphi)\,m_t + \varphi d_{k,t} - (1+\varphi)\,(a_t + a_{k,t}) \\ &\quad + (-\varphi + \varphi\eta)\,p_t + \varphi\,(\theta - \eta)\,p_{k,t}.\end{aligned} \tag{10}$$

The first row of the right hand side in (10) is a linear combination of exogenous processes, while the second row reveals the nature of pricing interactions across and within sectors. Essentially, compared to (9), an additional term, $\varphi\theta p_{k,t}$, appears as a result of labor market segmentation at the firm level. In this case, a firm's marginal cost depends on the firm-specific (not sector-specific) wage rates $(W_{k,t}(i))$ and thus on firm-specific labor inputs, which in turn are determined by the demand for the particular firm's product (rather than sectoral demand). This implies that a firm's price relative to the sectoral price, $(P_{k,t}(i)/P_{k,t})^{-\theta}$, in addition to the sectoral price relative to the aggregate price level, $(P_{k,t}/P_t)^{-\eta}$, enters a firm's marginal cost. Notice that since the sectoral price, $P_{k,t}$, appears both in the denominator and in the numerator in the demand function (3), the coefficient on $p_{k,t}$ in log-linear form is positive under the reasonable assumption that $\theta > \eta$.

Intuitively, the sectoral price has countervailing effects on a firm's marginal cost through *two* types of expenditure switching effects ($-\varphi\eta p_{k,t}$ and $\varphi\theta p_{k,t}$). A high level of $p_{k,t}$ decreases firm ik's marginal cost as it lowers the demand for the firm's product (and thus labor hours) through an *across-sector* expenditure switching effect, as in the model with sector-specific labor markets. A higher sectoral price, however, also has a completely opposite effect on the marginal cost through a *within-sector* expenditure switching effect. The latter effect dominates to the extent that the within-sector elasticity of substitution, θ, is greater than the across-sector elasticity, η. Under this plausible assumption, the model with firm-specific labor markets thus implies within-sector strategic complementarities in price setting.

Difference compared to the Gertler and Leahy (2008) model of local labor markets Gertler and Leahy (2008) develop a menu-cost model with local labor markets. Labor can flow freely across firms in the same "island," but cannot move across islands. In that dimension, their model is similar to our model of sectoral labor markets. However, the implications of labor market segmentation for the nature of pricing interactions in our models are different. Here we explain briefly why this is the case.

The difference lies in the assumption on "(a)synchronization" of pricing decisions within a sector. As laid out above, in our model the presence of "non-adjusting" firms induces adjusting firms to change their prices by more when a sectoral shock hits. In Gertler and Leahy (2008), because of the presence of firm-specific shocks, not all firms in an island necessarily change prices simultaneously. However, they all entertain a price change at the same time (subject to the menu cost) in response to "common" island-specific shocks – akin to sector-specific shocks in our model. In that sense, with respect to the response of the economy to "common" (aggregate and island-specific) shocks, the local labor market assumption of Gertler and Leahy (2008) is equivalent to one in which labor is firm-specific and wages are, nevertheless, taken as given.[20]

By contrast, in our model, pricing decisions are asynchronized even within a given sector. To gain intuition on the effects of within-sector asynchronization of price changes, consider the case of a negative sectoral productivity shock in a given sector – the same example considered above. If price changes are infrequent but fully synchronized in each sector, at some point all firms will respond simultaneously by increasing their prices, selling and producing less. Moreover, the (common) price that is chosen at that time will remain fixed until the next (synchronized) price change. Such decrease in production (and labor input) will lower the sector-specific wage rate and marginal costs. Therefore, firms in that sector will collectively increase their prices by a *smaller* amount than they would without synchronization.

4.2.3 The effect of "endogenous" monetary policy

In addition to the mechanisms discussed in the previous two subsections, a response of monetary policy to endogenous variables – according to a Taylor-type interest rate rule – also produces differential responses of sectoral prices to shocks. Under a Taylor rule, nominal consumption ($m_t \equiv p_t + c_t$) becomes endogenous. Hence, even in the absence of intermediate inputs and labor market segmentation ($\delta = 0$, $\varphi = 0$) – when a firm's frictionless optimal price is given by (7) – aggregate shocks should lead prices to respond differently from sector-specific shocks, since the former should affect p_t and c_t, whereas the latter should not (again, assuming atomistic sectors for the sake of exposition).

The presence of p_t in (7) leads to slower price responses to *aggregate* shocks for two reasons. First, as in the case of intermediate inputs, nominal rigidities and staggered pricing decisions lead p_t to adjust only partially in the short-run. Moreover, the Taylor rule, by responding to (P_t/P_{t-1}), impedes the adjustment of p_t even further. A similar intuition can be applied to the implication of c_t in (7).

[20] As Woodford (2003, ch. 3) discusses in detail, such a model with firm-specific labor can alternatively be thought of as featuring an additional continuum of firms producing sub-varieties of each variety of the consumption good, all of which use the same type of labor input hired in a competitive market, and change prices at the same time. These groups of firms, which Woodford refers to as "industries," are akin to the Gertler-Leahy islands.

The equivalence between firm-specific and "industry-" or "island-specific" labor markets breaks down in the presence of firm-specific shocks that wash out at the industry/island level. In that case the issue of whether a firm's labor demand actually affects the wage that it pays becomes crucial. If labor is trully firm-specific, changes in its demand for labor will affect the wage that it pays, and thus labor attachment will affect the firm's incentives to change prices in response to idiosyncratic shocks. Put in terms of the analysis of Ball and Romer (1990) and Kimball (1995), this amounts to a real rigidity that is internal to the firm, and is a source of $\omega-$type strategic complementarity in price setting (in the notation of Kimball 1995, which is also used by Nakamura and Steinsson 2010). In contrast, if firms are trully atomistic they can each change their labor demand in response to idiosyncratic shocks without affecting the wages that they pay. The latter case, which corresponds to Gertler and Leahy (2008), amounts to a real rigidity that is external to the firm, and is a source of $\Omega-$type strategic complementarity in price setting. This is why the assumption of labor segmentation does not hurt the ability of Gertler and Leahy's model to match the size of price changes observed in the data under reasonable parameter values. On that point see also the discussion in Nakamura and Steinsson (2010).

In contrast, both p_t and c_t are essentially unaffected by sector-specific shocks. Hence, in response to such shocks the model with a Taylor rule behaves similarly to a model with exogenous nominal consumption.

In summary, a Taylor rule and intermediate inputs generate pricing interactions that are qualitatively similar. Both "ingredients" slow down price responses to aggregate shocks, yet produce little pricing interactions conditional on sector-specific shocks. In contrast, labor market segmentation at the sectoral level creates pricing interactions with respect to both aggregate and sector-specific shocks: it speeds up price responses to sector-specific shocks, while slowing down price responses to aggregate shocks.

5 Quantitative analysis

5.1 Model estimation

To assess its ability to match the empirical facts summarized in Section 2, we estimate the model with the three mechanisms discussed above. To estimate and simulate the model, it is necessary to make distributional assumptions on the exogenous shocks. We assume they follow AR(1) processes:

$$\begin{aligned}
\gamma_{t+1} &= \rho_\Gamma \gamma_t + \sigma_\gamma \varepsilon_{\Gamma,t+1}, \\
a_{t+1} &= \rho_A a_t + \sigma_a \varepsilon_{A,t+1}, \\
\mu_{t+1} &= \rho_\mu \mu_t + \sigma_\mu \varepsilon_{\mu,t+1}, \\
a_{k,t+1} &= \rho_{A_k} a_{k,t} + \sigma_{A_k} \varepsilon_{A_k,t+1}, \\
d_{k,t+1} &= \rho_{D_k} d_{k,t} + \sigma_{D_k} \varepsilon_{D_k,t+1},
\end{aligned}$$

with every innovation being standard Gaussian white noise.

The model is estimated employing Bayesian methods. We take the model to exactly the same time series used in the FAVAR estimation in Section 2, except for aggregate consumption and inflation. They are omitted in our structural model estimation due to (near) stochastic singularity.[21] We also drop data for Sector 11 (Gasoline and other energy goods) from estimation.[22] Details of estimation are given in the online appendix.

5.2 Priors and posteriors

We assume that all parameters are independent in prior distribution. We fix the parameters β, φ, θ, η, δ, and $\{n_k\}_{k=1}^K$ in the estimation, setting them to conventional values found in the literature. The discount factor, β, equals 0.99, corresponding to a 4% annual steady-state interest rate. The parameter

[21] Aggregate consumption is simply the sum of sectoral consumption in the approximate model.

[22] The standard deviation of inflation in Sector 11 is larger by an order of magnitude than in the other sectors. Extensive analysis showed that this leads to overestimation of sectoral inflation volatility in most of the sectors – not just in Sector 11 – and hampers overall model fit. So we decided to keep the sector in the model, but to exclude its data in estimation. Accordingly we define the sectoral demand shock of Sector 11 as $d_{11,t} = 1 - (d_{1,t} + \cdots + d_{10,t} + d_{12,t} + \cdots + d_{K,t})$ and do not estimate it. The main results regarding sectoral price facts are robust even if data for Sector 11 is included in estimation (see online appendix).

φ is set equal to 2 so that the (Frisch) elasticity of labor supply is 0.5. We fix the within-sector elasticity of substitution between different varieties, θ, to 6, which implies a 20 percent steady-state mark-up for the firms. The across-sector elasticity of substitution, η, is set equal to 2. These elasticities are broadly in line with the range estimated by Hobijn and Nechio (2018). The elasticity of output with respect to intermediate inputs, δ, is set to 0.7. Sectoral weights $\{n_k\}_{k=1}^K$ are obtained by averaging PCE expenditure weights over our sample period, and are presented in Table 8.

As for the remaining parameters, our prior distribution mostly follows the convention in the literature on Bayesian estimation of DSGE models. The Taylor rule coefficients, ϕ_π and ϕ_c, follow normal distributions. The mean of ϕ_π is set to be 1.5 with standard deviation of 0.25. We set the mean of ϕ_c to be 0.5 and its prior standard deviation to be 0.05. The coefficient on the interest smoothing term, ρ_i follows a beta distribution with mean of 0.7 and standard deviation of 0.15.

Each of the Calvo parameters $\{\alpha_k\}_{k=1}^K$ follows a beta distribution with standard deviation of 0.1. The prior mean is set to one minus the empirical frequency of price changes constructed by suitably aggregating consumption categories from the Nakamura and Steinsson (2008) price-setting statistics.

Regarding shock processes, every autoregressive parameter of the exogenous shocks has a beta distribution with mean of 0.7 and standard deviation of 0.15, whereas the innovation parameters have an inverse gamma distribution. The innovation parameter of monetary shock, σ_μ, has a mean of 0.00125 and standard deviation of 0.005. We treat the aggregate demand and supply shocks, γ_t and a_t, symmetrically. The standard deviations of their innovations, σ_γ and σ_a, are assumed to have mean of 0.02 and standard deviation of 0.5. The sector-specific shocks are also symmetric in the prior distribution: we set the prior mean of σ_{A_k} and σ_{D_k} to 0.02 and the prior standard deviation to 0.5. The large standard deviation relative to the mean reflects our uncertainty about the size of the shocks as well as our ex-ante belief that the nature of the shocks are likely to be quite heterogenous across the sectors.

The appendix reports moments of the prior and posterior distributions. The posterior estimates of the structural parameters imply a large degree of cross-sector heterogeneity in price stickiness as well as in shock processes. In particular, the standard deviation of the sectoral (demand and supply) innovations ranges from 0.6% to 7.8% at the posterior mode. These estimates, on average, are greater than the estimates of the standard deviation of the aggregate shocks. Furthermore, the latter are somewhat smaller in our model, compared to typical estimates obtained from single-sector models, suggesting the presence of sector-specific shocks renders aggregate shocks less important. Finally, turning to the monetary policy parameters, the estimates imply a substantial degree of interest rate smoothing and aggressive responses to inflation, which are largely consistent with the results of previous studies.

5.3 Sectoral price facts in the estimated model

This subsection mirrors Section 2. We estimate a FAVAR on data generated by simulating the model at the posterior mode, and produce the results underlying figures and tables in the exact same way as in Section 2. The artificial dataset comprises (aggregate) consumption growth, inflation, the nominal interest rate, and all sectoral inflation and sectoral consumption growth rates. The specification of the FAVAR is identical to that of Section 2.

5.3.1 Facts on the speed of price adjustments

Figure 4 presents the IRFs from the FAVAR estimated on model-generated data.[23]

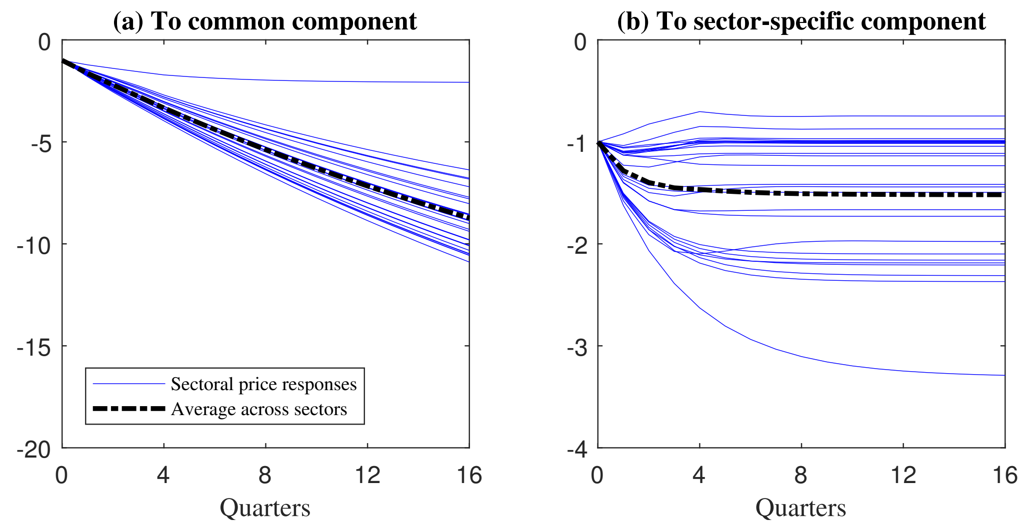

Figure 4: Impulse response of PCE price series

Figure 5 shows the distribution of the speed of the responses to an innovation to the common component (panel (a)) and to the sector-specific components (panel (b)). Table 3 reports descriptive statistics based on these two distributions.

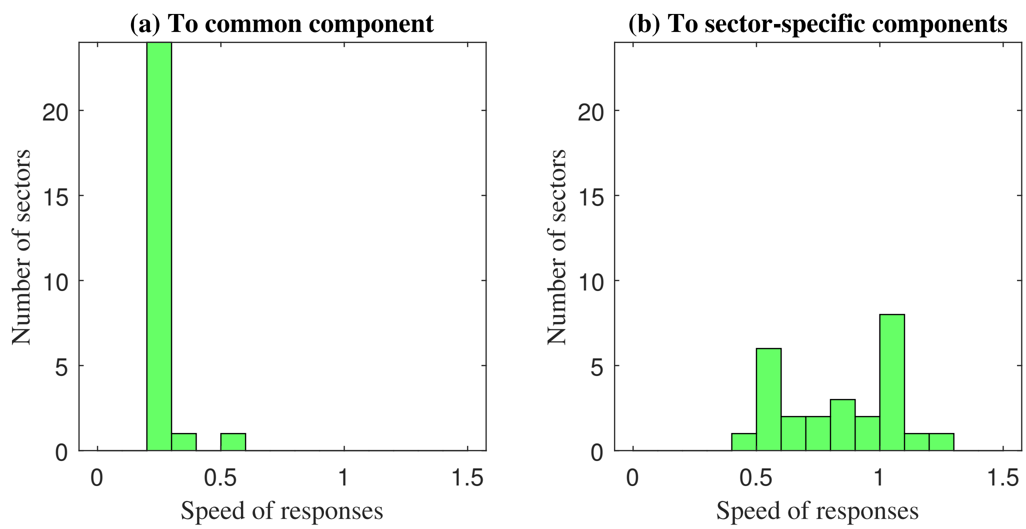

Figure 5: Cross-sectional distribution of speed of responses

[23] We produce a sample with twelve thousand observations and discard the first two thousand to minimize the effects of initial conditions. Drawing different samples of the same size had negligible effects on the results. They can thus be interpreted as"FAVAR-filtered population results."

Table 3: Statistics on the speed of responses to shocks

	Speed of sectoral price responses	
	to common component	to specific components
Mean	0.267	0.845
Median	0.253	0.844
Standard deviation	0.066	0.232
Corr. with sectoral frequencies	0.470	0.935
Correlation	0.273	

Comparing Table 3 to Table 1 reveals that the estimated model captures the main features of the cross-sectional distribution of the speed of price responses to common and sector-specific shocks very well. Specifically, i) the average speed of response of sectoral prices to sector-specific shocks is substantially higher than the average speed of response to shocks to the common component; ii) the cross-sectional standard deviation of the sectoral speeds of responses to shocks to the common component is smaller than the corresponding standard deviation for the responses to sector-specific shocks; iii) the correlation between the sectoral speeds of responses and the sectoral frequencies of price changes is positive for both the common and sector-specific components; iv) the correlation between the speed of responses to both types of shocks is positive.

In particular, the first two facts, i) and ii), can be ascribed to the strategic complementarities and substitutabilities implied by our model. These pricing interactions, as discussed in Section 4, naturally produce differential speed of price responses to different shocks and relatively stronger comovements of prices in response to aggregate shocks.

While Table 3 shows that the model captures well the key moments (mean, median and standard deviation) in the cross-section, we also find that the ranking of the sectors in the speed of responses implied by the model is largely consistent with what is implied by the data. The last four columns of Table 8 report the speed of price responses to common and sector-specific shocks based on the actual and model-simulated data for the 27 sectors. In addition, the results are illustrated by the scatter plots in Figure 6, which show the relationship between the speed of responses implied by the data (on the horizontal axis) and that implied by the model (on the vertical axis), along with a 45-degree line. We altogether find that sectors that adjust their prices faster to shocks in the data also tend to respond faster in the model.

Despite the overall success of the model in producing the stylized sectoral price facts, it does produce a few counterfactual results. In particular, the model noticeably overpredicts the speed of the response to aggregate shocks for one sector ("Furnishings and durable household equipment"); the model-implied speed is 0.57 while the data implies only 0.33. Regarding the responses to sector-specific shocks, non-negligible discrepancies between the model and the data are observed for a few sectors, such as "Furnishings and durable household equipment," "Professional and other services," and "Food and nonalcoholic beverages purchased for off-premises consumption." These discrepancies, however, do not show a strong one-sided tendency.

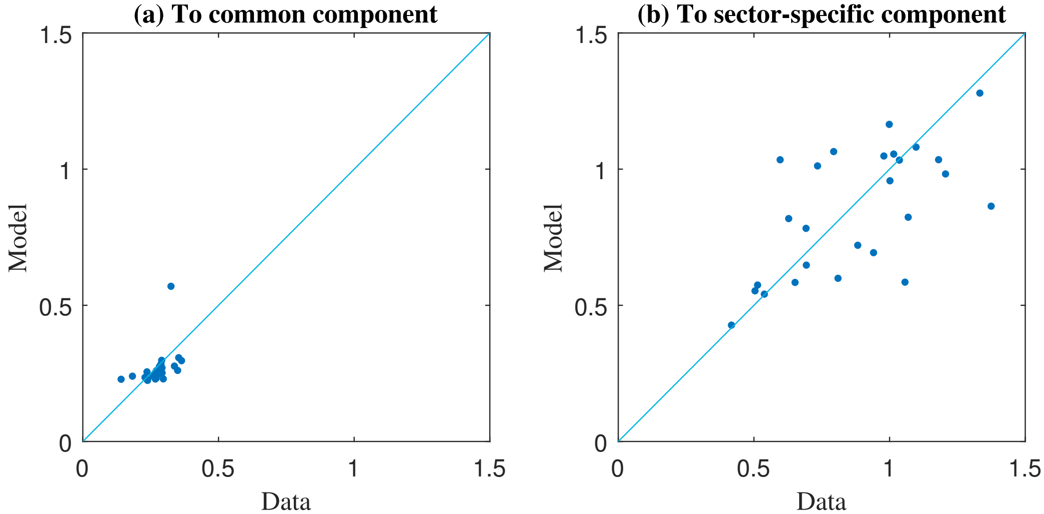

Figure 6: Speed of sectoral price responses in the data and in the estimated model

5.3.2 Additional facts on the correlations between prices and quantities

We report the results on the cross-section of correlations between the component of inflation rates and growth rate of quantities that are driven by the common components, and the cross-section of correlations between the sector-specific component of inflation rates and the corresponding sector-specific component of quantities (in growth rates). These are depicted in Figure 7, and summarized in Table 4.

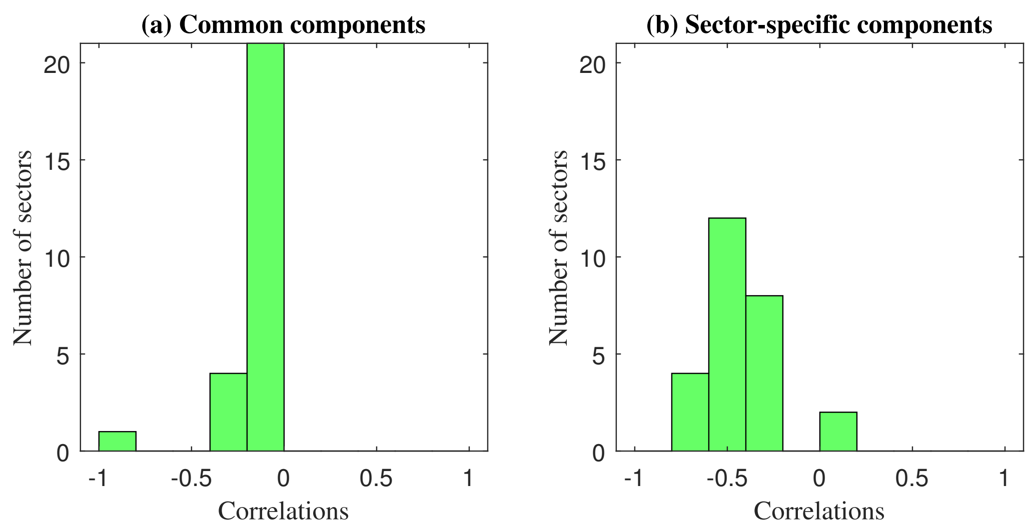

Figure 7: Cross-section of correlations between components of PCE prices and quantities.

A comparison of Tables 2 and 4 reveals that the estimated model captures the main qualitative features of the two distributions, although it misses some nuances. Importantly, the estimated model produces, *on average*, a negative correlation between the sector-specific component of inflation rates and the corresponding sector-specific component of the growth rates of consumption, and also between the component of inflation rates and growth rates of consumption that are driven by the common

Table 4: Statistics on the correlations between components of prices and quantities

	Correlation between inflation and growth of quantities	
	Common component	Specific components
Mean	−0.136	−0.414
Median	−0.078	−0.445
Max.	−0.039	0.080
Min.	−0.933	−0.769

components. Furthermore, although the model does not match precisely the empirical cross-sectional distributions, it correctly predicts a negative correlation for a majority of the sectors, which was also found in BGM. This is consistent with supply-type shocks driving most of the variation in these data.[24]

6 The role of each "ingredient"

Our analysis thus far has shown that the model with the three ingredients – intermediate inputs, "endogenous" monetary policy and sector-specific labor markets – accounts well for the sectoral price facts, both qualitatively and quantitatively. This finding, however, does not necessarily imply that all three mechanisms are equally important for the results. In this section, we assess the relative importance of the three ingredients, repeating the previous estimation exercise while shutting down each of the mechanisms at a time.

We find that all three features play a meaningful role: the model is less successful in matching the sectoral price facts with any combinations of two ingredients. As our earlier analysis indicates, they all are responsible, to some degree, for the slow price responses to aggregate shocks – endogenous monetary policy plays a predominant role. Labor market segmentation, in turn, provides the only mechanism that speeds up the responses of prices to sector-specific shocks. Hence, without this feature, the model does not match the fast price responses to sector-specific shocks as well.[25]

6.1 Intermediate inputs and endogenous monetary policy

As discussed in Section 4, intermediate inputs and a Taylor-type interest rate rule play the same role qualitatively. They both generate strategic complementarities with respect to aggregate shocks and close to strategic neutrality with respect to sector-specific shocks. Such pricing interactions lead to slower price responses to aggregate shocks, thereby producing differential speeds of responses depending on the type of shock.

Tables 5 and 6 report results analogous to those in Table 3, shutting down the effect of intermediate inputs and of the Taylor rule, respectively. Compared to Table 3, the mean (and median) speed of the responses to sector-specific shocks are nearly unchanged (around 0.85), reflecting approximate strategic neutrality. Both ingredients, however, have an important effect on the speed of price responses to

[24] To justify this interpretation we analyzed different model parameterizations in which we varied the relative variance of demand- and supply-type shocks, and verified that larger supply-type shocks produce more negative price-quantity correlations.

[25] The quantitative results are clearly model-specific. The relative importance of the three ingredients can be different in other price-setting models – such as the ones with menu costs.

aggregate shocks. The mean speed of responses to aggregate shocks in the model without intermediate inputs is roughly 0.37, which is larger than the corresponding value of 0.27 in the full model (Table 3). The difference is more pronounced in the absence of the Taylor rule (0.82 vs. 0.27).

Table 5: Statistics on the speed of responses to shocks - without intermediate inputs

	Speed of sectoral price responses	
	to common component	to specific components
Mean	0.369	0.850
Median	0.369	0.822
Standard deviation	0.058	0.245
Corr. with sectoral frequencies	0.946	0.925
Correlation	0.927	

Table 6: Statistics on the speed of responses to shocks - without "endogenous" monetary policy

	Speed of sectoral price responses	
	to common component	to specific components
Mean	0.822	0.868
Median	0.809	0.915
Standard deviation	0.156	0.258
Corr. with sectoral frequencies	0.909	0.942
Correlation	0.933	

We illustrate our finding using scatter plots analogous to those in Figure 6. Figure 8 shows that the absence of either intermediate inputs or endogenous monetary policy leads to higher speeds of price responses to aggregate shocks, while having little effect on the speed of price responses to sector-specific shocks.

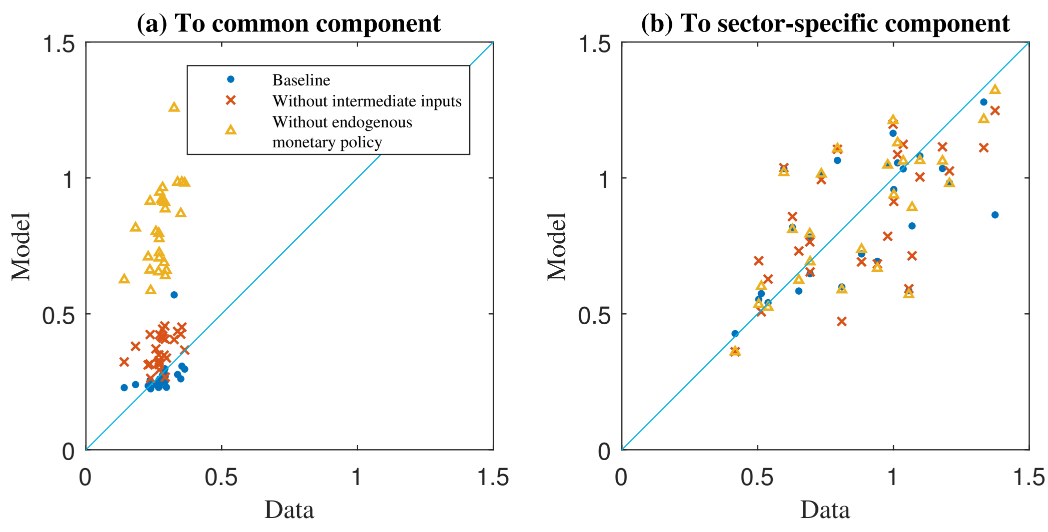

Figure 8: Comparison of the speed of sectoral price responses across different specifications

Another noteworthy result pertains to the correlation between speeds of price responses and sectoral frequencies of price changes, and to the correlation between the speeds of price responses to common and sector-specific shocks. A comparison of Tables 1, 3, 5, and 6 shows that the model with all three ingredients fares better along these dimensions than the models without either intermediate inputs or endogenous monetary policy.

6.2 Labor market segmentation

Unlike the previous two ingredients, labor market segmentation creates pricing interactions with respect to both aggregate and sector-specific shocks. Table 7 shows that, absent this feature, the model produces faster price responses to aggregate shocks (mean of 0.36 vs. 0.27) and slower responses to sector-specific shocks (0.77 vs. 0.85) relative to the baseline model. These results are consistent with the discussion in Section 4. Importantly, labor market segmentation is a unique ingredient in that it provides the only mechanism that speeds up the responses of sectoral prices to sector-specific shocks.[26] The scatter plots in Figure 9 provide more detail on these results.

Table 7: Statistics on the speed of responses to shocks - without labor market segmentation

	Speed of sectoral price responses	
	to common component	to specific components
Mean	0.358	0.775
Median	0.367	0.788
Standard deviation	0.082	0.295
Corr. with sectoral frequencies	0.884	0.807
Correlation	0.858	

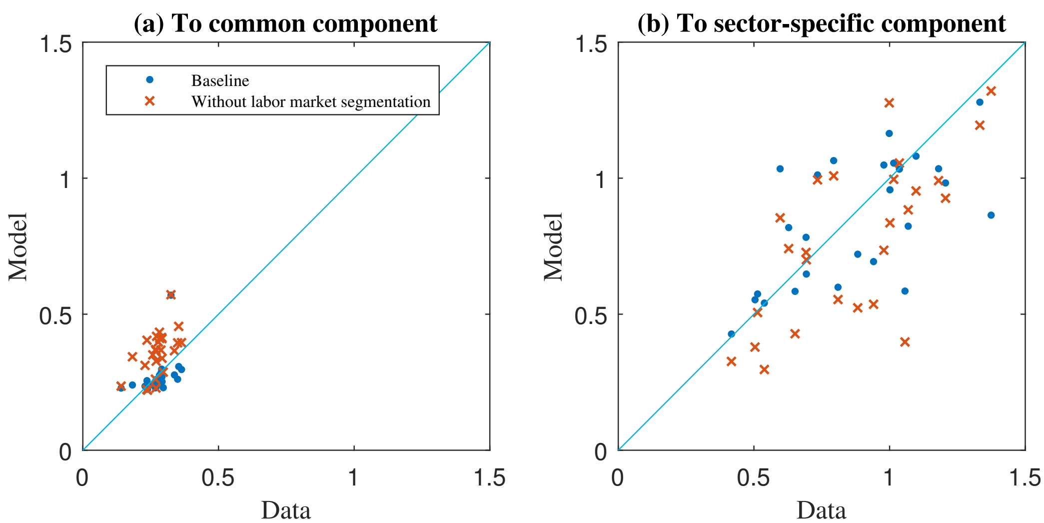

Figure 9: Comparison of the speed of sectoral price responses across different specifications

Finally, results on the correlation between speeds of price responses and sectoral frequencies of price changes, and on the correlation between the speeds of price responses to common and sector-specific shocks confirm our earlier findings. Namely, that the model with all three ingredients fares better along these dimensions than the models without either one of the three ingredients.

[26]We have also considered firm-specific labor markets. Under this assumption, the estimated model generates slower price responses to both aggregate and sector-specific shocks relative to the baseline model. This result is consistent with the discussion in Section 4. We provide complete details for this version of the model in the online appendix.

7 Discussion

7.1 Model fit

How well does our model fit the data? Our primary objectives are to study mechanisms that produce pricing interactions employing a standard model and to assess how well such a simple model fares in light of the documented sectoral price facts. To that end, we rely on a multisector extension of a textbook three-equation New Keynesian model with a few additional ingredients. The model abstracts from features that may help explain the data, such as habit formation in consumption, partial dynamic indexation in price setting, a time-varying inflation target, and a more flexible specification of exogenous processes. Given such simplicity of our framework – combined with the high dimensionality of the data (which include sectoral prices and quantities) – one may reasonably expect that the model will not equal the success of medium-scale DSGE models that usually fit only a handful of aggregate variables.

Nevertheless, it is still useful to provide an overall assessment of model fit, for at least two reasons. First, although our focus is on the highlighted sectoral price facts, researchers might be interest in learning about model fit along other dimensions. Second, recent research uses versions of this model to address various quantitative questions.[27] It is therefore useful to learn the dimensions along which a model of this type performs well or should be improved.

We assess the fit of the model by comparing a set of key statistics implied by the model to those obtained from the data. Overall, we find that the model explains the data reasonably well, especially the sectoral price data. The ensuing subsections confront our model with the data in terms of volatility and persistence measures, in turn.[28] We highlight the dimensions along which the model performs well, and point out where there is room for improvement.

7.1.1 Volatility

Figure 10 compares the standard deviation measured in the data to that implied by the model, by providing scatter plots. To obtain the latter, we employ the same simulated data used to fit the FAVAR.

Panel (a) reveals that the model matches the volatility of sectoral inflation remarkably well. The model also accounts fairly well for the volatility of sectoral consumption growth, although for most sectors the model overpredicts it somewhat (panel b). Finally, the model matches closely the standard deviation of the interest rate: it is 0.006 in the data and 0.008 in the model.

7.1.2 Persistence

Figure 11 compares a measure of persistence in the data to that implied by the model. To that end, we estimate an AR(4) on simulated data of each variable and use the sum of the estimated coefficients as our measure of the persistence.

[27] For example, Pasten, Schoenle and Weber (2016, 2018).

[28] Readers should keep in mind that our likelihood-based estimation method fits the model to the entire autocovariance function of the data – not only a few second moments. For the interested reader, we report other second moments, such as crosscorrelations, in the online appendix.

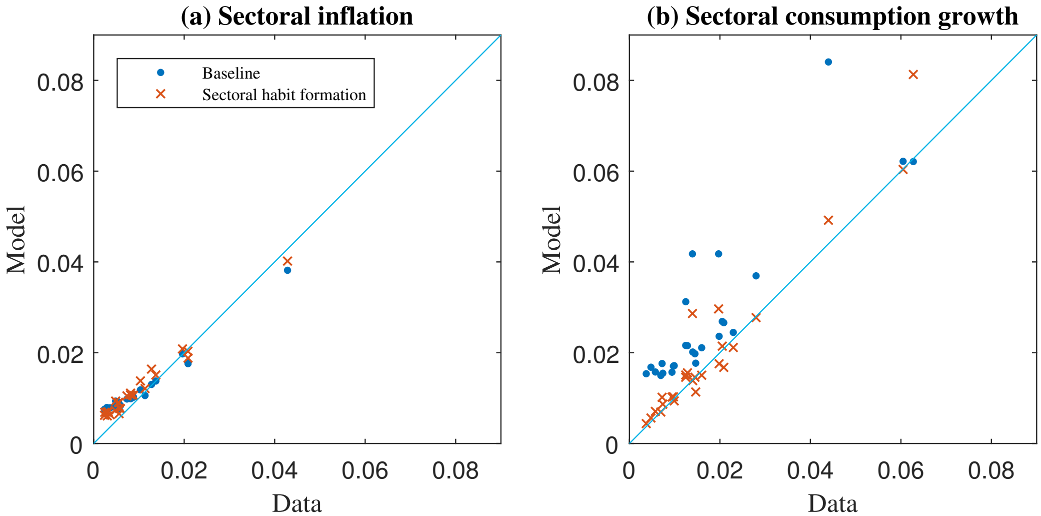

Figure 10: Comparison of volatility: baseline vs. sectoral habit formation

Panel (a) shows that the model matches the persistence of sectoral inflation fairly well, although it overpredicts it for many sectors. Regarding sectoral consumption data, the model tends to underpredict the (absolute) size of the persistence, as shown in panel (b). Lastly, the model matches quite well the persistence of the interest rate. It is 0.955 in the data and 0.963 in the model.

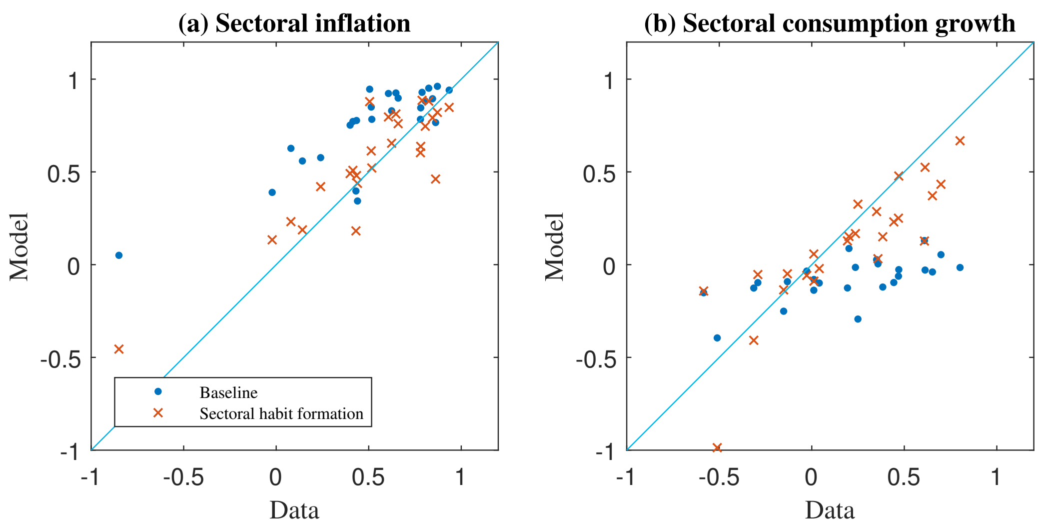

Figure 11: Comparison of persistence: baseline vs. sectoral habit formation

7.1.3 Habit formation in sectoral consumption

Sections 7.1.1 and 7.1.2 reveal that, while the baseline model matches the key moments of the data reasonably well, especially the sectoral price data, some noticeable discrepancies emerge – e.g. the model's underprediction of sectoral consumption growth persistence. This may reflect the fact that the demand function for sectoral consumption goods (equation 2), is too restrictive to capture richer dynamics in disaggregate consumption data, given sectoral price data.

To further analyze this issue, we estimated a version of the model with habit formation in sectoral consumption. This endows the model with an additional persistence mechanism, as well as some more flexibility.[29] Figure 11 shows that this additional feature enables the model to fit the persistence of sectoral consumption growth (and inflation) better. Furthermore, the more flexible specification also improves the model's prediction of the standard deviations of sectoral consumption growth, as shown in panel (b) of Figure 10.

7.1.4 Summary

In sum, our analysis in this subsection indicates that the model, while simple, fits the data fairly well – more so with respect to the sectoral price data than the quantity data. The baseline model, however, fails to match some key second moments due to its highly stylized nature.

Our exercise also suggests that a model of this type has the *potential* to match key aggregate and sectoral data better, and thus to form the basis for a more quantitative model, if more features (such as habit formation) are added, as often done in standard medium-scale DSGE models. Future research investigating how such a multisector extension of medium-scale DSGE models – along the lines of Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007) – would perform relative to a quantitative reduced-form model for sectoral data (such as a FAVAR) would certainly be of interest.

7.2 FAVAR and Dynamic Factor Model

Models in which price setters allocate limited information-processing capacity to track aggregate and sectoral conditions are also able to rationalize the empirical finding of differential speeds of responses of prices to different shocks (Maćkowiak and Wiederholt 2009; Maćkowiak et al. 2009). The reason is that sector-specific shocks tend to be more volatile, and thus take up most of firms' information-processing capacity. This leads them to react quickly to those shocks, at the expense of reacting slowly to aggregate shocks.[30]

When it comes to the cross-sectional dispersion in price responses, however, such models with *rational inattention* and our estimated model with infrequent price adjustment are poles apart. Since firms in the former models pay most of their attention to sector-specific conditions, there is little variation in how firms in different sectors respond to sector-specific shocks. As a consequence, such models predict a larger cross-sectional variation in the speed of price response to aggregate shocks than to sector-specific shocks. While this prediction is consistent with the evidence obtained from the dynamic factor model in Maćkowiak et al. (2009), it is the opposite of our result based on the FAVARs. For the following two reasons, we argue that Maćkowiak et al. (2009) are likely to overestimate the cross-sectional dispersion in the speed of responses to the aggregate shock.

[29] This extended model features sector-specific habit formation parameters, which are estimated. The details of the model and estimation results are in the online appendix.

[30] The literature on price setting based on the "rational inattention" theory, pioneered by Sims (2003), is relatively new. Rational inattention, however, is catching rapidly the attention of researchers as an alternative to adjustment costs for the primary source of price rigidity. Recent contributions include Paciello and Wiederholt (2013), Maćkowiak and Wiederholt (2015), Pasten and Schoenle (2016), and Afrouzi (2018).

First, we conjecture that the way the dynamic factor model is specified in Maćkowiak et al. (2009) leads to the overestimation of the cross-sectional dispersion of the speed of responses to an aggregate shock relatively more than to sector-specific shocks. Their dynamic factor model includes a larger number of lags of the aggregate shock than the number of lags of the sector-specific shocks. In their baseline specification, the lag length of the aggregate shock is 24 while the lag length of the sector-specific shocks is 6. Since more parameters are involved in the computation of impulse responses of sectoral inflation to the aggregate shock than to sector-specific shocks, the posterior distribution of the impulse responses of sectoral prices to the aggregate shock is likely to exhibit greater uncertainty in finite samples.

We verify this conjecture by simulation studies in which we progressively increase the size of the simulated sample. As we fit Maćkowiak et al.'s (2009) baseline dynamic factor model to larger and larger samples, the cross-sectional dispersion of the speed of responses to the aggregate shock shrinks relatively faster than the cross-sectional dispersion of the speed of responses to sector-specific shocks. Eventually, the cross-sectional dispersion of the speed of responses to the aggregate shock becomes smaller, which is in line with what we estimate with the FAVAR. We find that FAVARs do not suffer much from the same problem.

Second, the way Maćkowiak et al. (2009) compute the cross-sectional dispersion of the speed of responses tends to push the cross-sectional dispersion upward further, especially that of the speed of responses to the aggregate shock. In Figure 2 of their paper, they display the histogram of the posterior draws of the speed of responses taking into account both variation across sectors and parameter uncertainty. That is, they pool the speeds of responses to sector-specific shocks and to aggregate shocks, respectively, of all the sectors and of all the posterior draws of the parameters. We think that a more appropriate way to obtain the posterior distribution of the cross-sectional dispersion of the speed of responses is to compute the cross-sectional dispersion of the speed of responses across sectors *conditional on* each of the posterior draws of the parameters, and then pool them across the posterior draws to obtain the histogram of interest. The two approaches only yield the same results in very large samples. We found that the latter approach, which focuses on the posterior distributions of the objects of interest, reduces the cross-sectional dispersion of the speed of responses to the aggregate shock by a significantly larger margin.

We provide more details and the results of the simulation studies in the online appendix.

8 Conclusion

We construct a relatively simple variant of the New Keynesian model that can endogenously deliver differential responses of sectoral prices to aggregate and sector-specific shocks. In particular, contrary to what intuition suggests at a first pass, the model is able to produce faster response of sectoral prices to sector-specific shocks than to aggregate shocks. In fact, getting the model to produce the same response of prices to aggregate and sector-specific shocks proves to be somewhat difficult, in that it requires a parameterization of our model that is quite restrictive and arguably unrealistic.

We illustrate the economic mechanisms behind the endogenous differential response of prices to different shocks, and make a quantitative assessment of the model's ability to match facts about sectoral prices established by the recent empirical literature. Despite the fact that the model is highly stylized, we find the results to be close to the data.

In future work, it should be interesting to study whether the mechanisms considered here operate in a similar fashion in other price-setting models. Maćkowiak et al. (2009) argue that a menu cost model should face difficulties in matching the highlighted sectoral price facts. However, if the endogenous mechanisms analyzed here produce similar results in menu costs models, they might also help reconcile these models with sectoral price facts. In fact, Nakamura and Steinsson (2010) have convincingly shown that the introduction of intermediate inputs in a multisector state-dependent model generates a large amount of strategic complementarity in pricing decisions conditional on aggregate shocks. Adding segmented labor markets and an interest rate rule to their model to study sectoral price facts seems promising. In a different direction, it seems important to assess if the rational inattention mechanism advocated by Maćkowiak et al. (2009) would still be able to math sectoral price facts in the presence of nominal rigidity. A distinctive feature of many rational inattention models is that prices change continuously. This contrasts with the available microeconomic evidence of infrequent price changes. It is unclear whether a rational inattention model that is disciplined by the evidence of infrequent price changes would preserve its ability to produce faster responses of prices to sector-specific shocks relative to aggregate shocks, absent other endogenous mechanisms such as the ones we analyze in this paper. In our view this remains an important open question for the literature on price setting with limited information-processing capacity.[31]

Finally, the sectoral price facts that we focus on in this paper are not without credible critics (Beck et al. 2016; Andrade and Zachariadis 2016; De Graeve and Walentin 2015). More work is needed to advance our knowledge about this issue, and to clarify points in which different papers seem to produce conflicting findings. Due to the important role of price setting in macroeconomic models that are currently used for policy analysis, it will be important to confront those models with whatever new empirical evidence comes about regarding the behavior of disaggregated prices.

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Table 8: List of 27 sectors with weights, probabilities of no price changes and durations

Categories and subcategories	k	Weights (n_k)	α_k	Duration in quarters	Speed of sectoral price responses: Actual data, Common	Actual data, Sector	Model-simulated data, Common	Model-simulated data, Sector
Motor vehicles and parts								
New motor vehicles	1	4.78	0.519	2.08	0.292	0.693	0.252	0.648
Motor vehicle parts and accessories	1							
Net purchases of used motor vehicles	2	0.94	0.000	1.00	0.364	0.979	0.297	1.048
Furnishings and durable household equipment								
Furniture and furnishings	3	4.23	0.483	1.93	0.325	1.374	0.570	0.864
Household appliances	3							
Glassware, tableware, and household utensils	3							
Tools and equipment for house and garden	3							
Recreational goods and vehicles								
Video, audio, photographic, and information processing equipment and media	4	11.02	0.463	1.86	0.288	0.883	0.284	0.720
Sporting equipment, supplies, guns, and ammunition	5	1.67	0.691	3.23	0.270	1.069	0.246	0.823
Sports and recreational vehicles	5							
Recreational books	5							
Musical instruments	5							
Other durable goods								
Jewelry and watches	6	1.74	0.551	2.23	0.268	0.692	0.255	0.783
Therapeutic appliances and equipment	6							
Educational books	6							
Luggage and similar personal items	6							
Telephone and facsimile equipment	6							
Food and beverages purchased for off-premises consumption								
Food and nonalcoholic beverages purchased for off-premises consumption	7	8.64	0.318	1.47	0.278	0.597	0.248	1.034
Alcoholic beverages purchased for off-premises consumption	8	1.28	0.492	1.97	0.349	1.097	0.261	1.081
Food produced and consumed on farms	8							
Clothing and footwear								
Garments	9	5.61	0.314	1.46	0.272	1.181	0.261	1.035
Other clothing materials and footwear	10	1.15	0.409	1.69	0.284	1.015	0.260	1.055
Gasoline and other energy goods								
Motor vehicle fuels, lubricants, and fluids	11	4.13	0.003	1.00				
Fuel oil and other fuels	11							
Other nondurable goods								
Pharmaceutical and other medical products	12	1.27	0.613	2.58	0.229	0.513	0.235	0.574
Recreational items	13	2.38	0.755	4.09	0.258	0.628	0.240	0.818
Magazines, newspapers, and stationery	13							
Household supplies	14	2.54	0.582	2.39	0.183	1.206	0.240	0.982
Personal care products	14							
Tobacco	15	0.57	0.307	1.44	0.291	0.794	0.298	1.065
Housing and utilities								
Housing	16	12.15	0.722	3.59	0.141	0.504	0.228	0.553
Household utilities	17	2.72	0.212	1.27	0.292	1.001	0.270	0.957

Table 8: List of 27 sectors with weights, probabilities of no price changes and durations (continued)

Categories and subcategories	k	Weights (n_k)	α_k	Duration in quarters	Speed of sectoral price responses: Actual data, Common	Actual data, Sector	Model-simulated data, Common	Model-simulated data, Sector
Health care								
Outpatient services	18	8.31	0.857	7.01	0.267	0.538	0.229	0.541
Hospital and nursing home services	18							
Transportation services								
Motor vehicle services	19	2.21	0.503	2.01	0.270	0.810	0.232	0.599
Public transportation	20	0.99	0.181	1.22	0.353	1.036	0.308	1.033
Recreational services								
Membership clubs, sports centers, parks, theaters, and museums	21	3.01	0.727	3.66	0.270	0.941	0.236	0.693
Audio-video, photographic, and information processing equipment services	21							
Gambling	21							
Other recreational services	21							
Food services and accommodations								
Food services	22	5.25	0.850	6.67	0.239	0.417	0.224	0.427
Accommodations	23	0.55	0.247	1.33	0.282	1.333	0.276	1.279
Financial services and insurance								
Financial services	24	5.88	0.780	4.55	0.338	0.999	0.277	1.164
Insurance	24							
Other services								
Communication	25	2.41	0.313	1.46	0.236	0.734	0.256	1.012
Education services	26	0.93	0.822	5.60	0.296	0.652	0.230	0.584
Professional and other services	27	3.64	0.862	7.25	0.236	1.057	0.229	0.585
Personal care and clothing services	27							
Social services and religious activities	27							
Household maintenance	27							

Notes: Italics are used to indicate 15 major categories in PCE (the second-level disaggregation). Throughout the paper, sectors are indexed by k. The sectoral weights (n_k) are given by the PCE expenditure weights (in percentage) averaged over our sample period. The sectoral infrequency (α_k) is based on Nakamura and Steinsson (2008). The duration is the expected duration of price spells, which is equal to $(1-\alpha_k)^{-1}$.

Appendix

Table 9: The prior and posterior distribution for the baseline specification

Parameter	Prior distribution			Posterior distribution				
	Type	Mean	Std. deviation	Mode	Mean	[5%	Msedian	95%]
ϕ_π	Normal	1.5	0.25	2.684	2.577	2.315	2.570	2.861
ϕ_c	Normal	0.5	0.05	0.454	0.462	0.379	0.462	0.544
α_1	Beta	0.519	0.1	0.768	0.776	0.723	0.778	0.824
α_2	Beta	0.120	0.1	0.204	0.224	0.102	0.218	0.367
α_3	Beta	0.483	0.1	0.144	0.161	0.099	0.159	0.233
α_4	Beta	0.463	0.1	0.488	0.514	0.427	0.516	0.597
α_5	Beta	0.691	0.1	0.501	0.535	0.424	0.533	0.652
α_6	Beta	0.551	0.1	0.431	0.452	0.343	0.452	0.563
α_7	Beta	0.318	0.1	0.156	0.184	0.098	0.180	0.282
α_8	Beta	0.492	0.1	0.273	0.292	0.193	0.290	0.400
α_9	Beta	0.314	0.1	0.169	0.191	0.105	0.189	0.286
α_{10}	Beta	0.409	0.1	0.234	0.262	0.164	0.258	0.371
α_{11}	Beta	0.120	0.1	0.049	0.100	0.012	0.091	0.217
α_{12}	Beta	0.613	0.1	0.613	0.632	0.536	0.632	0.726
α_{13}	Beta	0.755	0.1	0.420	0.449	0.340	0.448	0.562
α_{14}	Beta	0.582	0.1	0.364	0.395	0.286	0.392	0.514
α_{15}	Beta	0.307	0.1	0.134	0.153	0.077	0.149	0.243
α_{16}	Beta	0.722	0.1	0.694	0.718	0.641	0.720	0.789
α_{17}	Beta	0.212	0.1	0.220	0.212	0.097	0.210	0.334
α_{18}	Beta	0.857	0.1	0.672	0.695	0.612	0.696	0.774
α_{19}	Beta	0.503	0.1	0.604	0.624	0.530	0.626	0.712
α_{20}	Beta	0.181	0.1	0.100	0.109	0.034	0.104	0.202
α_{21}	Beta	0.727	0.1	0.514	0.542	0.439	0.542	0.648
α_{22}	Beta	0.850	0.1	0.802	0.827	0.748	0.827	0.908
α_{23}	Beta	0.247	0.1	0.094	0.121	0.048	0.115	0.215
α_{24}	Beta	0.780	0.1	0.169	0.188	0.117	0.184	0.270
α_{25}	Beta	0.313	0.1	0.202	0.216	0.130	0.215	0.308
α_{26}	Beta	0.822	0.1	0.681	0.707	0.607	0.708	0.801
α_{27}	Beta	0.862	0.1	0.642	0.669	0.568	0.668	0.773
ρ_i	Beta	0.7	0.15	0.739	0.769	0.706	0.771	0.824
ρ_μ	Beta	0.7	0.15	0.916	0.594	0.267	0.560	0.935
ρ_γ	Beta	0.7	0.15	0.936	0.939	0.895	0.942	0.973
ρ_a	Beta	0.7	0.15	0.990	0.988	0.976	0.989	0.997
ρ_{A_1}	Beta	0.7	0.15	0.846	0.834	0.745	0.837	0.911
ρ_{A_2}	Beta	0.7	0.15	0.890	0.889	0.823	0.889	0.957
ρ_{A_3}	Beta	0.7	0.15	0.918	0.914	0.836	0.921	0.971
ρ_{A_4}	Beta	0.7	0.15	0.989	0.984	0.972	0.985	0.994
ρ_{A_5}	Beta	0.7	0.15	0.911	0.887	0.783	0.897	0.960
ρ_{A_6}	Beta	0.7	0.15	0.978	0.971	0.944	0.973	0.991
ρ_{A_7}	Beta	0.7	0.15	0.938	0.927	0.873	0.928	0.976
ρ_{A_8}	Beta	0.7	0.15	0.868	0.863	0.772	0.865	0.944
ρ_{A_9}	Beta	0.7	0.15	0.921	0.915	0.849	0.918	0.972
$\rho_{A_{10}}$	Beta	0.7	0.15	0.895	0.889	0.813	0.892	0.956
$\rho_{A_{11}}$	Beta	0.7	0.15	0.943	0.940	0.892	0.945	0.974
$\rho_{A_{12}}$	Beta	0.7	0.15	0.987	0.983	0.967	0.985	0.995
$\rho_{A_{13}}$	Beta	0.7	0.15	0.975	0.967	0.935	0.970	0.990
$\rho_{A_{14}}$	Beta	0.7	0.15	0.851	0.833	0.697	0.841	0.942
$\rho_{A_{15}}$	Beta	0.7	0.15	0.924	0.916	0.857	0.918	0.970
$\rho_{A_{16}}$	Beta	0.7	0.15	0.939	0.926	0.875	0.929	0.969
$\rho_{A_{17}}$	Beta	0.7	0.15	0.986	0.966	0.930	0.969	0.992
$\rho_{A_{18}}$	Beta	0.7	0.15	0.989	0.985	0.971	0.987	0.995
$\rho_{A_{19}}$	Beta	0.7	0.15	0.977	0.959	0.910	0.965	0.989

Table 9: The prior and posterior distribution for the baseline specification (continued)

Parameter	Prior distribution			Posterior distribution				
	Type	Mean	Std. deviation	Mode	Mean	[5%	Median	95%]
$\rho_{A_{20}}$	Beta	0.7	0.15	0.934	0.923	0.870	0.925	0.970
$\rho_{A_{21}}$	Beta	0.7	0.15	0.974	0.951	0.891	0.959	0.988
$\rho_{A_{22}}$	Beta	0.7	0.15	0.968	0.943	0.880	0.949	0.983
$\rho_{A_{23}}$	Beta	0.7	0.15	0.734	0.700	0.555	0.704	0.831
$\rho_{A_{24}}$	Beta	0.7	0.15	0.829	0.809	0.718	0.812	0.887
$\rho_{A_{25}}$	Beta	0.7	0.15	0.949	0.944	0.898	0.947	0.982
$\rho_{A_{26}}$	Beta	0.7	0.15	0.934	0.916	0.849	0.920	0.968
$\rho_{A_{27}}$	Beta	0.7	0.15	0.959	0.944	0.897	0.948	0.980
ρ_{D_1}	Beta	0.7	0.15	0.773	0.775	0.700	0.776	0.849
ρ_{D_2}	Beta	0.7	0.15	0.925	0.928	0.876	0.927	0.988
ρ_{D_3}	Beta	0.7	0.15	0.818	0.819	0.728	0.820	0.908
ρ_{D_4}	Beta	0.7	0.15	0.978	0.971	0.943	0.973	0.994
ρ_{D_5}	Beta	0.7	0.15	0.897	0.899	0.838	0.900	0.959
ρ_{D_6}	Beta	0.7	0.15	0.977	0.971	0.945	0.972	0.992
ρ_{D_7}	Beta	0.7	0.15	0.969	0.973	0.946	0.974	0.994
ρ_{D_8}	Beta	0.7	0.15	0.962	0.964	0.934	0.965	0.989
ρ_{D_9}	Beta	0.7	0.15	0.967	0.955	0.916	0.956	0.987
$\rho_{D_{10}}$	Beta	0.7	0.15	0.938	0.932	0.883	0.934	0.976
$\rho_{D_{12}}$	Beta	0.7	0.15	0.962	0.960	0.926	0.961	0.990
$\rho_{D_{13}}$	Beta	0.7	0.15	0.981	0.976	0.952	0.977	0.993
$\rho_{D_{14}}$	Beta	0.7	0.15	0.949	0.937	0.882	0.940	0.981
$\rho_{D_{15}}$	Beta	0.7	0.15	0.929	0.928	0.876	0.929	0.974
$\rho_{D_{16}}$	Beta	0.7	0.15	0.967	0.965	0.935	0.967	0.989
$\rho_{D_{17}}$	Beta	0.7	0.15	0.961	0.960	0.924	0.961	0.990
$\rho_{D_{18}}$	Beta	0.7	0.15	0.990	0.986	0.972	0.987	0.996
$\rho_{D_{19}}$	Beta	0.7	0.15	0.977	0.972	0.947	0.973	0.991
$\rho_{D_{20}}$	Beta	0.7	0.15	0.918	0.904	0.833	0.906	0.967
$\rho_{D_{21}}$	Beta	0.7	0.15	0.948	0.939	0.886	0.942	0.983
$\rho_{D_{22}}$	Beta	0.7	0.15	0.963	0.970	0.939	0.972	0.993
$\rho_{D_{23}}$	Beta	0.7	0.15	0.953	0.942	0.895	0.945	0.982
$\rho_{D_{24}}$	Beta	0.7	0.15	0.807	0.802	0.708	0.803	0.893
$\rho_{D_{25}}$	Beta	0.7	0.15	0.963	0.959	0.926	0.961	0.987
$\rho_{D_{26}}$	Beta	0.7	0.15	0.942	0.951	0.907	0.953	0.987
$\rho_{D_{27}}$	Beta	0.7	0.15	0.973	0.965	0.934	0.967	0.989
σ_μ	Inverted Gamma	0.00125	0.005	0.0003	0.0005	0.0003	0.0005	0.0009
σ_γ	Inverted Gamma	0.02	0.5	0.013	0.015	0.008	0.014	0.027
σ_a	Inverted Gamma	0.02	0.5	0.003	0.003	0.003	0.003	0.004
σ_{A_1}	Inverted Gamma	0.02	0.5	0.026	0.030	0.020	0.029	0.043
σ_{A_2}	Inverted Gamma	0.02	0.5	0.021	0.022	0.019	0.022	0.027
σ_{A_3}	Inverted Gamma	0.02	0.5	0.049	0.051	0.044	0.051	0.060
σ_{A_4}	Inverted Gamma	0.02	0.5	0.015	0.016	0.013	0.016	0.019
σ_{A_5}	Inverted Gamma	0.02	0.5	0.011	0.013	0.009	0.012	0.019
σ_{A_6}	Inverted Gamma	0.02	0.5	0.012	0.013	0.011	0.013	0.017
σ_{A_7}	Inverted Gamma	0.02	0.5	0.006	0.006	0.005	0.006	0.008
σ_{A_8}	Inverted Gamma	0.02	0.5	0.010	0.011	0.009	0.011	0.014
σ_{A_9}	Inverted Gamma	0.02	0.5	0.009	0.009	0.008	0.009	0.011
$\sigma_{A_{10}}$	Inverted Gamma	0.02	0.5	0.009	0.010	0.008	0.010	0.012
$\sigma_{A_{11}}$	Inverted Gamma	0.02	0.5	0.078	0.091	0.073	0.090	0.110
$\sigma_{A_{12}}$	Inverted Gamma	0.02	0.5	0.009	0.010	0.008	0.010	0.014
$\sigma_{A_{13}}$	Inverted Gamma	0.02	0.5	0.007	0.008	0.006	0.008	0.010
$\sigma_{A_{14}}$	Inverted Gamma	0.02	0.5	0.006	0.007	0.005	0.006	0.009
$\sigma_{A_{15}}$	Inverted Gamma	0.02	0.5	0.020	0.020	0.017	0.020	0.024
$\sigma_{A_{16}}$	Inverted Gamma	0.02	0.5	0.007	0.008	0.005	0.007	0.011
$\sigma_{A_{17}}$	Inverted Gamma	0.02	0.5	0.015	0.015	0.013	0.015	0.018
$\sigma_{A_{18}}$	Inverted Gamma	0.02	0.5	0.007	0.008	0.006	0.008	0.011

Table 9: The prior and posterior distribution for the baseline specification (continued)

Parameter	Prior distribution			Posterior distribution				
	Type	Mean	Std. deviation	Mode	Mean	[5%	Median	95%]
$\sigma_{A_{19}}$	Inverted Gamma	0.02	0.5	0.007	0.008	0.006	0.008	0.011
$\sigma_{A_{20}}$	Inverted Gamma	0.02	0.5	0.020	0.020	0.018	0.020	0.024
$\sigma_{A_{21}}$	Inverted Gamma	0.02	0.5	0.006	0.007	0.005	0.007	0.009
$\sigma_{A_{22}}$	Inverted Gamma	0.02	0.5	0.009	0.013	0.007	0.011	0.029
$\sigma_{A_{23}}$	Inverted Gamma	0.02	0.5	0.010	0.011	0.009	0.011	0.013
$\sigma_{A_{24}}$	Inverted Gamma	0.02	0.5	0.013	0.014	0.012	0.014	0.017
$\sigma_{A_{25}}$	Inverted Gamma	0.02	0.5	0.009	0.009	0.008	0.009	0.011
$\sigma_{A_{26}}$	Inverted Gamma	0.02	0.5	0.009	0.011	0.007	0.010	0.019
$\sigma_{A_{27}}$	Inverted Gamma	0.02	0.5	0.006	0.007	0.005	0.007	0.011
σ_{D_1}	Inverted Gamma	0.02	0.5	0.059	0.060	0.053	0.059	0.067
σ_{D_2}	Inverted Gamma	0.02	0.5	0.072	0.074	0.066	0.073	0.083
σ_{D_3}	Inverted Gamma	0.02	0.5	0.042	0.042	0.038	0.042	0.048
σ_{D_4}	Inverted Gamma	0.02	0.5	0.018	0.018	0.016	0.018	0.021
σ_{D_5}	Inverted Gamma	0.02	0.5	0.021	0.021	0.019	0.021	0.024
σ_{D_6}	Inverted Gamma	0.02	0.5	0.017	0.017	0.015	0.017	0.020
σ_{D_7}	Inverted Gamma	0.02	0.5	0.010	0.010	0.009	0.010	0.012
σ_{D_8}	Inverted Gamma	0.02	0.5	0.015	0.015	0.013	0.015	0.017
σ_{D_9}	Inverted Gamma	0.02	0.5	0.012	0.012	0.010	0.012	0.013
$\sigma_{D_{10}}$	Inverted Gamma	0.02	0.5	0.012	0.012	0.011	0.012	0.014
$\sigma_{D_{12}}$	Inverted Gamma	0.02	0.5	0.016	0.017	0.015	0.017	0.019
$\sigma_{D_{13}}$	Inverted Gamma	0.02	0.5	0.010	0.010	0.009	0.010	0.011
$\sigma_{D_{14}}$	Inverted Gamma	0.02	0.5	0.007	0.007	0.006	0.007	0.008
$\sigma_{D_{15}}$	Inverted Gamma	0.02	0.5	0.037	0.038	0.034	0.038	0.042
$\sigma_{D_{16}}$	Inverted Gamma	0.02	0.5	0.007	0.007	0.006	0.007	0.008
$\sigma_{D_{17}}$	Inverted Gamma	0.02	0.5	0.036	0.037	0.033	0.037	0.041
$\sigma_{D_{18}}$	Inverted Gamma	0.02	0.5	0.009	0.009	0.008	0.009	0.011
$\sigma_{D_{19}}$	Inverted Gamma	0.02	0.5	0.012	0.012	0.011	0.012	0.013
$\sigma_{D_{20}}$	Inverted Gamma	0.02	0.5	0.035	0.036	0.032	0.036	0.040
$\sigma_{D_{21}}$	Inverted Gamma	0.02	0.5	0.008	0.008	0.007	0.008	0.009
$\sigma_{D_{22}}$	Inverted Gamma	0.02	0.5	0.010	0.010	0.009	0.010	0.012
$\sigma_{D_{23}}$	Inverted Gamma	0.02	0.5	0.024	0.024	0.022	0.024	0.028
$\sigma_{D_{24}}$	Inverted Gamma	0.02	0.5	0.027	0.027	0.024	0.027	0.030
$\sigma_{D_{25}}$	Inverted Gamma	0.02	0.5	0.016	0.016	0.015	0.016	0.018
$\sigma_{D_{26}}$	Inverted Gamma	0.02	0.5	0.006	0.006	0.006	0.006	0.007
$\sigma_{D_{27}}$	Inverted Gamma	0.02	0.5	0.006	0.006	0.006	0.006	0.007

Note: there are no parameters for $d_{11,t}$ because data for Sector 11 are used in the estimation.