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Abstract

We develop a multi-sector sticky-price DSGE (dynamic stochastic general equilibrium) model that can endogenously deliver differential responses of prices to aggregate and sectoral shocks. Input-output production linkages induce across-sector pricing complementarities that contribute to a slow response of prices to aggregate shocks. In turn, input-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. Estimating the factor-augmented vector autoregression specification of Boivin, Giannoni, and Mihov (2009) on data generated by a parameterized version of our model, we find results that resemble what they obtain with disaggregated data for the U.S. economy. We then employ Bayesian methods to estimate the model using aggregate and sectoral data, and find that it accounts extremely well for a wide range of sectoral price facts.

Key words: heterogeneity, price stickiness, sectoral data, FAVAR, aggregate shocks, sectoral shocks

1   Introduction

The increasing availability of very disaggregated price data has generated a renewed flurry of activity around models of price setting. In particular, there is growing interest in taking models that have been reasonably successful in accounting for the dynamic behavior of aggregate variables and used for policy analysis, and confronting their implications for variables at more disaggregated levels with the new evidence. In addition to the results from the recent literature that analyzes micro price data sets (Bils and Klenow 2004, and all subsequent papers), we now have a small set of well-established empirical facts based on sectoral data: data with varying degrees of disaggregation, that fall between the actual micro price data and aggregate price indices.

A prominent recent paper that produces empirical price facts using sectoral data is Boivin et al. (2009) (henceforth BGM). They employ a Factor Augmented Vector Autoregression (FAVAR) framework to analyze the response of quite disaggregated sectoral prices and quantities to different shocks, considering the natural partition of shocks into common and series-specific that is inherent in their empirical methodology. Among their many interesting findings, one seems to have caught the attention of researchers interested in confronting available models of price-setting with new empirical evidence: sectoral prices seem to respond faster to "idiosyncratic" (series-specific) shocks than to "aggregate" (common) shocks.[1]

At first pass this result may seem hard to square with most available models of price setting. Take, for example, a version of the Calvo (1983) model of price setting with aggregate and sectoral shocks. The frequency of price changes is exogenous, and the same for all types of shocks. Thus, intuition might suggest that this model should not be able to produce responses with different speeds to different shocks. Alternatively, consider a (menu-cost) model in which firms optimally choose when to incur a fixed cost to change prices. Since paying the cost allows a firm to choose whichever price it desires, it should take the opportunity to respond to all relevant shocks.

In this paper we assess the ability of a relatively standard sticky-price model to account for the recently established empirical facts on sectoral prices. Our multi-sector model features input-output relations, sector-specific input markets, and heterogeneity in Calvo-type price stickiness across sectors. In addition to aggregate shocks, the economy is driven by sector-specific demand and supply shocks.

In order to establish a benchmark for comparisons and develop intuition, we start by finding restrictions on parameter values under which the model conforms with the first-pass intuition laid out above and delivers the exact same response of sectoral prices to aggregate and sectoral shocks. The specification that produces this result features an "exogenous monetary policy," coupled with what we refer to as "strategic neutrality in price setting." Because of these two ingredients, nominal marginal

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[1] Maćkowiak et al. (2009) emphasize their similar findings regarding the fast speed of price responses to series-specific shocks.

costs become a combination of *exogenous* driving processes. In that case, if aggregate and sectoral 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."

However, we find that more generally our multi-sector sticky-price DSGE model does *endogenously* deliver differential responses of prices to aggregate and sectoral shocks. The reason is that, in general, a firm's nominal marginal cost depends on endogenous variables - in particular, on other prices. Thus, despite the frequency of price changes being independent of the nature of the shock, to the extent that those endogenous variables exhibit differential responses to different shocks, so do sectoral prices.[2]

We identify three departures from the aforementioned first-pass specification which deliver endogenous differential responses of marginal costs to aggregate and sectoral shocks in our model. The first departure is the input-output production structure, borrowed from Basu (1995). Firms use other goods as production inputs, and this creates a direct dependence of their marginal costs on the aggregate price level - what we refer to as a "uniform" strategic complementarity in price setting. In this context, whenever a shock affects the aggregate price level, such complementarity interacts with the staggering of price changes to produce a sluggish response of prices - in particular, of sectoral prices - to that shock. This is what happens when the economy is hit with an aggregate shock. In contrast, because individual sectors are small, a sectoral shock in our model has only a negligible effect on the aggregate price level - thus rendering that pricing complementarity irrelevant. As a result, nominal marginal costs are driven essentially by the exogenous shock, as in the first-pass specification discussed above.

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 dependence of a firm's marginal cost on its sectoral *relative* price, because of an "expenditure switching effect." A higher sectoral relative price implies less demand for the sector's output, which translates into lower demand for the sector-specific input, 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 produces what we refer to as a "non-uniform" pricing interaction: a strategic complementarity in price setting across sectors, and a strategic substitutability within sectors. The strategic complementarity across sectors contributes to a differential response of sectoral prices to aggregate and sectoral shocks for the reason outlined in the previous paragraph. In turn, because sectoral shocks do affect prices in the sector, the within-sector strategic substitutability works to speed up their response to these shocks.[3] This pattern of non-uniform pricing interactions is impossible to replicate with a version of

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[2]The last statement is somewhat circular - this is inherent in general equilibrium models. The reason why pricing interactions can produce differential responses to shocks will become clear subsequently.

[3]This effect at the sectoral level is exactly analogous to the effect that strategic substitutability in price setting has in terms of speeding up the response of the aggregate price level to aggregate shocks in standard one-sector sticky-price

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the model that features an economy-wide market for the second production input, and requires an arguably unrealistic parameterization of the model in the case in which that second input is attached to firms, as opposed to sectors. 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 markets are segmented at the sectoral level.

The third departure from the first-pass specification is a standard assumption that monetary policy responds to endogenous variables - in particular, it takes the form of a Taylor interest-rate rule. This has the implication of turning the nominal wage from an exogenous variable (under the exogenous monetary policy) into an endogenous one. This change induces a differential response of prices to aggregate and sectoral shocks for reasons similar to the ones spelled out previously. A sectoral shock has little effect on aggregate variables, and thus switching from an exogenous to an endogenous monetary policy specification that responds to aggregate variables does not matter much. As a result, the response of prices to the shock remains similar to the one in 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. To that end we apply a Bayesian approach to estimate the model using aggregate and sectoral price and quantity data. We present results based on the impulse responses implied by the estimated model, and also by estimating a FAVAR similar to BGM's on model-generated data. We find that the model has the ability to match the differential speed of responses of sectoral prices to aggregate and sectoral shocks, as well as additional sectoral price facts.

Because of the "ingredients" that we use in the model, our paper is obviously 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, and the growing literature that incorporates heterogeneity in price setting behavior in dynamic macroeconomic models.[4] In addition, our assumption of labor market segmentation relates our work to the sticky-price literature that relies on input specificity as a source of real rigidity (e.g., Woodford 2003, and Gertler and Leahy 2008). However, for reasons that we discuss in detail subsequently, the implications of input-market segmentation in our model are quite different from the results available in this literature.[5] Finally, our use of sectoral data in the estimation of the structural model connects our paper with Lee (2007) and Bouakez et al.

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models.

[4] For brevity we refer the reader to Carvalho and Schwartzman (2008) for a review of this literature.

[5] 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 pricing interactions among firms.

(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, based on the 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 sectoral shocks quickly in her model.

While the pattern of price responses produced by Shamloo's model is consistent with the findings of Maćkowiak et al. (2009) - who emphasize that the distribution of the speed of responses of sectoral prices to sectoral 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).[6]

To our knowledge, our paper is the first to undertake a quantitative assessment of the ability of a fully-specified DSGE model to match the sectoral price facts documented by BGM and related papers. We also produce a novel empirical fact regarding sectoral prices. In addition, we provide a novel mechanism to produce what we refer to as non-uniform price interactions across sectors, which helps the model match the empirical evidence on the differential response of sectoral prices to common and sectors-specific shocks. Finally, our approach of analyzing both the data and the results of our

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[6]The implication produced by 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 dispersion of the speeds of responses to aggregate and sectoral shocks.

estimated model through the lens of a FAVAR produces a tangential contribution to the FAVAR literature, by providing evidence that such statistical models can reasonably recover some properties of structural models. At the same time, this approach uncovers differences between model-implied and FAVAR based impulse response functions that might be important to account for when drawing conclusions about the ability of structural models to match empirical facts derived from reduced-form statistical models.

2   The model

The model is a variant of the standard new Keynesian sticky-price model, from which we make four departures. These are: i) multiple sectors with heterogeneity in price stickiness; ii) sector-specific demand and supply shocks; iii) intermediate inputs in production; and iv) sector-specific labor markets. We follow Woodford (2003) in working with the cashless limit of a monetary economy.

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 $i \in [0, 1]$ and each firm belongs to one of 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, denoted n_k, gives the size of (mass of firms belonging to) the sector.

2.1   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

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

where C_t denotes the household's consumption of the composite consumption 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. The aggregate preference shock is denoted by Γ_t.

The flow budget constraint of the household is given by

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

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 minimizes total expenditure $P_t C_t$:

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

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. Given $C_{k,t}$, the optimal demand for firm ik's good, $C_{k,t}(i)$, is:

$$
C_{k,t}(i) = \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} C_{k,t}.
$$

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

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

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

2.2 Firms

Firms use sector-specific labor and other (intermediate) goods in production 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 (η):

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

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 similarly 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 the 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:

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

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

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

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 as:

$$
\begin{aligned}
P_{k,t} &= \left[\frac{1}{n_k} \int_{\mathcal{I}_{k,t}^*} P_{k,t}^{*\,1-\theta} di + \frac{1}{n_k} \int_{\mathcal{I}_k - \mathcal{I}_{k,t}^*} P_{k,t-1}(i)^{1-\theta} di \right]^{\frac{1}{1-\theta}} \\
&= \left[(1-\alpha_k) P_{k,t}^{*\,1-\theta} + \alpha_k P_{k,t-1}^{1-\theta} \right]^{\frac{1}{1-\theta}},
\end{aligned}
\tag{2}
$$

where $P_{k,t}^*$ is the common price chosen by the firms that adjust at time t. These firms are grouped into the 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:

$$
\begin{aligned}
Q_{t,t+s} &= \beta^s \left(\frac{\Gamma_t}{\Gamma_{t+s}} \right) \left(\frac{C_t}{C_{t+s}} \right) \left(\frac{P_t}{P_{t+s}} \right) \\
\Pi_{k,t+s}(i) &= P_{k,t}(i) Y_{k,t+s}(i) - W_{k,t+s} H_{k,t+s}(i) - P_{t+s} Z_{k,t+s}(i).
\end{aligned}
$$

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 $MC_{k,t+s} = P_{t+s} A_{t+s}^{-1} A_{k,t+s}^{-1} \frac{1}{1-\delta} \left(\frac{\delta}{1-\delta} \right)^{-\delta} \left(\frac{W_{k,t+s}}{P_{t+s}} \right)^{1-\delta}$ is the nominal marginal cost of firm ik at time $t+s$. Together with (2), optimal price setting determines equilibrium dynamics of sectoral prices. The aggregate price dynamics are then determined by aggregation of such sectoral prices.

2.3 Monetary policy[7]

To close the model, we will make one of two assumptions: i) that monetary policy is explicitly characterized by a Taylor-type interest-rate rule; or ii) that policy is such that nominal aggregate consumption follows a given stochastic process.

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

$$
I_t = \beta^{-1} \left(\frac{P_t}{P_{t-1}} \right)^{\phi_\pi} \left(\frac{C_t}{C} \right)^{\phi_y} \exp(\mu_t),
$$

where μ_t is a monetary policy shock, and C is the zero-inflation-steady-state level of consumption.

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[7]For simplicity we abstract from any influence of fiscal policy on equilibrium. We assume that the government does not collect taxes or purchase goods.

Under the alternative assumption for 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.

2.4 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:[8]

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

The first equation is the asset market clearing condition; the second is the labor market clearing condition for each sector; the last 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, $\sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i',i)di'$.

For later use, we define aggregate wage and hours indices as follows:

$$
\begin{aligned}
W_t &\equiv \sum_k n_k W_{k,t} \\
H_t &\equiv \sum_k H_{k,t}.
\end{aligned}
$$

2.5 Log-linear approximate model

We solve the model by log-linearizing the equilibrium conditions around the deterministic zero-inflation steady state. The Appendix provides a detailed derivation of the steady-state equilibrium as well as the full set of log-linearized equations. Here we only present the equations necessary to characterize the equilibrium of the variables of interest:

$$
\{c_t, \pi_t, i_t, m_t, h_t, (w_t - p_t)\} \text{ and } \{c_{k,t}, \pi_{k,t}\}_{k=1}^{K},
$$

where lowercase letters denote log-deviation from their steady state counterparts, and $\pi_t \equiv p_t - p_{t-1}$ denotes inflation. The following $6 + (2 \times K)$ equations determine the equilibrium dynamics of the

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

variables above:

$$c_t = E_t\left[c_{t+1}\right] - \left(i_t - E_t\pi_{t+1}\right) + \left(\gamma_t - E_t\gamma_{t+1}\right), \tag{3}$$

$$w_t - p_t = \varphi h_t + c_t, \tag{4}$$

$$(1-\psi)c_t + \psi z_t = a_t + \sum_k n_k a_{k,t} + (1-\delta)h_t + \delta z_t, \tag{5}$$

$$w_t - p_t = z_t - h_t, \tag{6}$$

$$\pi_{k,t} = \beta E_t\pi_{k,t+1} + \frac{1-\alpha_k}{\alpha_k\left(1-\alpha_k\beta\right)^{-1}}\left[\begin{array}{c}\left(\frac{(1-\delta)\varphi}{1+\delta\varphi}+\frac{1}{\eta}\right)c_{k,t} + \left(\frac{(1-\delta)(1-\psi\varphi)}{1+\delta\varphi}-\frac{1}{\eta}\right)c_t + \frac{(1-\delta)\psi\varphi}{1+\delta\varphi}z_t \\ -\frac{1+\varphi}{1+\delta\varphi}a_t - \frac{1+\varphi}{1+\delta\varphi}a_{k,t} - \frac{1}{\eta}d_{k,t}\end{array}\right], \tag{7}$$

$$\pi_t = \sum_k n_k \pi_{k,t}, \tag{8}$$

$$\Delta\left(c_{k,t+1} - c_{t+1}\right) = -\eta\left(\pi_{k,t+1} - \pi_{t+1}\right) + \Delta d_{k,t+1}, \tag{9}$$

$$\begin{aligned}i_t &= \phi_\pi\pi_t + \phi_c c_t + \mu_t\\ &or\\ m_t &= exogenous\ stochastic\ process,\end{aligned} \tag{10}$$

where $\psi = \delta\left(\theta-1\right)/\theta$. The first equation (3) is the household's consumption Euler equation, often referred to as the dynamic IS equation; (4) is obtained by aggregating the household's intra-temporal optimality conditions over sectors, and can be interpreted as an aggregate labor supply schedule; (5) is obtained by integrating the production functions over all firms; (6) results from the aggregation of cost minimization conditions; (7) gives the sectoral Phillips curves and (8) delivers aggregate inflation; the demand function for sectoral consumption goods is given by (9); the last equation, (10), closes the model.

3 Inspecting the mechanisms

In this section we analyze the mechanisms through which our model can deliver a differential response of prices to sectoral and aggregate shocks. In the loglinear-approximate version of the model, when a firm sets a new price it chooses (a markup over) an expected discounted weighted average of future nominal marginal costs. Given that the frequency of price changes is the same for all types of shocks, any differential speed in the response of sectoral prices to different shocks can be traced back to differences in the dynamics of nominal marginal costs in response to these shocks.

It turns out that there are three sources of endogenous responses of marginal costs to shocks: i) pricing interactions produced by intermediate inputs; ii) pricing interactions produced by labor

market segmentation; and iii) monetary policy responses to endogenous variables.

We start our discussion from a special case in which the first-pass intuition that the Calvo model should not be able to produce responses with different speeds depending on the shock 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.

In our analysis, it will be useful to focus on the equations for the sectoral price levels that obtain from the sectoral Phillips curves (and some additional algebra):

$$
p_{k,t} = \lambda_1 p_{k,t-1} + \frac{1-\alpha_k}{\alpha_k \left(1-\alpha_k\beta\right)^{-1}} \frac{1}{\lambda_2} \sum_{s=0}^{\infty} \left(\frac{1}{\lambda_2}\right)^s E_t \left[\begin{array}{c} \frac{(1-\delta)\left(1-\delta\frac{\theta-1}{\theta}\varphi+\varphi\right)}{1+\delta\varphi}c_{t+s} + \frac{(1-\delta)\delta\frac{\theta-1}{\theta}\varphi}{1+\delta\varphi}z_{t+s} \\ + \left(1+\frac{1-\delta}{1+\delta\varphi}\varphi\eta\right)p_{t+s} \\ +\frac{1-\delta}{1+\delta\varphi}\varphi d_{k,t+s} - \frac{1+\varphi}{1+\delta\varphi}\left(a_{k,t+s}+a_{t+s}\right) \end{array} \right], \quad (11)
$$

where λ_1 and λ_2 are the roots of the characteristic polynomial

$$
f(\lambda) = \beta\lambda^2 - (\beta+1+\frac{1-\alpha_k}{\alpha_k\left(1-\alpha_k\beta\right)^{-1}}\left(1+\frac{1-\delta}{1+\delta\varphi}\varphi\eta\right))\lambda + 1,
$$

and satisfy $0 < \lambda_1 < 1 < \lambda_2$. Equation (11) indicates how sectoral price levels evolve, through partial-adjustment ($\lambda_1 p_{k,t-1}$), toward a weighted average of current and expected future values of exogenous and endogenous variables.

3.1 Identical responses

To get the model to produce the same response of sectoral prices to aggregate and sectoral shocks we start by abstracting from intermediate inputs ($\delta = 0$). In addition, we assume linear disutility of labor ($\varphi = 0$). This eliminates the effects of labor market segmentation, equalizing wages across sectors. Under these assumptions the model exhibits what we refer to as "strategic neutrality" - as opposed to strategic complementarity or substitutability - in price setting, and the sectoral price equations (11) simplify to:

$$
p_{k,t} = \lambda_1 p_{k,t-1} + \frac{1-\alpha_k}{\alpha_k \left(1-\alpha_k\beta\right)^{-1}} \frac{1}{\lambda_2} \sum_{s=0}^{\infty} \left(\frac{1}{\lambda_2}\right)^s E_t \left[m_{t+s} - a_{t+s} - a_{k,t+s}\right]. \quad (12)
$$

Under the additional assumption that nominal consumption evolves exogenously, it is clear that the speed of the response of sectoral prices to the various shocks will be the same if the shocks have the same dynamics.[9] This result follows from the fact that, under these conditions, nominal marginal costs equal a linear combination of the exogenous stochastic processes.

---

[9]Note that in this case demand shocks have no effect on sectoral prices. This arises because wage equalization implies that pure relative-demand shifts have no effect on marginal costs.

3.2 Differential responses

From the result in the last subsection, it follows trivially that one source of differential dynamics in the response to shocks are differences in the 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 in Section 5.2.

Departing from the particular parameterization of the previous subsection, in general the infinite sum in (11) will involve current and expected future values of endogenous variables. This follows directly from the fact that, in general, nominal marginal costs depend on endogenous variables. Thus, any difference in the speed of response to two given shocks will depend on how these shocks affect the relevant endogenous variables.

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

We continue to eliminate the effect of labor market segmentation by setting $\varphi = 0$, and maintain the assumption of exogenous nominal consumption. This leads to the following sectoral price equations:

$$ p_{k,t} = \lambda_1 p_{k,t-1} + \frac{1 - \alpha_k}{\alpha_k \left(1 - \alpha_k \beta\right)^{-1}} \frac{1}{\lambda_2} \sum_{s=0}^{\infty} \left(\frac{1}{\lambda_2}\right)^s E_t \left[\begin{array}{c} \left(1 - \delta\right) m_{t+s} - \left(a_{k,t+s} + a_{t+s}\right) \\ + \delta p_{t+s} \end{array} \right]. \tag{13} $$

In the expression between square brackets, the first line only involves exogenous processes, and can be thought of as giving the direct effect of the shocks on sectoral prices. The second line, however, involves the aggregate price level. To the extent that the latter responds to shocks differently, the same will happen to sectoral prices. Note that this involves a circular argument, since the aggregate price level is simply a combination of sectoral prices. Thus, understanding the mechanism through which the model delivers a differential response of prices to shocks amounts to understanding the dynamics of prices in equilibrium.

Relative to aggregate shocks, sectoral (productivity) shocks have only a small effect on the aggregate price level - which for expositional purposes we take to be zero.[10] Thus the speed of the response of sectoral prices to the latter shocks is mechanically dictated by the dynamics of the shocks themselves, since they determine the evolution of nominal marginal costs - just as in the case of identical responses analyzed previously.

In contrast, an aggregate shock does move the aggregate price level, and thus the speed of its response matters. As is well known, intermediate inputs lead to strategic complementarity in pricing decisions: when adjusting their prices, firms do not adjust as much in response to shocks since nominal marginal costs are "held back" by prices that have not yet adjusted. This interdependence of pricing

---

[10]Recall that this is a statement about the effect of identical shocks.

decisions manifests itself through the terms $E_t[\delta p_{t+s}]$ in equation (13). This mechanism implies a slower response of prices to aggregate shocks when compared to the case of identical responses analyzed previously - and thus a slower response relative to sectoral shocks.

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

We continue to assume exogenous nominal consumption (output), but now abstract from intermediate inputs ($\delta = 0$). This leads to the following sectoral price equations:

$$
p_{k,t} = \lambda_1 p_{k,t-1} + \frac{1-\alpha_k}{\alpha_k \left(1-\alpha_k\beta\right)^{-1}} \frac{1}{\lambda_2} \sum_{s=0}^{\infty} \left(\frac{1}{\lambda_2}\right)^s E_t \begin{bmatrix} (1+\varphi)\, m_{t+s} - (1+\varphi)\, a_{t+s} \\ -\left(1+\varphi\right) a_{k,t+s} + \varphi d_{k,t+s} \\ +\varphi\left(\eta-1\right) p_{t+s} \end{bmatrix}. \tag{14}
$$

In the expression between square brackets, the first two lines only involve exogenous processes. The third line, however, involves the aggregate price level, and, just like in the previous subsection, the speed of its response matters in the case of aggregate shocks.

Equation (14) is consistent with sectoral prices displaying a slower or faster response to aggregate shocks - relative to sectoral shocks, depending on whether the coefficient in front of the aggregate price level is, respectively, positive or negative. As we discuss in detail in Subsection (3.3), the sign of this coefficient depends on whether pricing decisions of firms in any given sector are strategic complements or substitutes relative to pricing decisions elsewhere in the economy. Pricing decisions exhibit this type of complementarity (substitutability) when the coefficient $\varphi\left(\eta-1\right)$ is positive (negative).[11]

In the $\varphi\left(\eta-1\right)$ coefficient on the aggregate price level, the $-\varphi$ term is reminiscent of models with an economy-wide labor market, and pushes toward across-sector strategic substitutability in price setting.[12] The $\varphi\eta$ term, which arises precisely because of the sectoral labor market assumption, unequivocally pushes toward across-sector strategic complementarity in price setting. This effect is stronger the lower the (Frisch) elasticity of labor supply is (higher φ) and the higher the elasticity of substitution across sectors, η, is. In Subsection 3.3 we discuss the intuition behind the roles of these two parameters.

3.2.3 Taylor rule

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 - may also produce

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[11] From this coefficient it may appear that in general $\eta = 1$ is a borderline case between complementarity and substitutability. However, this is only the case because we assumed logarithmic consumption utility. In the general case of CRRA preferences with coefficient of intertemporal substitution in consumption σ^{-1}, the condition for strategic neutrality in price setting is $(1 + \varphi\eta - (\sigma + \varphi)) = 0$.

[12] In the general case of CRRA preferences with coefficient of intertemporal substitution in consumption σ^{-1}, the corresponding term would be $1 - (\sigma + \varphi)$.

differential responses of sectoral prices to shocks. A convenient way to think about this case is to factor in that now nominal consumption ($m_t \equiv p_t + c_t$) is endogenous. Thus, even in the simplifying case of strategic neutrality in price setting ($\delta = 0$, $\varphi = 0$), aggregate shocks should lead prices to respond differently from sectoral shocks, since the former should affect p_t and c_t.

3.3 The nature of pricing interactions

The previous analysis highlights pricing interactions as a feature that gives the model the ability to deliver relatively more sluggish responses of sectoral prices to aggregate shocks vis-a-vis sectoral shocks endogenously. In our model, these interactions may arise due to input-output linkages, and sectoral labor market segmentation.

Input-output linkages produce complementarities "uniformly" across all pricing decisions, in the sense that other prices only matter as an average - in particular, the aggregate price level. To see this, assume linear labor disutility ($\varphi = 0$) to shut down the effect of labor market segmentation. This produces the following expression for firm ik's *frictionless optimal price* $p_{k,t}^{**}(i)$:[13]

$$
\begin{aligned}
p_{k,t}^{**}(i) &= p_t + (1 - \delta) c_t - a_t - a_{k,t} \\
&= (1 - \delta) m_t + \delta p_t - a_t - a_{k,t}.
\end{aligned}
$$

Note that only the aggregate price level appears, multiplied by the the elasticity of output with respect to intermediate inputs - which in this case dictates the strength of the pricing complementarities. This mechanism operates in the same way in models with economy-wide labor markets (as in the RBC tradition) or firm-specific labor (as advocated by Woodford 2003). It follows directly from the fact that goods are inputs to production, and thus their prices affect marginal costs.

In contrast, labor market segmentation at the sectoral level produces a different type of pricing interactions. To see this, abstract from intermediate inputs ($\delta = 0$) and make labor segmentation relevant by assuming $\varphi > 0$. This produces the following expression for firm ik's frictionless optimal price:

$$
\begin{aligned}
p_{k,t}^{**}(i) &= (1 + \varphi) m_t - \varphi p_t + \varphi \eta p_t - \varphi \eta p_{k,t} \\
&\quad + \varphi d_{k,t} - (1 + \varphi) (a_t + a_{k,t}).
\end{aligned} \tag{15}
$$

The first two terms on the right-hand-side of (15) are reminiscent of models with an economy-wide labor market. They imply a strategic substitutability in price setting. Sectoral labor market segmentation creates a direct dependence of a firm's marginal cost on its sectoral *relative* price, because of an "expenditure switching effect." This effect shows up in the third and fourth terms on the right-

---

[13]This is the price that firm ik would choose if it could change prices continuously.

hand-side of (15). A higher sectoral relative price implies lower demand for the sector's output, which translates into a lower sectoral wage and thus lower marginal costs. This new positive dependence of a firm's marginal cost on the aggregate price level, and negative dependence on its own sectoral price level produce a "non-uniform" pricing interaction: a strategic complementarity in price setting across sectors ($\varphi\eta p_t$ term), and a strategic substitutability within sectors ($-\varphi\eta p_{k,t}$ term). These non-uniform pricing interactions are more relevant the stronger the expenditure switching effect is. In turn, the latter is stronger the more elastic the demand for a sector's output is (higher η), and the less elastic the sectoral labor supply is (higher φ). The reason is that the combination of these two parameters is what determines the effect that a change in a sector's relative price has on its sectoral wage.

The combination of intermediate inputs with sectoral labor market segmentation endows the model with the ability to produce various configurations of within-sector and across-sector pricing interactions. This can be seen from the equation for the frictionless optimal price in the general case ($\delta, \varphi > 0$):

$$
\begin{aligned}
p_{k,t}^{**}(i) \;\; = \;\; & \frac{(1-\delta)\left(1+\varphi-\delta\frac{\theta-1}{\theta}\varphi\right)}{1+\delta\varphi}m_t \\
& + \left(1+\delta\varphi-(1-\delta)\left(1+\varphi-\delta\frac{\theta-1}{\theta}\varphi-\varphi\eta\right)\right)p_t - \frac{1-\delta}{1+\delta\varphi}\varphi\eta p_{k,t} \\
& + \frac{(1-\delta)\,\delta\frac{\theta-1}{\theta}\varphi}{1+\delta\varphi}z_t + \frac{(1-\delta)\,\varphi}{1+\delta\varphi}d_{k,t} - \frac{1+\varphi}{1+\delta\varphi}\left(a_t+a_{k,t}\right).
\end{aligned}
$$

3.3.1 Economy-wide labor market

A version of the model with an economy-wide labor market does not have the flexibility of producing different configurations of within-sector and across-sector pricing interactions. In the absence of intermediate inputs, it produces strategic substitutability uniformly across all pricing decisions (unless one assumes linear disutility of labor, in which case it produces strategic neutrality).[14] Intermediate inputs move the model toward generating uniform pricing complementarities.

---

[14]Since these results are well known, for brevity we omit the relevant equations and refer the interested reader to Woodford (2003).

3.3.2 Firm-specific labor

A model with firm-specific labor leads to the following equation for the frictionless optimal price:[15]

$$
\begin{aligned}
p_{k,t}^{**}(i) \;=\;& \frac{(1-\delta)\left(1+\varphi-\delta\frac{\theta-1}{\theta}\varphi\right)}{1+\delta\varphi+(1-\delta)\varphi\theta}m_t \\
&+\left(1+\frac{(1-\delta)\varphi\left(\eta-\theta\right)-(1-\delta)\left(1+\varphi-\delta\frac{\theta-1}{\theta}\varphi\right)}{1+\delta\varphi+(1-\delta)\varphi\theta}\right)p_t+\frac{(1-\delta)\varphi}{1+\delta\varphi+(1-\delta)\varphi\theta}\left(\theta-\eta\right)p_{k,t} \\
&+\frac{(1-\delta)\varphi\delta\frac{\theta-1}{\theta}}{1+\delta\varphi+(1-\delta)\varphi\theta}z_t+\frac{1-\delta}{1+\delta\varphi+(1-\delta)\varphi\theta}\varphi d_{k,t}-\frac{1+\varphi}{1+\delta\varphi+(1-\delta)\varphi\theta}\left(a_t+a_{k,t}\right).
\end{aligned}
$$

This model can also break the uniformity of pricing interactions as long as the elasticities of substitution between varieties within (θ) and across (η) sectors are different. Under the reasonable assumption that $\theta > \eta$, the model strengthens within-sector complementarities at the expense of across-sector complementarities. Producing either within-sector complementarities that are weaker than across-sector, or within-sector strategic substitutability requires $\theta < \eta$.

3.3.3 Difference relative 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 this is equivalent to our model of sectoral labor markets. However, the implications of labor segmentation for the nature of pricing interactions in our models are quite different. Here we explain why this is the case.

From the point of view of 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. In fact, 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.[16] As is well known, this setup gives rise to strategic complementarities in price setting across firms in different islands (industries).[17]

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[15] While we refer to this model as featuring firm-specific labor, in some contexts it might also be consistent with different intepretations. See our discussion in the next subsection.

[16] In Gertler and Leahy (2008) not all firms in an island necessarily end up changing prices at the same time. However, whenever an island-specific shock hits they all entertain a price change at the same time (subject to the menu cost). Moreover, none of them change prices in periods in which island-specific shocks do not hit. As will become clear shortly, the resulting pattern of "synchronization" of price changes is what matters, and turns out to imply pricing complementarities just as in the alternative interpretation of Woodford's model, in which all firms in the industry do change prices at the same time.

[17] 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

In our multi-sector model with labor segmentation, price changes 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 positive sectoral productivity shock in a given sector. If price changes are infrequent but fully synchronized in each sector, at some point all firms will respond simultaneously by lowering their prices, selling more and producing more. Moreover, the (common) price that is chosen at that time will remain fixed until the next (synchronized) price change. All else equal, the lower the sectoral price is, the higher are sectoral demand, production, labor input, and wages. The negative dependence of the sectoral wage on the sectoral relative price, coupled with the fact that price changes in the sector are synchronized and infrequent, implies a strategic complementarity of the same kind as in the Gertler and Leahy (2008) model.

Now imagine that price adjustments within the sector are staggered uniformly over time, as in our model. Relative to the full-synchronization case, firms that do not cut prices produce and sell less, and thus demand less (sector-specific) labor. This puts downward pressure on the sectoral wage, and thus induces firms that do change prices to cut them by more than in the case of full synchronization. Moreover, going forward other firms in the sector will adjust their prices while (some of) the first movers keep their prices temporarily fixed. The resulting fluctuations in the relative sectoral price will induce fluctuations in the sectoral wage that are unrelated to the prices chosen by the first movers.[18] This is exactly what produces the within-sector substitutability in pricing decisions that we highlight in Subsection 3.3.[19]

_____

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 it does not hurt their model's ability 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).

[18]This is in contrast with the case of full synchronization, in which the sectoral price remains fixed until the next episode of synchronized price changes in the sector. In that case the initial price-setting decisions keep influencing what happens to the sectoral wage as long as the sectoral price level remains constant.

[19]Another way to make sense of the implications of our assumption of sectoral labor markets with asynchronized price changes is as follows. As in the model with an economy-wide labor market, pricing decisions of firms that share the same labor input are strategic substitutes. What those two assumptions add, then, is an expenditure switching effect that pushes toward across-sector strategic complementarity, as discussed previously.

4 Empirical sectoral price facts

4.1 BGM FAVAR

We start with results based on BGM's FAVAR, using the exact same specification and data.[20] Figures 1-2 present the IRFs obtained from their FAVAR. The left figure shows the responses of sectoral PCE prices (red dotted lines) to an innovation to the common component in their dynamic factor model, and the corresponding unweighted average of the IRFs (black solid line). The right figure shows the responses of sectoral PCE prices to an innovation to their respective sector-specific components (red dotted lines), and the corresponding unweighted average of the IRFs (black solid line). The responses are scaled so that the initial impact equals minus one for all series.[21]

Figures 1-2: Empirical IRFs - FAVAR
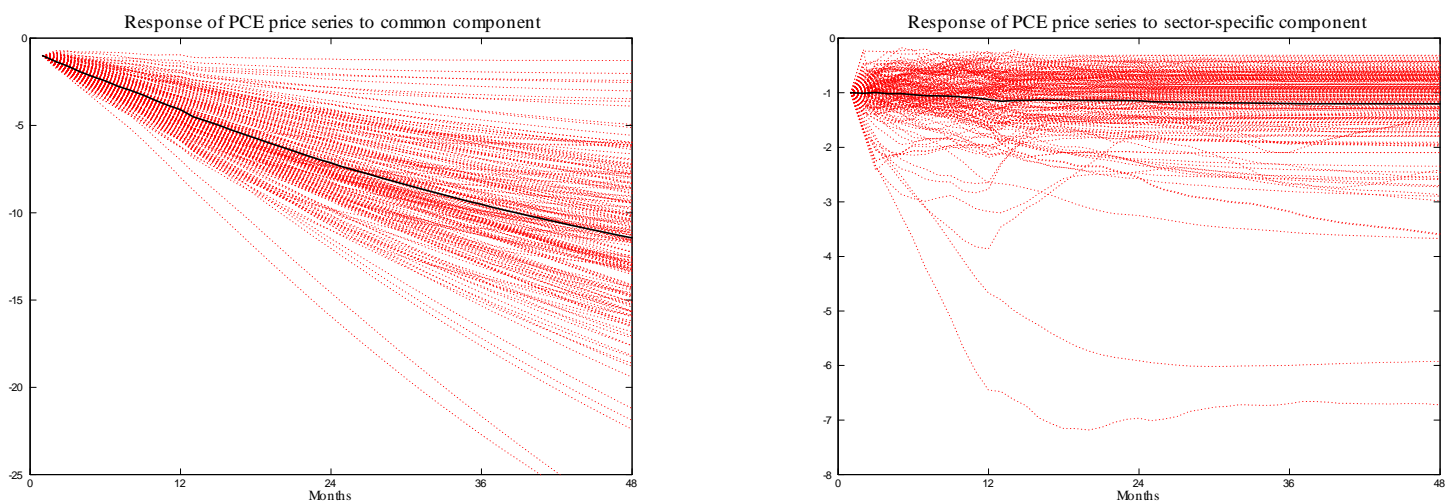
From these IRFs we compute measures of the speed of the responses to each component, following Maćkowiak et al. (2009). Given an impulse response function denoted IRF_t, the speed of the response is given by the ratio of the average "short-run" response (first 6 months) to the average "long-run" response (last 6 months in the two-year horizon):

$$speed\ of\ response = \frac{\sum_{t=0}^{5}|IRF_t|}{\sum_{t=19}^{24}|IRF_t|}. \tag{16}$$

Figures 3-4 show the distribution of the speed of the responses of sectoral prices to an innovation to the common component (left figure), and to their respective sector-specific components (right figure). Table 1 reports some descriptive statistics based on these two distributions.

---

[20] We thank the authors for making their code and data available on their websites. We also thank Marc Giannoni for providing us with their mapping between the disaggregated PCE price data and the Bils and Klenow (2004) statistics on the frequency of price changes. For brevity we refer the reader to BGM for details on the FAVAR model that they employ.

[21] We apply the same normalization to all IRFs presented sebsequently.

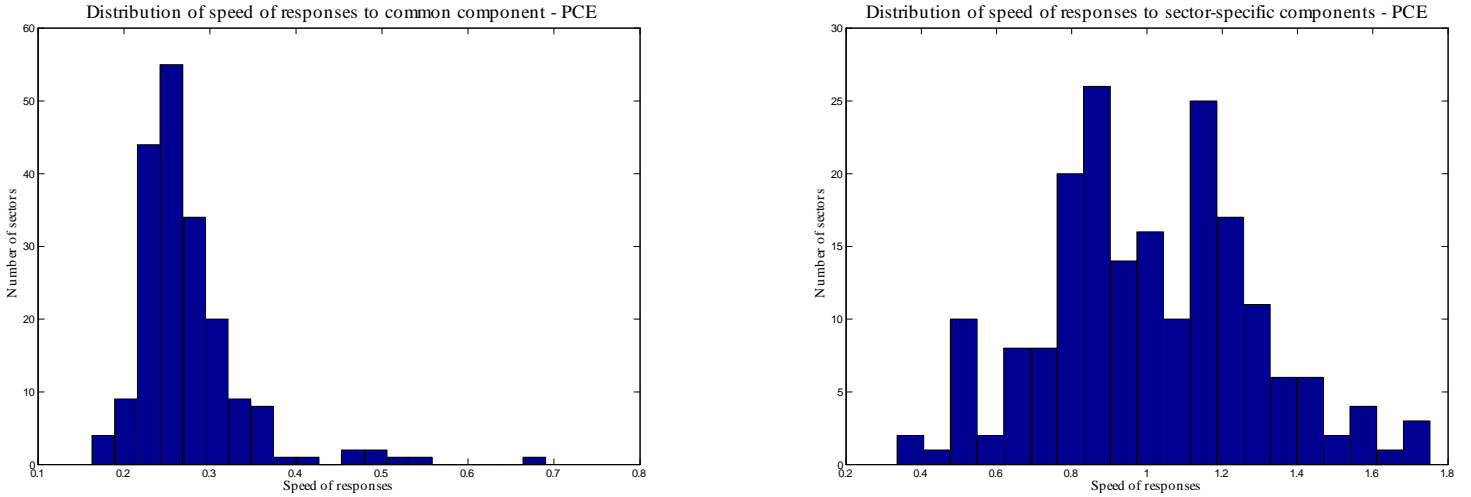Figures 3-4: Cross-sectional distribution of speed of responses

Distribution of speed of responses to common component - PCE

Distribution of speed of responses to sector-specific components - PCE

Table 1: Statistics on the speed of responses to shocks

	Speed of response		
	to common component		to specific components
Average	0.274		1.010
Median	0.261		1.001
Std. deviation	0.066		0.281
Coeff. of variation	0.239		0.278
Corr.with $1 - \alpha_k$	$0.422^{1)}$		$0.188^{1)}$
Correlation	–	0.306	–

Note: 1) based on a mapping between 108 (out of the 192) PCE price series included in BGM's FAVAR and the Bils and Klenow (2004) statistics on the frequency of price changes.

The average speed of response of sectoral prices to sector-specific components is substantially higher than to common components. This conclusion is common to BGM and Maćkowiak et al. (2009). 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. It is higher for the common component (0.42 vs. 0.19). This is consistent with related regression results reported by Maćkowiak et al. (2009). A novel price fact is that 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 BGM's FAVAR this correlation is 0.31.

If measured by the standard deviation, the cross-sectional dispersion in the speed of the responses to common shocks is smaller than the dispersion in the speed of the responses to specific shocks. This essentially reflects the different central tendencies of the two cross-sectional distributions, as the coefficients of variation of the two distributions are quite similar.[22]

---

[22] Our finding on the cross-sectional dispersion of the speed of responses is at odds with the results of Maćkowiak et al. (2009). They conclude that "the cross-section of the speed of response to sector-specific shocks is tight, while the cross-section of the speed of response to aggregate shocks is dispersed." We conjecture that the discrepancy is due

Finally, we reproduce 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 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 Figures 5-6. 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.

Figures 5-6: Cross-section of correlations between components of prices and quantities
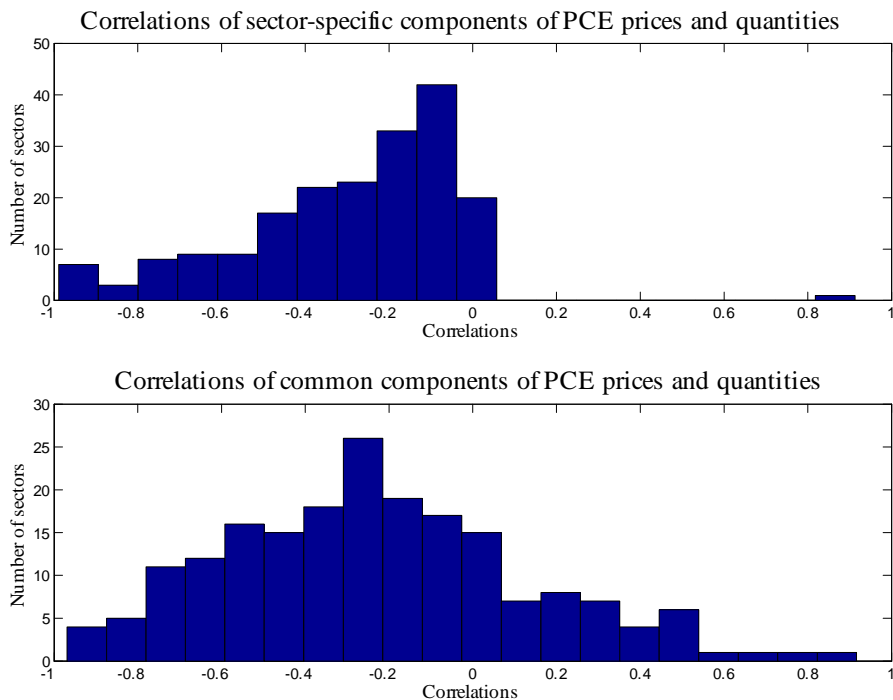
4.2 15-sector FAVAR

In our structural estimation in Section 5.2, for computational reasons we use the second-level disaggregation of the PCE data, which consists of 15 sectors. To allow a more direct comparison between our structural and reduced-form empirical results, here we redo the FAVAR analysis of the previous subsection using only the data that we include in the structural estimation. The observables are the

to differences in empirical methodology between their paper and BGM's. A first difference between the two papers is that BGM's dataset includes sectoral quantities and other macroeconomic and financial variables besides price series, whereas Maćkowiak et al. (2009) only use sectoral inflation data. In terms of modeling assumptions, BGM allow for as many as 5 unobserved common factors in their estimation, and impose a vector-autoregressive structure on all of them. They impose weak regularity conditions on the sector-specific components. In contrast, Maćkowiak et al. (2009) impose one common inflation component, and assume time-series processes of different families for their sectoral and common components: while the sectoral components follow AR(6) processes, the common component follows an MA(24) process. Maćkowiak et al.'s (2009) robustness analysis, showing that their results are somewhat sensitive to the number of common factors (section 6.3 of their paper), hints that these differences is modeling assumptions might be important. Finally, Maćkowiak et al. (2009) use a Bayesian approach, whereas BGM use a classical estimation approach. We believe this set of methodological differences between the two papers is potentially important, and their implications should be further investigated in future research.
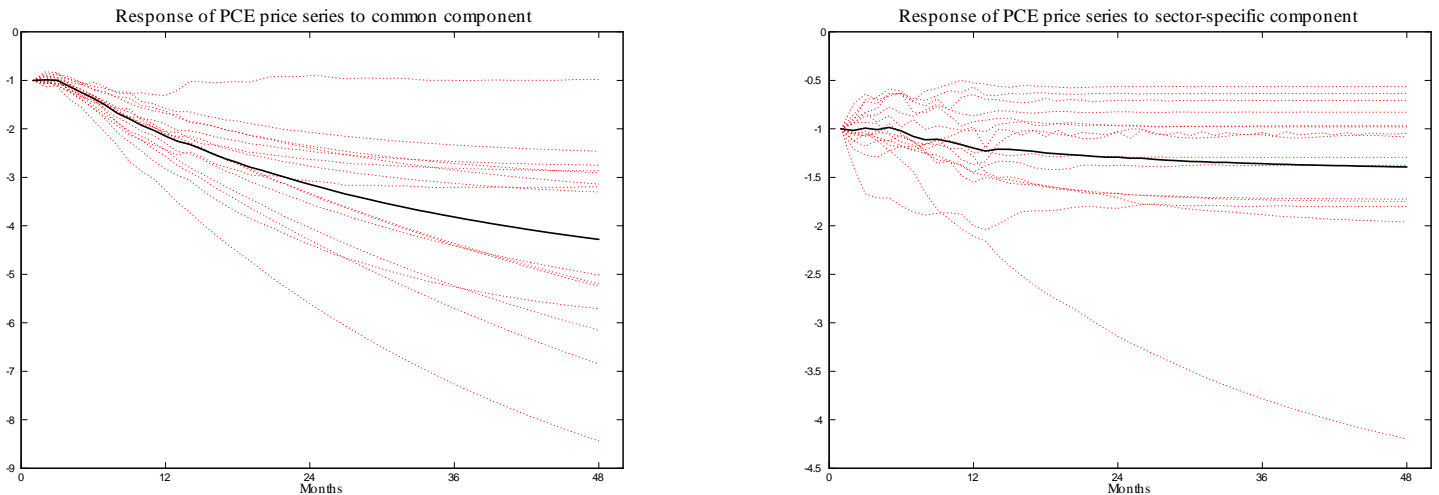
Table 2: Statistics on the correlations between components of prices and quantities

	Correlation between inflation and growth of quantities	
	Common component	Specific components
Average	−0.229	−0.296
Median	−0.260	−0.239
Max.	0.917	0.913
Min.	−0.969	−0.990

nominal interest rate (i_t), hours growth (Δh_t), and all sectoral inflation and sectoral consumption growth rates $\{\pi_{k,t}, \Delta c_{k,t}\}_{k=1}^{K}$. We use total hours from the nonfarm business sector as a measure of hours, and the effective federal funds rate as the nominal interest rate. Consumption is given by personal consumption expenditures (PCE), with the corresponding price deflators as the measure of prices. We otherwise keep the same parameterization of the BGM FAVAR model (5 common factors, 13 lags in the VAR). The data are monthly, and the sample period is 1983:M1 to 2008:M12. In the Appendix we present details of the sectors used in the estimation.

Figures 7-12 and Tables 3-4 report the results analogous to those in Figures 1-6 and Tables 1-2. The correlations between the speeds of responses and the frequencies of price changes are based on our mapping of the price-setting statistics for posted prices reported by Nakamura and Steinsson (2008) to the 15-sector disaggregation of the PCE.

Figures 7-8: Empirical IRFs - FAVAR

Response of PCE price series to common component

Response of PCE price series to sector-specific component

Figures 9-10: Cross-sectional distribution of speed of responses

Distribution of speed of responses to common component - PCE

Distribution of speed of responses to sector-specific components - PCE
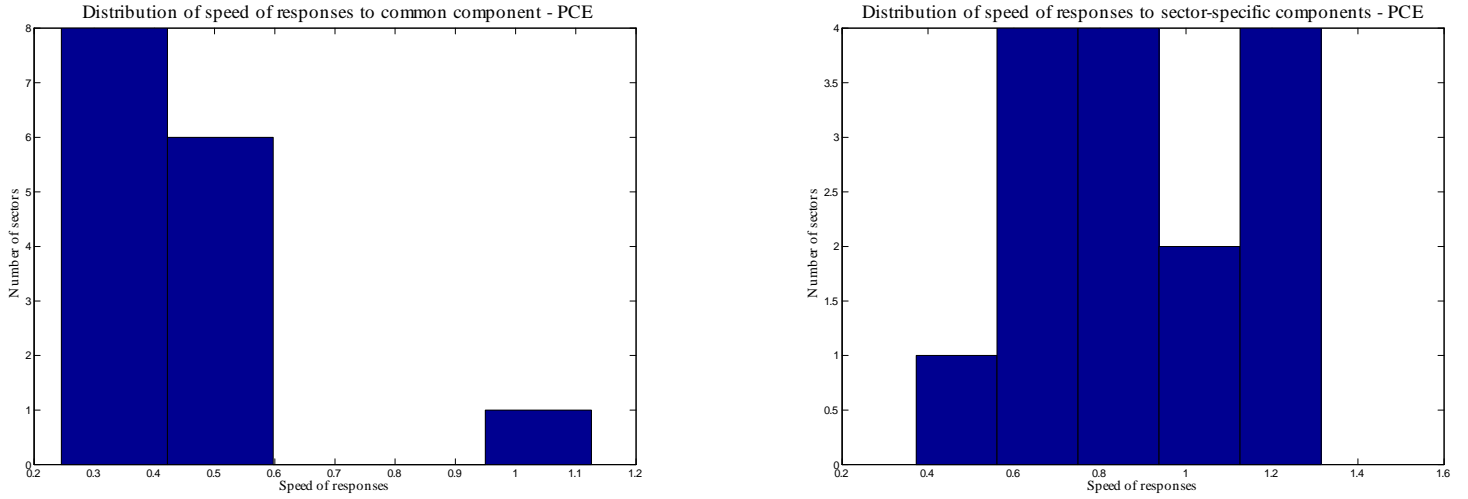
Table 3: Statistics on the speed of responses to shocks - 15-sector FAVAR

| | Speed of response | |
	to common component	to specific components
Average	0.423	0.889
Median	0.397	0.855
Std. deviation	0.208	0.269
Coeff. of variation	0.491	0.303
Corr. with $1 - \alpha_k$	0.755	0.331
Correlation	− 0.350	−

Table 4: Statistics on the correlations between components of prices and quantities - 15-sector FAVAR

| | Correlation between inflation and growth of quantities | |
	Common component	Specific components
Average	−0.327	−0.109
Median	−0.331	−0.149
Max.	0.201	0.144
Min.	−0.932	−0.394

Figures 11-12: Cross-section of correlations between components of prices and quantities

Correlations of sector-specific components of PCE prices and quantities

Correlations of common components of PCE prices and quantities
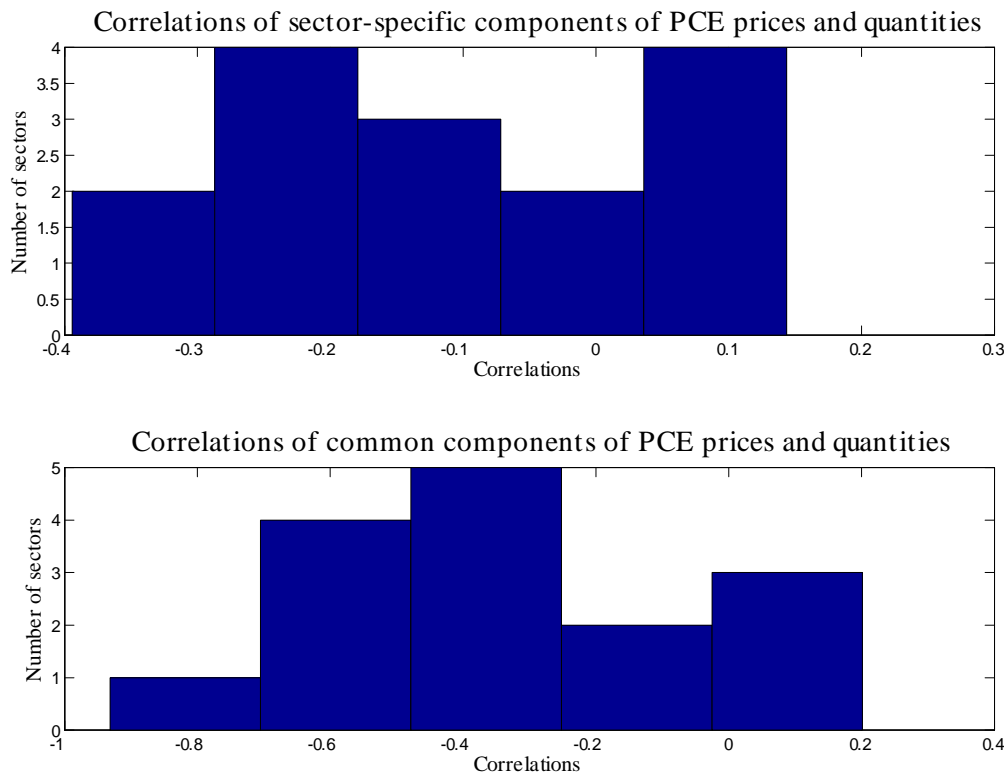
The results are quite similar across the two FAVAR specifications. Moreover, in our robustness analysis (reported in the Appendix) we show that these findings also hold in a FAVAR with 50 sectors, corresponding to the third level of disaggregation of the PCE data. We thus summarize the empirical evidence with the following facts: i) the average speed of response of sectoral prices to sector-specific shocks is significantly higher than the average speed of response to shocks to the common component (by a factor of 2-4); ii) 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 - it is higher for the common component; iii) The correlation between the speed of responses to both types of shocks is positive; iv) 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; v) the cross-sectional mean of the correlations between the sector-specific component of PCE in‡ation rates and the corresponding sector-specific component of the growth rate in quantities is negative - the same applies to the fluctuations that are driven by the common component.

5   Quantitative analysis

We focus on the model in which monetary policy responds to endogenous variables according to a Taylor-type interest-rate rule. To simulate (and subsequently estimate) the model, it is necessary to

make distributional assumptions on the exogenous shocks. We assume they follow AR(1) processes:

$$
\begin{aligned}
\gamma_{t+1} &= \rho_\Gamma \gamma_t + \sigma_\Gamma \varepsilon_{\Gamma,t+1}, \\
a_{t+1} &= \rho_A a_t + \sigma_A \varepsilon_{A,t+1}, \\
\mu_{t+1} &= \rho_\mu \mu_t + \sigma_\mu \varepsilon_{\mu,t+1}, \\
a_{k,t+1} &= \rho_{A_k} a_{k,t} + \sigma_{A_k} \varepsilon_{A_k,t+1}, \\
d_{k,t+1} &= \widetilde{d}_{k,t+1} - \sum_{k=1}^{K} n_k \widetilde{d}_{k,t}, \text{ where } \widetilde{d}_{k,t+1} = \rho_{D_k} \widetilde{d}_{k,t} + \sigma_{D_k} \varepsilon_{D_k,t+1},
\end{aligned}
$$

with every epsilon being standard Gaussian white noise.

As a preliminary step, in the next subsection we study the properties of a simply parameterized version of our model to assess whether it can endogenously produce meaningful differences in the speed of responses of sectoral prices to aggregate and sectoral shocks. We present both results obtained directly from the solution of the model (what we refer to as "model-implied results"), and results obtained by estimating a FAVAR on model-generated data. We then move to the estimation of the model using Bayesian methods, which is the basis for our ultimate quantitative analysis.

5.1 Preliminaries

5.1.1 Model parameterization

As highlighted in Section 3, the speed of the adjustment of sectoral prices depends on the specification of the dynamics of the exogenous shocks. To isolate the differential response of sectoral prices to aggregate and sectoral shocks delivered endogenously by the model, here we assume that every exogenous shock has the same degree of persistence. Assuming the unit of time is one month, we set every autoregressive coefficient to be $0.9^{1/3}$, which is equivalent to 0.9 in a quarterly model. In Section 5.2 we estimate the parameters of the shock processes maintaining the AR(1) assumption.

We set the other parameters to conventional values found in the literature. The discount factor, β, equals 0.9967, to achieve a 4% annual steady state interest rate. The parameter φ is set equal to 2 so that the (Frisch) elasticity of labor supply is 0.5. We set 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. The elasticity of output with respect to intermediate inputs, δ, is set to 0.7. We adopt standard values for the policy parameters, setting ϕ_π and ϕ_c equal to 1.5 and 0.5/12, respectively.

The size of the shocks does not matter for the results based on "theoretical" impulse response functions (i.e. those obtained from the solution of the model). But it does matter for the results obtained by estimating a FAVAR on model-generated data, due to the reduced-form nature of the estimated shocks. For the aggregate productivity and preference shocks we assume a standard deviation of $0.01/\sqrt{3}$ (1% quarterly); for the monetary shock we assume $0.002/\sqrt{3}$. Sectoral shocks are likely much larger than aggregate shocks. For sectoral demand shocks we assume $\sigma_{D_k} = 0.025/\sqrt{3}$, and for sectoral productivity shocks we assume that innovations are three times as volatile, and set

$\sigma_{A_k} = 0.075/\sqrt{3}.$[23]

We simulate the parameterized economy with 50 sectors, mirroring the third-level disaggregation of PCE data. The corresponding distribution of price stickiness is constructed by suitably aggregating consumption categories from the Nakamura and Steinsson (2008) price-setting statistics. The sectoral weights are the PCE expenditure weights averaged over our sample period.

5.1.2 Model-implied results

We start with results taken directly from the solution of the parameterized model. Figures 13-14 present the theoretical IRFs of sectoral prices to an aggregate productivity shock, and to the respective sectoral productivity shocks. In the sequence, Figures 15-16 show the distributions of the speed of the responses to an aggregate productivity shock (left figure), and to the respective sector-specific productivity shocks (right figure). Table 5 reports descriptive statistics based on these two distributions.

Figures 13-14: Theoretical IRFs
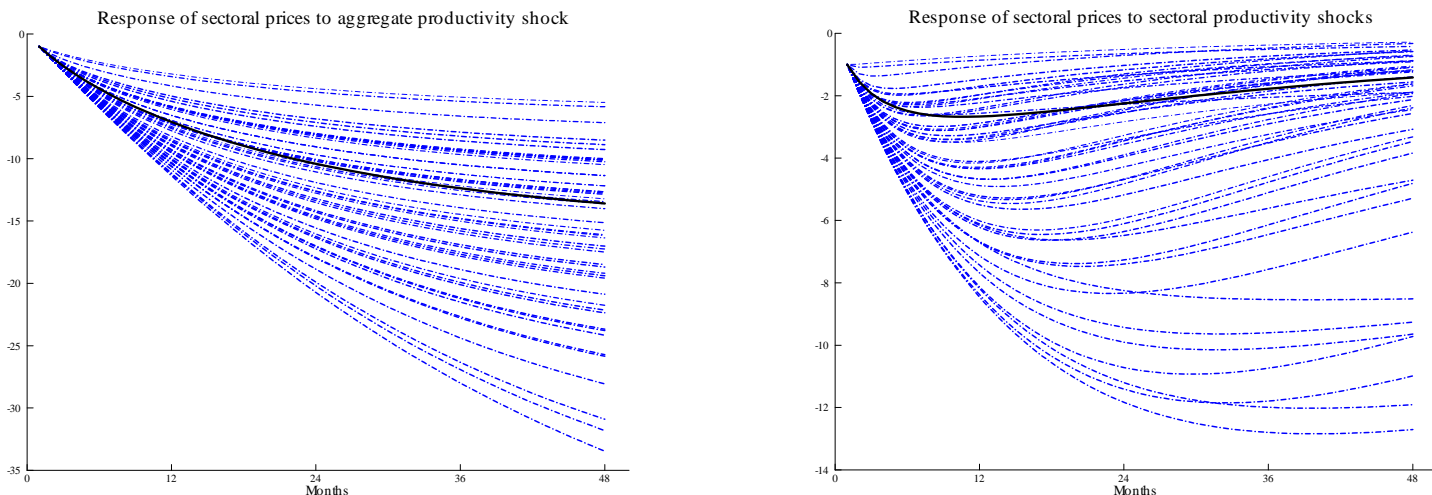
The cross-sectional distributions of the speed of responses to both shocks, calculated according to (16), are shown in Figures 15-16. Summary statistics are provided in Table 5.

Table 5: Speed of response to productivity shocks

	Speed of response		
	to aggregate shock		to sectoral shock
Average	0.268		0.824
Median	0.262		0.726
Std. deviation	0.061		0.428
Coeff. of variation	0.226		0.519
Corr.with $1 - \alpha_k$	0.880		0.899
Correlation	–	0.977	–

[23]This is motivated by the results in Burstein and Hellwig (2008).

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Figures 15-16: Cross-sectional distribution of speed of responses

Distribution of speed of responses to aggregate productivity shock

Distribution of speed of responses to sectoral productivity shocks
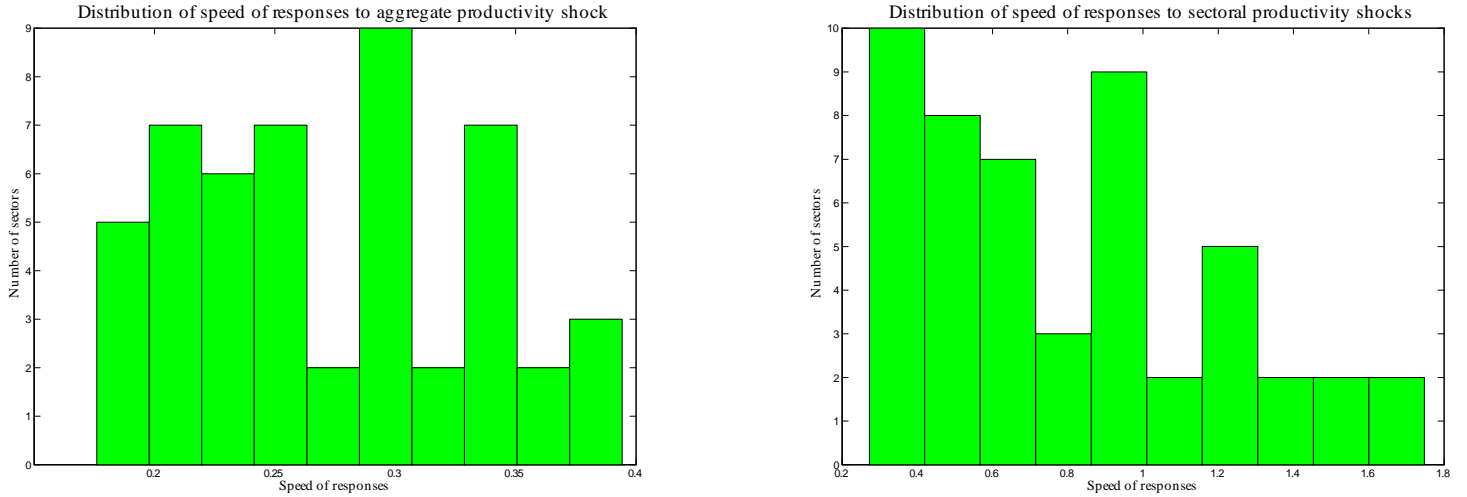
The results illustrate the potential of the model to deliver relatively faster responses of sectoral prices to sector-specific productivity shocks, when compared to aggregate productivity shocks.[24] Given that all shocks are assumed to follow the same exogenous dynamics, these results reflect the ability of the parameterized model to produce such differential responses endogenously. The model also endogenously produces less dispersion in the speed of responses of sectoral prices to the aggregate shock when compared to the responses to sectoral shocks.[25] This result arises naturally from the pattern of pricing complementarities and substitutabilities implied by our model, which produces relatively stronger comovement of sectoral prices in response to aggregate shocks (see the discussion in Section 3).

This simply parameterized model also produces the right signs for the correlations between the speed of responses to shocks and the frequencies of price changes, and for the correlation between the speeds of responses to the two types of shocks. However, because the dynamics of the exogenous shocks are identical, heterogeneity in the frequency of price changes is the only relevant source of differences across sectors. As a result, there is a very tight link between the speeds of responses to aggregate and sectoral shocks and the frequencies of price changes, which is apparent in the very high correlations reported in Table 5.

The role of each "ingredient" We also analyze the model by introducing each of the three ingredients discussed in Section 3 at a time into the first-pass specification with strategic neutrality in price setting and exogenous monetary policy. We then combine the Taylor rule with each of the other two ingredients. In quantitative terms, the combination of the endogenous response of monetary policy through the Taylor rule with labor-market segmentation seems to be the driving force behind the ability of the model to produce price responses to sectoral and aggregate shocks with differential

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[24]The patterns with other types of shocks are similar.

[25]Recall that in the first-pass specification without the three "ingredients" discussed in detail in Section (3), the impulse response functions of sectoral prices to both types of shocks are indentical. As a result, the cross-sectional distributions of the speeds of responses to both types of shocks are also identical.

speeds. For brevity we present the details of this analysis in the Appendix, and from now on we focus on the quantitative performance of the model with all three ingredients.

5.1.3   FAVAR results with model-generated data

While the results of the previous subsection involve responses conditional on particular shocks, the empirical evidence that we summarize in Subsection 4 involves responses to shocks extracted from the statistical FAVAR framework. As such, they can be thought of as involving a combination of structural shocks. To produce results from the model that are more comparable to the empirical evidence, we estimate a FAVAR on data generated by simulating the model with all the shocks, and produce the results underlying figures and tables in the exact same way as in Subsection 4. The artificial dataset comprises consumption growth, inflation, the nominal interest rate, hours growth, and all sectoral inflation and sectoral consumption growth rates. The specification of the FAVAR is identical to the one we estimate for the 15-sector disaggregation of the PCE data (Subsection 4.2).

Figures 17-18 present the IRFs from the FAVAR estimation on artificial data.[26]

Figures 17-18: IRFs from FAVAR
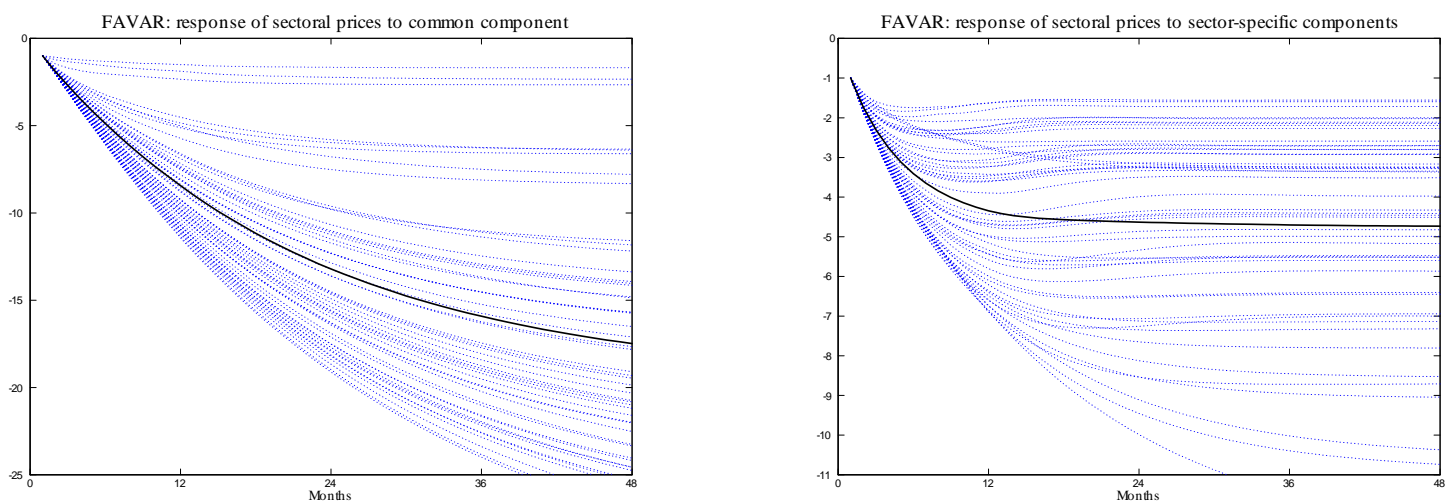
Figures 19-20 show the distribution of the speed of the price responses to an innovation to the common component (left figure), and to the sector-specific components (right figure). Table 6 reports descriptive statistics based on these two distributions.

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[26]We produce a sample with twelve thousand observations and discard the first two thousand to minimize the effects of initial conditions.

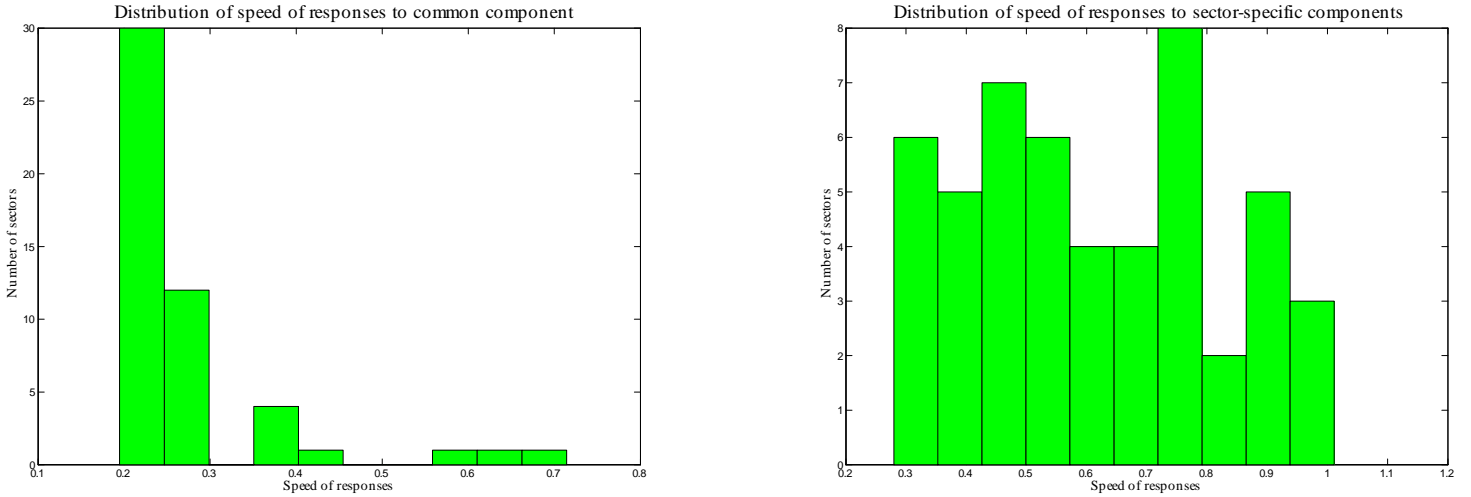Figures 19-20: Cross-sectional distribution of speed of responses

Distribution of speed of responses to common component

Distribution of speed of responses to sector-specific components

Table 6: Statistics on the speed of responses to shocks

	Speed of response		
	to common component		*to specific components*
Average	0.271		0.613
Median	0.227		0.576
Std. deviation	0.111		0.207
Coeff. of variation	0.411		0.339
Corr.with $1 - \alpha_k$	0.955		0.527
Correlation	—	0.438	—

A comparison between Tables 5 and 6 reveals that, qualitatively, the FAVAR framework captures all of implications of our structural model for those sectoral-price statistics. At first this may seem surprising, since the artificial data underlying the results in Table 6 are driven by a variety of shocks. As such, they are not conditional on (aggregate and sectoral) productivity shocks, unlike the model-implied results reported in Table 5. The reason why conditional and "unconditional" results are somewhat close is this simply parameterized model produces similar statistics in response to the other structural shocks.

Finally, we report the results on the cross-section of correlations between the sector-specific component of inflation rates and the corresponding sector-specific component of quantities (in growth rates), and the cross-section of correlations between the component of inflation rates and growth rate of quantities that are driven by the common components. These are depicted in Figures 21-22, and summarized in Table 7.

Figures 21-22: Cross-section of correlations between components of prices and quantities
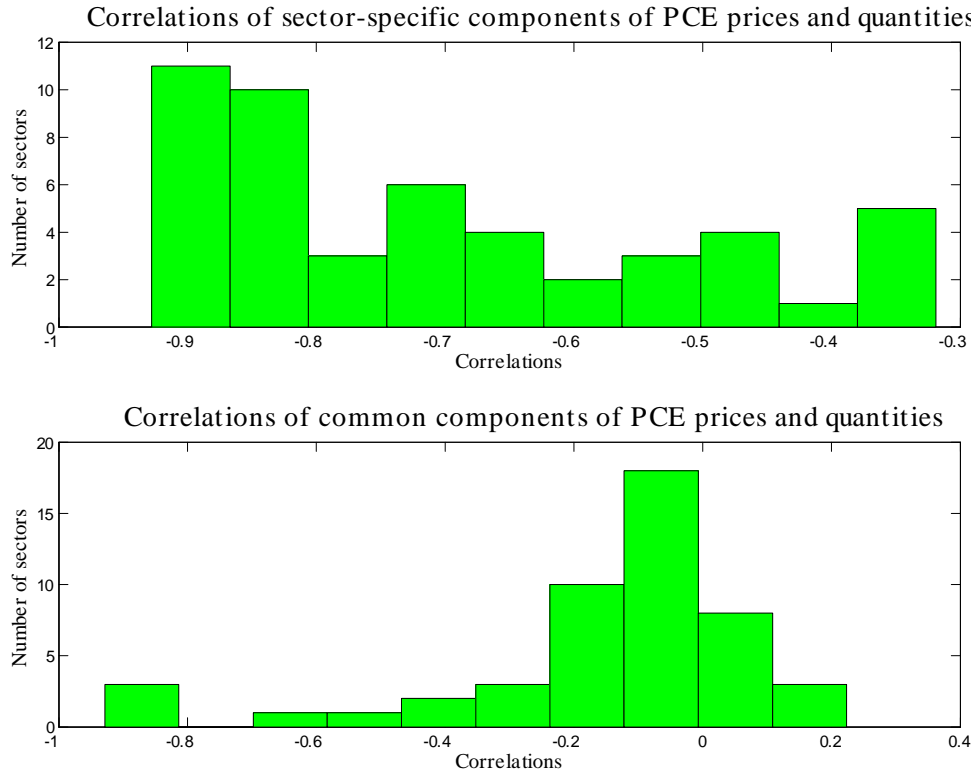
Correlations of sector-specific components of PCE prices and quantities

Correlations of common components of PCE prices and quantities

Table 7: Statistics on the correlations between components of prices and quantities

	Correlation between inflation and growth of quantities	
	Common component	*Specific components*
Average	−0.151	−0.701
Median	−0.084	−0.738
Max.	0.224	−0.319
Min.	−0.929	−0.928

Overall, the results show that in response to "reduced-form" sectoral and common shocks extracted through the FAVAR framework, the model manages to produce results that are qualitatively similar to the empirical facts summarized in the previous section. In addition to the statistics on the speed of sectoral price adjustment to shocks, the results on the cross-section of correlations between inflation rates and the growth rates of quantities are also in line with the empirical evidence - in particular the negative correlations between the sector-specific component of inflation rates and the corresponding sector-specific component of the growth rate in quantities.[27]

The quantitative analysis carried out in this and the previous subsections suggests that the model has enough flexibility to produce quantitative results that are consistent with to the empirical facts

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[27]In unreported results we confirm BGM's conjecture that such negative correlations arise when supply-type shocks are dominant.

summarized in the previous section. This underscores our effort to move to estimation of the structural model in order to assess its ability to match those facts.

5.2 Model estimation

Although the parameterized version of the model analyzed in the previous subsections is a useful starting point for a quantitative analysis, it only provides a partial picture about the ability of our model to match the empirical findings reported in Section 4. In particular, because the response of sectoral prices depends on the dynamic properties of exogenous shocks, parameterizing the shocks symmetrically can be problematic.

In this section we estimate the model employing Bayesian methods. We incorporate prior information about the structural parameters $\boldsymbol{\theta}$ by specifying a prior distribution $f(\boldsymbol{\theta})$. With data set $\mathbf{X}^T$, we can obtain the likelihood function $f(\mathbf{X}^T|\boldsymbol{\theta})$ implied by the model economy. The posterior distribution of $\boldsymbol{\theta}$, $f(\boldsymbol{\theta}|\mathbf{X}^T)$ is then determined by Bayes theorem: $f(\boldsymbol{\theta}|\mathbf{X}^T) = f(\mathbf{X}^T|\boldsymbol{\theta})f(\boldsymbol{\theta})/\int f(\mathbf{X}^T|\boldsymbol{\theta})f(\boldsymbol{\theta})d\boldsymbol{\theta}$. We simulate the posterior distribution by Markov Chain Monte Carlo methods as detailed in the Appendix.

We take the model to the aggregate and sectoral data described in Subsection 4.2. We normalize total hours and the sectoral consumption measures by the total civilian non-institutional population over age of 16. We also detrend the real variables using a linear trend, and demean the nominal interest rate and the sectoral inflation rates. The sectoral weights are set to the expenditure weights averaged over our sample period.

5.2.1 Priors and posteriors

We fix some parameters in the estimation, setting the same values as in the parameterized version of the model studied in previous subsections. The fixed parameters are β, φ, θ, η, δ, and $\{\alpha_k, n_k\}_{k=1}^K$. As for the remaining parameters, our prior distribution mostly follows the convention in the literature on Bayesian estimation of DSGE models. Regarding the Taylor rule coefficients, we select 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 0.5/12 and its prior standard deviation to be 0.05. The autoregressive parameter of monetary shock, ρ_μ, has a beta distribution with mean of 0.7 and standard deviation of 0.1, whereas the innovation parameter, σ_μ, has an inverse gamma distribution with mean of 0.125% and standard deviation of 0.125%.

Similarly to the monetary shock, we assume that the autoregressive parameters for the remaining exogenous shocks have a beta distribution and the coefficients on the innovations have an inverse gamma distribution. We treat the aggregate shocks, γ_t and a_t, symmetrically. The prior mean of ρ_Γ and ρ_A is 0.7, and the standard deviation is 0.1. The standard deviations of the innovations σ_Γ and σ_A are assumed to have mean of 0.5% and standard deviation of 0.5%.

We also treat the sectoral shocks symmetrically in the prior distribution. The autoregressive parameters have the same prior distribution as their counterparts in aggregate shocks. However, due to the likely more volatile nature of sectoral shocks, we set the prior mean of σ_{A_k} and σ_{D_k} to

5% and the prior standard deviation to 2%. Finally, we assume that all parameters are distributed independently.

The Appendix reports the point estimates of the parameters at the joint posterior mode, along with moments from the prior distributions. The quantitative analysis that follows is based on these point estimates.

5.2.2 Results

For comparability with the empirical evidence we present results obtained by estimating a FAVAR on artificial data generated by the model.[28] The artificial dataset comprises consumption growth, inflation, the nominal interest rate, hours growth, and all sectoral inflation and sectoral consumption growth rates. The specification of the FAVAR is identical to that of Subsection 5.1.3.

Figures 23-24 present the IRFs from the FAVAR estimation on model-generated data.

Figures 23-24: IRFs from FAVAR - 15 sectors
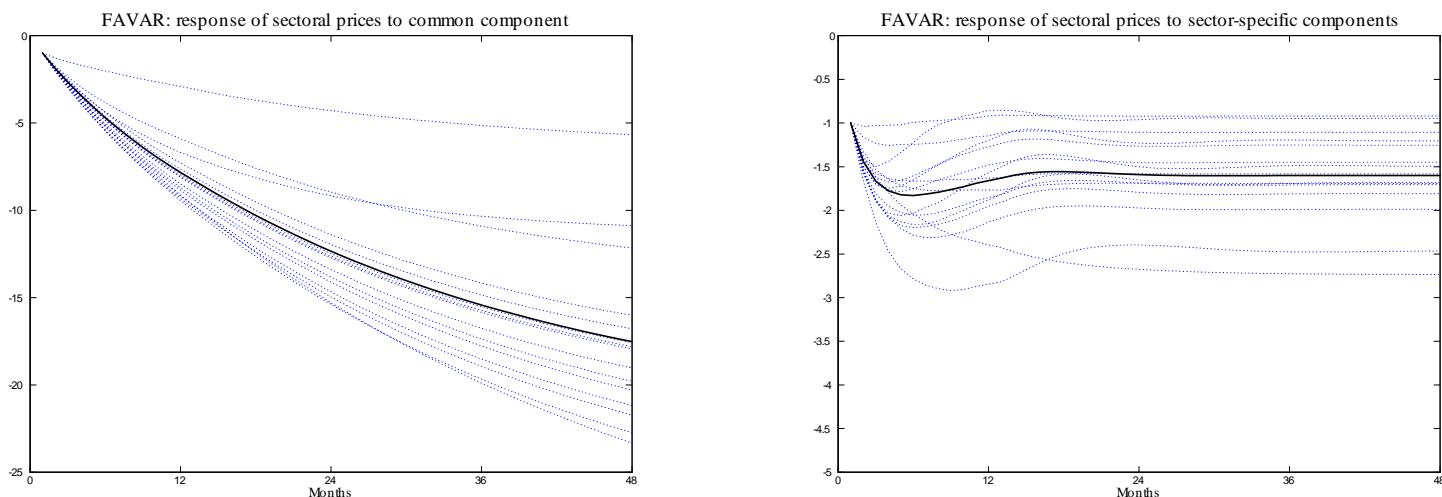
Figures 25-26 show the distribution of the speed of the responses to an innovation to the common component (left figure), and to the sector-specific components (right figure). Table 8 reports descriptive statistics based on these two distributions.

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[28]Iin the Appendix we reproduce the estimated-model-implied impulse responses of sectoral prices to aggregate and sectoral productivity and shocks, as well as to the aggregate preference and sectoral demand shocks.

Table 8: Statistics on the speed of responses to shocks - estimated 15-sector model

	Speed of response		
	to common component		to specific components
Average	0.258		1.050
Median	0.248		1.080
Std. deviation	0.041		0.185
Coeff. of variation	0.158		0.177
Corr.with $1 - \alpha_k$	0.682		0.383
Correlation	–	0.151	–

Figures 25-26: Cross-sectional distribution of speed of responses - 15 sectors

Distribution of speed of responses to common component

Distribution of speed of responses to sector-specific components
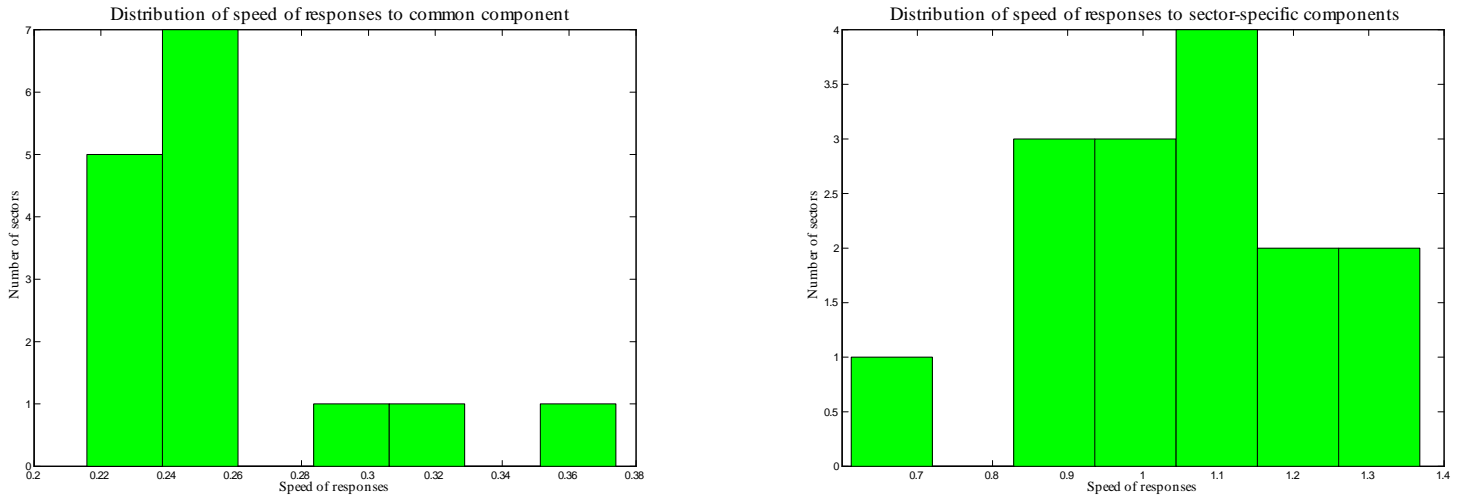
Finally, we report the results that the estimated model produces for the cross-section of correlations between the sector-specific component of inflation rates and the corresponding sector-specific component of quantities (in growth rates), and the cross-section of correlations between the component of inflation rates and growth rate of quantities that are driven by the common components. These are depicted in Figures 27-28, and summarized in Table 9.

Table 9: Statistics on the correlations between components of prices and quantities - estimated 15-sector model

	Correlation between inflation and growth of quantities	
	Common component	Specific components
Average	−0.188	−0.304
Median	−0.157	−0.461
Max.	0.186	0.856
Min.	−0.677	−0.690

Figures 27-28: Cross-section of correlations between components of prices and quantities - 15 sectors

Correlations of sector-specific components of PCE prices and quantities

Correlations of common components of PCE prices and quantities
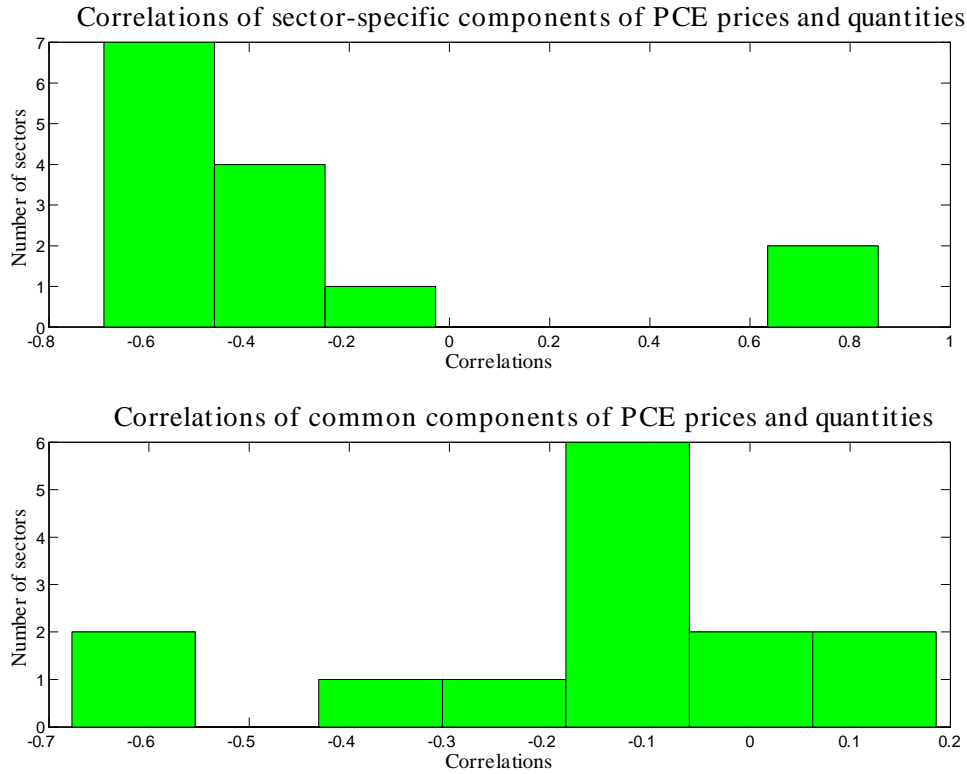
Regarding the joint distribution of the speed of price responses to common and sector-specific components, a comparison of Tables 1 and 8 reveals that the estimated model captures its main features very well. Specifically, i) the average speed of response of sectoral prices to sector-specific shocks is roughly four times higher than the average speed of response to shocks to the common component; ii) 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 - it is higher for the common component; iii) The correlation between the speed of responses to both types of shocks is positive; iv) 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; v) the cross-sectional mean of the correlations between the sector-specific component of PCE inflation rates and the corresponding sector-specific component of the growth rate in quantities is negative - the same applies to the fluctuations that are driven by the common component.

A major improvement in quantitative performance relative to the simply parameterized model of Subsection Subsections 5.1.2 and 5.1.3 is the much lower correlation between the speed of price responses to common and specific shocks produced by the estimated model. In those subsections, with identically-parameterized sectoral shocks, the model produces an extremely high correlation between those speeds of price responses, due to their tight link with the sectoral frequencies of price changes. Heterogeneity in the estimated shock dynamics breaks that tight link and helps the estimated model get closer to the data. This result underscores the importance of accounting for heterogeneity in the

dynamics of the shocks.

Regarding the cross-section of correlations between components of inflation and growth rates of consumption, a comparison of Tables 2 and 4 with Table 9 reveals that the estimated model captures the main qualitative features of the two distributions, although it misses more nuanced features such as the tails. 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 rate of quantities, and also between the component of inflation rates and growth rate of quantities that are driven by the common component. This is consistent with supply-type shocks driving most of the variation in these series, which in turn is consistent with our point estimates for the parameters of the sectoral shocks (see Tables 18 and 19 in the Appendix).

6   Conclusion

We construct a relatively simple variant of the new Keynesian model that can endogenously deliver differential responses of sectoral prices to aggregate and sectoral shocks. In particular, and contrary to the first-pass intuition, 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 sectoral shocks proves to be somewhat difficult, in that it requires a special parameterization of our general model.

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 still highly stylized, we find the results to be quite close to the data.

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A   The mechanism: the role of each ingredient

Table 10 reports the results for the first-pass specification. After that, Tables 11-15 present the results for specifications that deviate from the first-pass one by "activating" the three ingredients of our model. Table 11 considers only the Taylor rule, Table 12 considers only input-output linkages, and Table 13 considers only labor segmentation. After that, Tables 14 and 15 consider specifications that combine the Taylor rule with, respectively, input-output linkages, and labor segmentation. The values for the model parameters are the ones described in Subsection 5.1, and the results are based on theoretical impulse responses to the aggregate and sectoral productivity shocks.

Table 10: Speed of response to productivity shocks - first-pass specification

	Speed of response		
	to aggregate *shock*		*to sectoral* *shock*
Average	0.810		0.810
Median	0.678		0.678
Std. deviation	0.433		0.433
Coeff. of variation	0.535		0.535
Corr.with $1 - \alpha_k$	0.936		0.936
Correlation	–	1.0	–

Table 11: Speed of response to productivity shocks - Taylor rule only

	Speed of response		
	to aggregate *shock*		*to sectoral* *shock*
Average	0.263		0.768
Median	0.252		0.653
Std. deviation	0.060		0.403
Coeff. of variation	0.228		0.525
Corr.with $1 - \alpha_k$	0.890		0.929
Correlation	–	0.984	–

Table 12: Speed of response to productivity shocks - input-output only

	Speed of response		
	to aggregate *shock*		*to sectoral* *shock*
Average	0.550		0.799
Median	0.487		0.671
Std. deviation	0.238		0.427
Coeff. of variation	0.433		0.535
Corr.with $1 - \alpha_k$	0.922		0.936
Correlation	–	0.998	–

Table 13: Speed of response to productivity shocks - labor segmentation only

	Speed of response		
	to aggregate shock		*to sectoral shock*
Average	0.989		1.184
Median	0.993		1.181
Std. deviation	0.348		0.454
Coeff. of variation	0.352		0.383
Corr.with $1 - \alpha_k$	0.799		0.807
Correlation	–	0.999	–

Table 14: Speed of response to productivity shocks - Taylor rule and input-output linkages

	Speed of response		
	to aggregate shock		*to sectoral shock*
Average	0.287		0.757
Median	0.272		0.645
Std. deviation	0.077		0.400
Coeff. of variation	0.266		0.529
Corr.with $1 - \alpha_k$	0.900		0.925
Correlation	–	0.985	–

Table 15: Speed of response to productivity shocks - Taylor rule and labor segmentation

	Speed of response		
	to aggregate shock		*to sectoral shock*
Average	0.238		1.085
Median	0.242		1.092
Std. deviation	0.026		0.417
Coeff. of variation	0.109		0.385
Corr.with $1 - \alpha_k$	0.742		0.770
Correlation	–	0.960	–

B   Details of the estimation algorithm

Our specific estimation strategy is as follows. We run two numerical optimization routines sequentially in order to maximize the posterior distribution. This determines the starting point of the Markov chain and provides a first crude estimate of the covariance matrix for our Random-Walk Metropolis Gaussian jumping distribution. The first optimization routine is `csminwel` by Chris Sims, while the second is `fminsearch` from Matlab's optimization toolbox. Following the first optimization, we run additional rounds, starting from initial values obtained by perturbing the original initial values, and then the estimate of the first optimization round.

Before running the Markov chains we transform all parameters to have full support on the real line. Then we run a so-called *adaptive phase* of the Markov chain, with three sub-phases of 100, 200, and 600 thousand iterations, respectively. At the end of each sub-phase we discard the first half of the draws, update the estimate of the posterior mode, and compute a sample covariance matrix to be used in the jumping distribution in the next sub-phase. Finally, in each sub-phase we rescale the covariance matrix inherited from the previous sub-phase in order to get a *fine-tuned covariance matrix* that yields rejection rates as close as possible to 0.77.[29] Next we run the so-called *fixed phase* of the MCMC. We take the estimate of the posterior mode and sample covariance matrix from the adaptive phase, and run 5 parallel chains of 300,000 iterations each. Again, before making the draws that will form the sample we rescale such covariance matrix in order to get rejection rates as close as possible to 0.77. To initialize each chain we draw from a candidate normal distribution centered on the posterior mode estimate, with covariance matrix given by 9 times the fine-tuned covariance matrix. We check for convergence for the latter 2/3s of the draws of all 5 chains by calculating the potential scale reduction[30] (PSR) factors for each parameter and inspecting the histograms of all marginal distributions across the parallel chains. Upon convergence, the latter 2/3s of the draws of all 5 chains are combined to form a posterior sample of 1 million draws.

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[29] This is the optimal rejection rate under certain conditions. See Gelman et al. (2003, p. 306).

[30] For each parameter, the PSR factor is the ratio of (square root of) an estimate of the marginal posterior variance to the average variance within each chain. This factor expresses the potential reduction in the scaling of the estimated marginal posterior variance relative to the true distribution by increasing the number of iterations in the Markov-chain algorithm. Hence, as the PSR factor approaches unity, it is a sign of convergence of the Markov-chain for the estimated parameter. See Gelman et al. (2003, p. 294 ff) for more information. For all specifications we require that the factor be below 1.01 for all parameters.

C   About the estimated model

Table 16: Sectors and weights, 15-sector model

k	Categories	Weights (n_k) in %	$\alpha_k^{1)}$	Duration[2] in months
1	Motor vehicles and Parts	4.56	0.596	2.48
2	Furnishings and durable household equipment	2.41	0.785	4.64
3	Recreational goods and vehicles	1.82	0.826	5.75
4	Other durable goods	1.27	0.82	5.55
5	Food and beverages purchased for off-premises consumption	8.97	0.689	3.21
6	Clothing and footwear	3.32	0.692	3.25
7	Gasoline and other energy goods	4.19	0.148	1.17
8	Other nondurable goods	7.48	0.815	5.41
9	Housing and utilities	19.59	0.596	2.48
10	Health care	15.65	0.95	20.00
11	Transportation services	3.35	0.721	3.59
12	Recreation services	3.68	0.899	9.90
13	Food services and Accommodations	6.65	0.843	6.36
14	Financial services and insurance	8.10	0.921	12.60
15	Other services	8.97	0.864	7.35

1) monthly "infrequency" of price changes. 2) expected duration of price spells:$(1 - \alpha_k)^{-1}$.

Table 17: Priors and posteriors - Taylor rule and aggregate shocks, 15-sector model

	Prior	Prior Mean (Std)	Posterior Mode
ϕ_y	N	0.5/12 (0.05)	2×10^{-14}
ϕ_π	N	1.5 (0.25)	1.04
ρ_μ	B	0.7 (0.1)	0.39
ρ_γ	B	0.7 (0.1)	0.99
ρ_a	B	0.7 (0.1)	0.98
σ_μ	IG	0.00125 (0.00125)	0.0022
σ_γ	IG	0.005 (0.005)	0.0102
σ_a	IG	0.005 (0.005)	0.0033

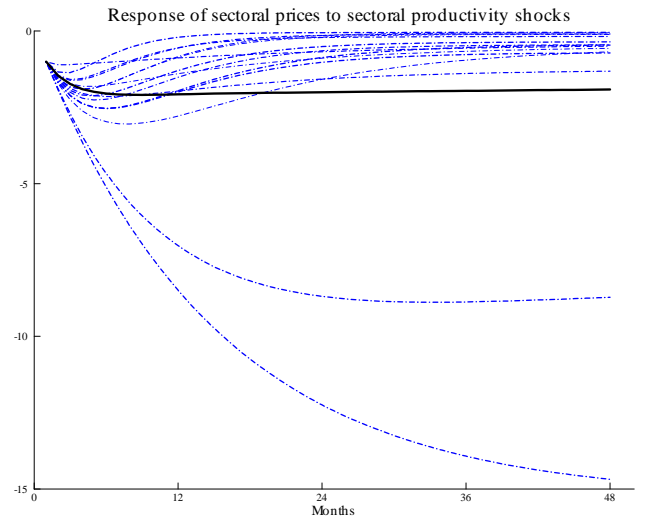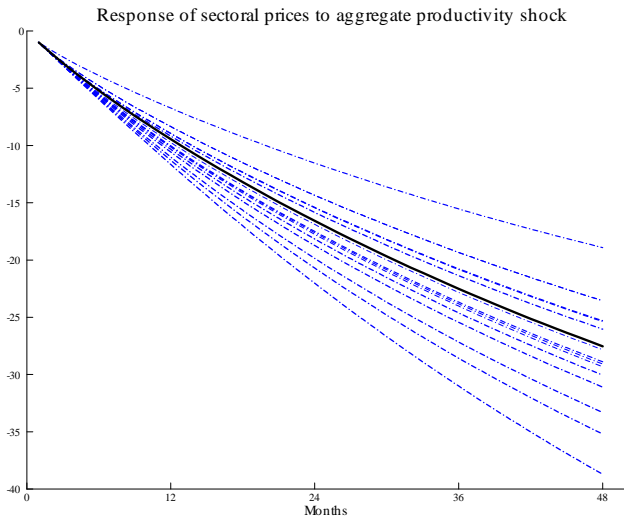Table 18: Priors and posteriors - sectoral productivity shocks, 15-sector model

	Prior	Prior Mean (Std)	Posterior Mode		Prior	Prior Mean (Std)	Posterior Mode
ρ_{A_1}	B	0.7 (0.1)	0.93	σ_{A_1}	IG	0.05 (0.02)	0.0124
ρ_{A_2}	B	0.7 (0.1)	0.80	σ_{A_2}	IG	0.05 (0.02)	0.0346
ρ_{A_3}	B	0.7 (0.1)	0.93	σ_{A_3}	IG	0.05 (0.02)	0.0304
ρ_{A_4}	B	0.7 (0.1)	0.77	σ_{A_4}	IG	0.05 (0.02)	0.0910
ρ_{A_5}	B	0.7 (0.1)	0.77	σ_{A_5}	IG	0.05 (0.02)	0.0141
ρ_{A_6}	B	0.7 (0.1)	0.81	σ_{A_6}	IG	0.05 (0.02)	0.0243
ρ_{A_7}	B	0.7 (0.1)	0.95	σ_{A_7}	IG	0.05 (0.02)	0.0407
ρ_{A_8}	B	0.7 (0.1)	0.82	σ_{A_8}	IG	0.05 (0.02)	0.0325
ρ_{A_9}	B	0.7 (0.1)	0.92	σ_{A_9}	IG	0.05 (0.02)	0.0057
$\rho_{A_{10}}$	B	0.7 (0.1)	0.94	$\sigma_{A_{10}}$	IG	0.05 (0.02)	0.0569
$\rho_{A_{11}}$	B	0.7 (0.1)	0.66	$\sigma_{A_{11}}$	IG	0.05 (0.02)	0.0358
$\rho_{A_{12}}$	B	0.7 (0.1)	0.78	$\sigma_{A_{12}}$	IG	0.05 (0.02)	0.0689
$\rho_{A_{13}}$	B	0.7 (0.1)	0.77	$\sigma_{A_{13}}$	IG	0.05 (0.02)	0.0265
$\rho_{A_{14}}$	B	0.7 (0.1)	0.95	$\sigma_{A_{14}}$	IG	0.05 (0.02)	0.1681
$\rho_{A_{15}}$	B	0.7 (0.1)	0.80	$\sigma_{A_{15}}$	IG	0.05 (0.02)	0.0334

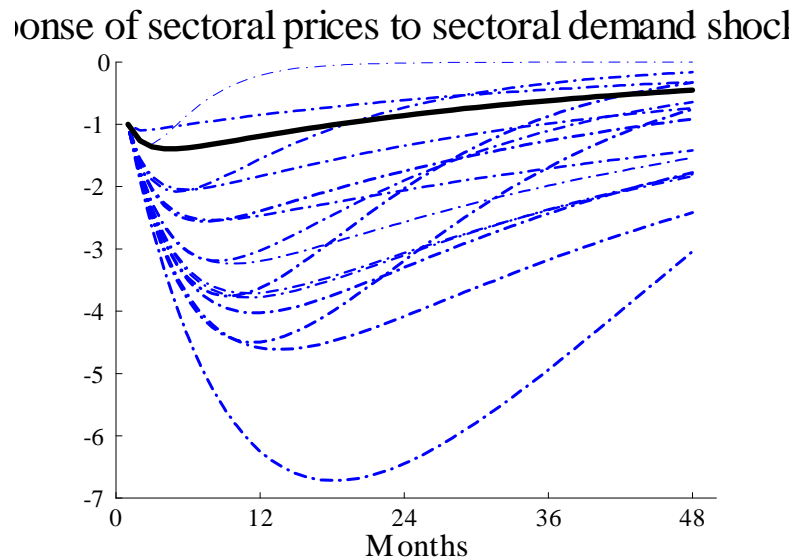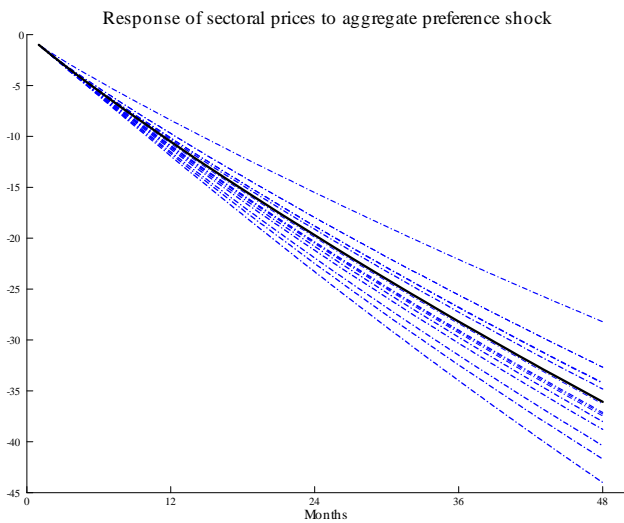Table 19: Priors and posteriors - sectoral demand shocks, 15-sector model

	Prior	Prior Mean (Std)	Posterior Mode		Prior	Prior Mean (Std)	Posterior Mode
ρ_{D_1}	B	0.7 (0.1)	0.78	σ_{D_1}	IG	0.05 (0.02)	0.0594
ρ_{D_2}	B	0.7 (0.1)	0.98	σ_{D_2}	IG	0.05 (0.02)	0.0099
ρ_{D_3}	B	0.7 (0.1)	0.98	σ_{D_3}	IG	0.05 (0.02)	0.0137
ρ_{D_4}	B	0.7 (0.1)	0.98	σ_{D_4}	IG	0.05 (0.02)	0.0158
ρ_{D_5}	B	0.7 (0.1)	0.98	σ_{D_5}	IG	0.05 (0.02)	0.0081
ρ_{D_6}	B	0.7 (0.1)	0.94	σ_{D_6}	IG	0.05 (0.02)	0.0128
ρ_{D_7}	B	0.7 (0.1)	0.97	σ_{D_7}	IG	0.05 (0.02)	0.0867
ρ_{D_8}	B	0.7 (0.1)	0.95	σ_{D_8}	IG	0.05 (0.02)	0.0076
ρ_{D_9}	B	0.7 (0.1)	0.97	σ_{D_9}	IG	0.05 (0.02)	0.0104
$\rho_{D_{10}}$	B	0.7 (0.1)	0.99	$\sigma_{D_{10}}$	IG	0.05 (0.02)	0.0064
$\rho_{D_{11}}$	B	0.7 (0.1)	0.97	$\sigma_{D_{11}}$	IG	0.05 (0.02)	0.0133
$\rho_{D_{12}}$	B	0.7 (0.1)	0.92	$\sigma_{D_{12}}$	IG	0.05 (0.02)	0.0074
$\rho_{D_{13}}$	B	0.7 (0.1)	0.97	$\sigma_{D_{13}}$	IG	0.05 (0.02)	0.0086
$\rho_{D_{14}}$	B	0.7 (0.1)	0.93	$\sigma_{D_{14}}$	IG	0.05 (0.02)	0.0169
$\rho_{D_{15}}$	B	0.7 (0.1)	0.98	$\sigma_{D_{15}}$	IG	0.05 (0.02)	0.0086

C.1 Model-implied IRFs

Figures 29-30: Estimated-model-implied IRFs - 15 sectors

Response of sectoral prices to aggregate productivity shock

Response of sectoral prices to sectoral productivity shocks

Figures 31-32: Estimated-model-implied IRFs - 15 sectors

Response of sectoral prices to aggregate preference shock

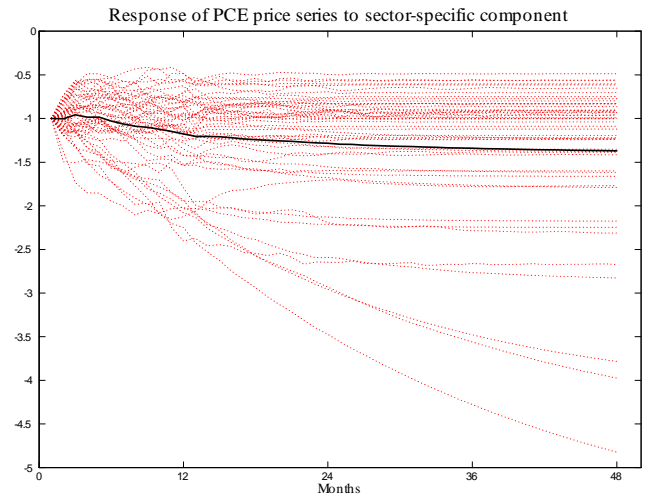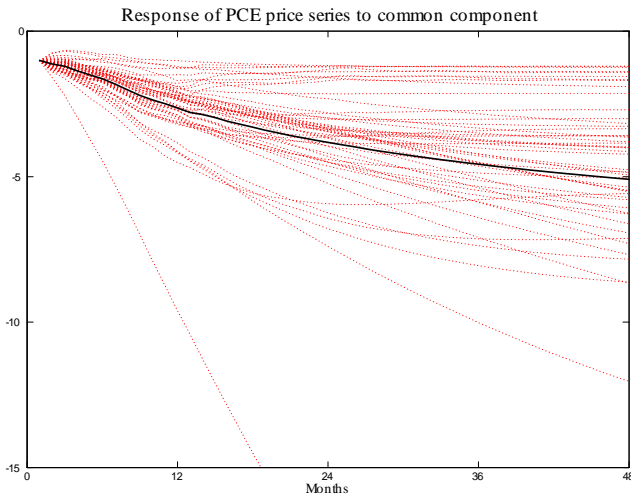Response of sectoral prices to sectoral demand shock

D   Robustness

D.1   50-sector FAVAR

We re-estimate the FAVAR using the nominal interest rate, hours growth, and all sectoral inflation and sectoral consumption growth rates for the 50 sectors in the third-level disaggregation of the PCE.

Figures 33-34 and Tables 20-21 report the results analogous to those in Figures 1-6 and Tables 1-2. The bottom line is that the results are very similar to those of the 15-sector FAVAR.

Figures 33-34: Empirical IRFs - FAVAR

Response of PCE price series to common component

Response of PCE price series to sector-specific component

Figures 35-36: Cross-sectional distribution of speed of responses

Distribution of speed of responses to common component - PCE

Distribution of speed of responses to sector-specific components - PCE
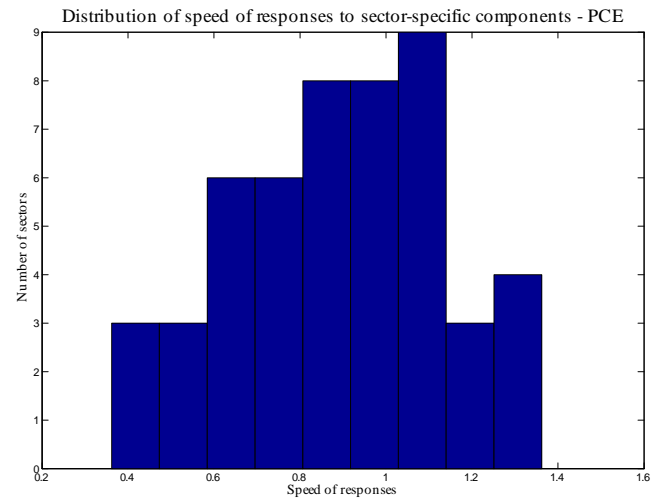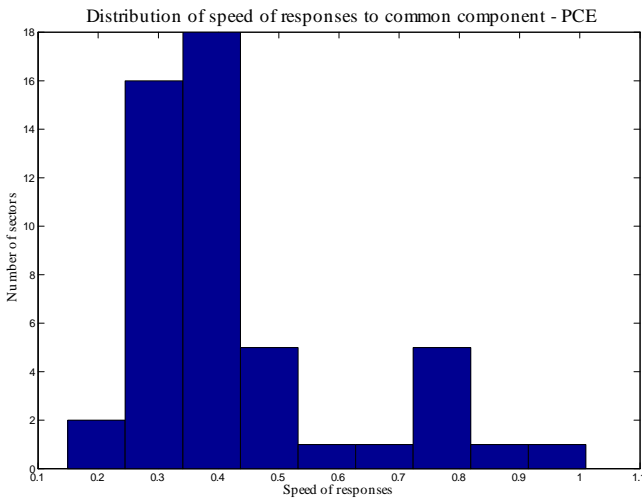
Table 20: Statistics on the speed of responses to shocks - 50-sector FAVAR

	Speed of response		
	to common component		*to specific components*
Average	0.427		0.891
Median	0.370		0.912
Std. deviation	0.184		0.249
Coeff. of variation	0.431		0.280
Corr.with $1 - \alpha_k$	0.427		0.264
Correlation	−	0.177	−

Figures 37-38: Cross-section of correlations between components of prices and quantities

Correlations of sector-specific components of PCE prices and quantities

Correlations of common components of PCE prices and quantities
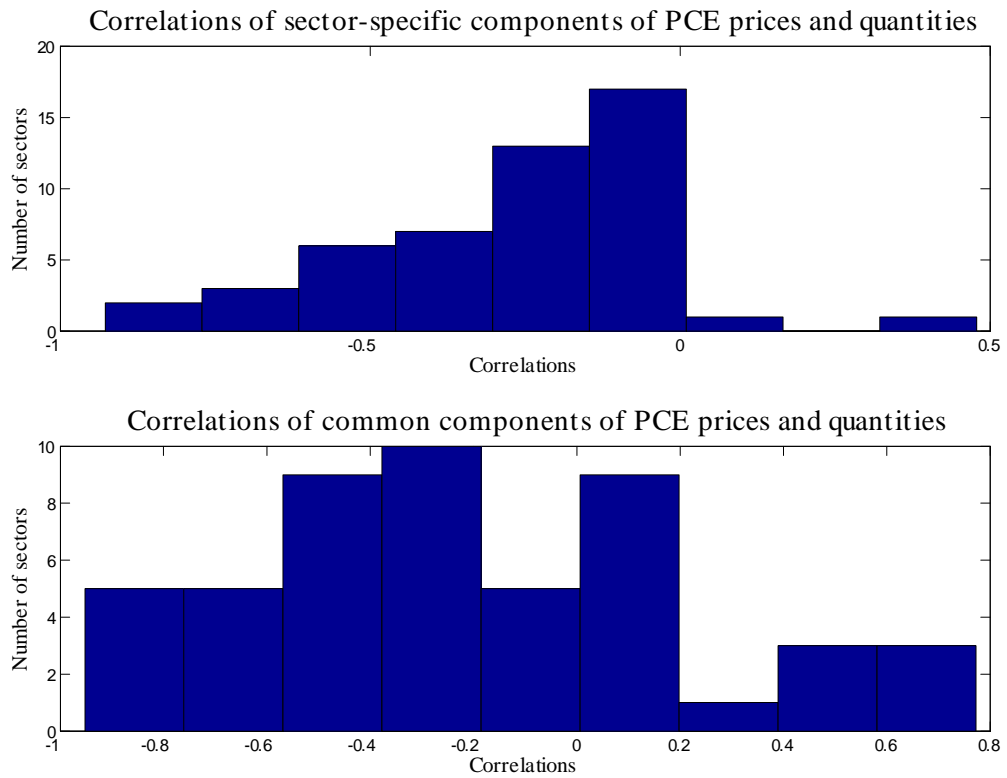

Table 21: Statistics on the correlations between components of prices and quantities - 50-sector FAVAR

	Correlation between inflation and growth of quantities	
	Common component	*Specific components*
Average	−0.204	−0.261
Median	−0.252	−0.186
Max.	0.773	0.478
Min.	−0.952	−0.927

E Steady state

As mentioned in the main text, we solve the model by log-linearizing equilibrium conditions around a symmetric non-stochastic zero-inflation steady state, which is detailed here. A non-stochastic steady-state equilibrium is, in fact, not generally symmetric. In particular, it depends on the steady-state levels of sector-specific productivity $\{A_k\}_{k=1}^K$, and the sector-specific parameters that measure the relative disutilities of supplying hours, $\{\omega_k\}_{k=1}^K$. For simplicity, we make two assumptions that deliver a symmetric steady state: i) the steady-state levels of sector-specific productivities are the same across sectors: specifically, $A_k = 1$ for all k, without loss of generality;[31] ii) $\omega_k = n_k^{-\varphi}$ for all k. This last assumption relates the relative disutilies of labor to the size of the sectors, and equalizes steady-state sectoral wages.

We solve for $\{Y, C, Z, H, \frac{W}{P}, \frac{\Pi}{P}\}$: the steady state values of aggregate gross output, aggregate value added-output (i.e. GDP), aggregate intermediate input usage, aggregate hours, real wage, and real profits. Once we obtain these aggregate variables, it is trivial to characterize the steady-state values for sectoral and micro variables using the symmetric nature of the steady state (i.e. $Y_k = n_k Y_k(i) = n_k Y$, $C_k = n_k C_k(i) = n_k C$, $Z_k = n_k Z_k(i) = n_k Z$, $H_k = n_k H_k(i) = n_k H$, $\Pi_k(i) = \Pi$, $W_k = W$, and $\frac{P(i)}{P} = \frac{P_k}{P} = 1$).

After exploiting the symmetry and market-clearing conditions, the system of equilibrium conditions can be reduced to the following seven equations:

$$C = \left(\frac{W}{P}\right) H + \left(\frac{\Pi}{P}\right) \tag{17}$$

$$\left(\frac{W}{P}\right) = H^\varphi C \tag{18}$$

$$Y = H^{1-\delta} Z^\delta \tag{19}$$

$$Y = C + Z \tag{20}$$

$$\left(\frac{\Pi}{P}\right) = Y - \left(\frac{W}{P}\right) H - Z \tag{21}$$

$$Z = \frac{\delta}{1-\delta} \left(\frac{W}{P}\right) H \tag{22}$$

$$1 = \left(\frac{\theta}{\theta-1}\right) \chi \left(\frac{W}{P}\right)^{1-\delta}, \tag{23}$$

where $\chi \equiv \frac{1}{1-\delta} \left(\frac{\delta}{1-\delta}\right)^{-\delta}$.

First, it is trivial to solve for the real wage from (23):

$$\left(\frac{W}{P}\right) = \left(\frac{1}{\chi} \frac{\theta-1}{\theta}\right)^{\frac{1}{1-\delta}}.$$

---

[31] Similary, we fix the steady-state level of all other exogenous processes at unity.

Next, we substitute out Z in (19) and (21) using (22), which gives:

$$Y = H \left(\frac{\delta}{1-\delta}\right)^{\delta} \left(\frac{W}{P}\right)^{\delta}$$

$$\left(\frac{\Pi}{P}\right) = Y - \left[\frac{1}{1-\delta}\right] \left(\frac{W}{P}\right) H.$$

Combining the two equations above, we substitute out H and express real profits as a function of the real wage and output:

$$\left(\frac{\Pi}{P}\right) = \left[1 - \chi \left(\frac{W}{P}\right)^{1-\delta}\right] Y.$$

But $\chi \left(\frac{W}{P}\right)^{1-\delta} = \frac{\theta-1}{\theta}$ from (23), and consequently we obtain:

$$\left(\frac{\Pi}{P}\right) = \frac{1}{\theta} Y.$$

Equation (17) indicates that aggregate value-added output should be equal to the sum of labor income and real profits:

$$
\begin{aligned}
C &= \left(\frac{W}{P}\right) H + \left(\frac{\Pi}{P}\right) \\
&= \frac{1-\delta}{\delta} Z + \frac{1}{\theta} Y \\
&= \frac{1-\delta}{\delta} (Y - C) + \frac{1}{\theta} Y \\
\implies C &= \left[1 - \delta \left(\frac{\theta-1}{\theta}\right)\right] Y.
\end{aligned}
$$

Consequently, aggregate intermediate input usage is obtained as:

$$
\begin{aligned}
Z &= Y - C = Y - \left[1 - \delta \left(\frac{\theta-1}{\theta}\right)\right] Y \\
\implies Z &= \delta \left(\frac{\theta-1}{\theta}\right) Y.
\end{aligned}
$$

From (22), total labor hours are given by:

$$
\begin{aligned}
H &= \frac{1-\delta}{\delta} \left(\frac{W}{P}\right)^{-1} Z \\
&= \left(\frac{W}{P}\right)^{-1} (1-\delta) \left(\frac{\theta-1}{\theta}\right) Y \\
&= \left(\frac{1}{\chi} \frac{\theta-1}{\theta}\right)^{\frac{-1}{1-\delta}} (1-\delta) \left(\frac{\theta-1}{\theta}\right) Y \\
&= \left[\delta \left(\frac{\theta-1}{\theta}\right)\right]^{-\frac{\delta}{1-\delta}} Y.
\end{aligned}
$$

So far, we have expressed the steady-state values of $\left\{Y, C, Z, H, \frac{\Pi}{P}\right\}$ in terms of Y, which can be obtained using (18):

$$\left(\frac{W}{P}\right) = H^\varphi C$$

$$\left(\frac{W}{P}\right) = \left[\delta\left(\frac{\theta-1}{\theta}\right)\right]^{-\frac{\delta\varphi}{1-\delta}}\left[1-\delta\left(\frac{\theta-1}{\theta}\right)\right]Y^{1+\varphi}$$

$$\left(\frac{1}{\chi}\frac{\theta-1}{\theta}\right)^{\frac{1}{1-\delta}} = \left[\delta\left(\frac{\theta-1}{\theta}\right)\right]^{-\frac{\delta\varphi}{1-\delta}}\left[1-\delta\left(\frac{\theta-1}{\theta}\right)\right]Y^{1+\varphi}$$

$$Y^{1+\varphi} = \left(\frac{1}{\chi}\right)^{\frac{1}{1-\delta}}\left(\frac{\theta-1}{\theta}\right)^{\frac{1}{1-\delta}}\left[\delta\left(\frac{\theta-1}{\theta}\right)\right]^{\frac{\delta\varphi}{1-\delta}}\left[1-\delta\left(\frac{\theta-1}{\theta}\right)\right]^{-1}$$

$$Y = \left\{\left(\frac{1}{\chi}\right)^{\frac{1}{1-\delta}}\left(\frac{\theta-1}{\theta}\right)^{\frac{1}{1-\delta}}\left[\delta\left(\frac{\theta-1}{\theta}\right)\right]^{\frac{\delta\varphi}{1-\delta}}\left[1-\delta\left(\frac{\theta-1}{\theta}\right)\right]^{-1}\right\}^{\frac{1}{1+\varphi}}.$$

In the special case in which $\delta = 0$, the expression for aggregate gross output simplifies to $Y = \left(\frac{\theta-1}{\theta}\right)^{\frac{1}{1+\varphi}}$, which is the standard result in models without intermediate inputs.

F   Loglinear approximation

Here we present full set of log-linearized equations.

F.1   CES Aggregates, market clearing, and definitions

$$p_t = \sum_k n_k p_{k,t}, \qquad p_{k,t} = \frac{1}{n_k}\int_{\mathcal{I}_k} p_{k,t}(i)di,$$

$$y_t = \sum_k n_k y_{k,t}, \qquad y_{k,t} = \frac{1}{n_k}\int_{\mathcal{I}_k} y_{k,t}(i)di,$$

$$c_t = \sum_k n_k c_{k,t}, \qquad c_{k,t} = \frac{1}{n_k}\int_{\mathcal{I}_k} c_{k,t}(i)di,$$

$$z_{k,t}(i) = \sum_{k'} n_k z_{k,k',t}(i), \qquad z_{k,k',t}(i) = \frac{1}{n_k}\int_{\mathcal{I}_{k'}} z_{k,k',t}(i,i')di',$$

$$h_{k,t} = \frac{1}{n_k}\int_{\mathcal{I}_k} h_{k,t}(i)di, \qquad y_t = (1-\psi)c_t + \psi z_t, \text{ with}$$

$$\psi \equiv \delta\left(\frac{\theta-1}{\theta}\right) \text{ and } z_t \equiv \sum_k \int_{\mathcal{I}_k} z_{k,t}(i)di.$$

F.2 Demand functions

$$
\begin{aligned}
y_{k,t} - y_t &= -\eta \left(p_{k,t} - p_t \right) + d_{k,t}, \\
y_{k,t}(i) - y_{k,t} &= -\theta \left(p_{k,t}(i) - p_{k,t} \right), \\
c_{k,t} - c_t &= -\eta \left(p_{k,t} - p_t \right) + d_{k,t}, \\
c_{k,t}(i) - c_{k,t} &= -\theta \left(p_{k,t}(i) - p_{k,t} \right), \\
z_{k,k',t}(i) - z_{k,t}(i) &= -\eta \left(p_{k',t} - p_t \right) + d_{k',t}, \\
z_{k,k',t}(i,i') - z_{k,k',t}(i) &= -\theta \left(p_{k',t}(i) - p_{k',t} \right).
\end{aligned}
$$

F.3 Household's additional FOCs

$$
c_t = E_t \left[c_{t+1} \right] - \left(i_t - E_t \pi_{t+1} \right) + \left(\gamma_t - E_t \gamma_{t+1} \right),
$$

$$
w_{k,t} - p_t = \varphi h_{k,t} + c_t.
$$

F.4 Firms

Production function:

$$
y_{k,t}(i) = a_t + a_{k,t} + (1 - \delta) h_{k,t}(i) + \delta z_{k,t}(i).
$$

Cost minimization:

$$
w_{k,t} - p_t = z_{k,t}(i) - h_{k,t}(i).
$$

A firm's nominal marginal cost:

$$
mc_{k,t} = (1 - \delta) \left(w_{k,t} - p_t \right) - a_{k,t} - a_t + p_t.
$$

Here we provide a little detail on the derivation of the generalized Phillips curves presented in the text. To derive the Phillips curve, log-linearize the firm's FOC:

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

It yields:

$$
E_t \sum_{s=0}^{\infty} \alpha_k^s \beta^s p_{k,t}^* = E_t \sum_{s=0}^{\infty} \alpha_k^s \beta^s mc_{k,t+s}.
$$

Solve for $p_{k,t}^*$:

$$
p_{k,t}^* = (1 - \alpha_k \beta) E_t \sum_{s=0}^{\infty} \alpha_k^s \beta^s mc_{k,t+s}.
$$

$$
p_{k,t}^* = (1 - \alpha_k \beta) \left[mc_{k,t} - p_{k,t} + p_{k,t} \right] + \alpha_k \beta E_t \left[p_{k,t+1}^* \right].
$$

Loglinearizing (2) yields:

$$
p_{k,t} = (1 - \alpha_k) p_{k,t}^* + \alpha_k p_{k,t-1}.
$$

Combining the two delivers the sectoral Phillips curve:

$$\pi_{k,t} = \beta E_t \pi_{k,t+1} + \frac{1-\alpha_k}{\alpha_k (1-\alpha_k\beta)^{-1}} [mc_{k,t} - p_{k,t}].$$

Note that from the two equations:

$$
\begin{aligned}
w_{k,t} - p_t &= \varphi h_{k,t} + c_t \text{ (labor supply)}, \\
w_{k,t} - p_t &= z_{k,t} - h_{k,t} \text{ (cost minimization)},
\end{aligned}
$$

we can obtain:

$$z_{k,t} = (1+\varphi) h_{k,t} + c_t.$$

Also, from the production function, we get:

$$
\begin{aligned}
y_{k,t} &= a_t + a_{k,t} + (1-\delta) h_{k,t} + \delta z_{k,t} \\
&= a_t + a_{k,t} + (1-\delta) h_{k,t} + (\delta + \delta\varphi) h_{k,t} + \delta c_t \\
&= a_t + a_{k,t} + (1+\delta\varphi) h_{k,t} + \delta c_t.
\end{aligned}
$$

Therefore we obtain:

$$h_{k,t} = \frac{1}{1+\delta\varphi} y_{k,t} - \frac{\delta}{1+\delta\varphi} c_t - \frac{1}{1+\delta\varphi} a_{k,t} - \frac{1}{1+\delta\varphi} a_t.$$

Then:

$$
\begin{aligned}
mc_{k,t} &= (1-\delta)(w_{k,t} - p_t) - a_{k,t} - a_t + p_t \\
&= (1-\delta)\left(\frac{\varphi}{1+\delta\varphi} y_{k,t} - \frac{\delta\varphi}{1+\delta\varphi} c_t - \frac{\varphi}{1+\delta\varphi} a_{k,t} - \frac{\varphi}{1+\delta\varphi} a_t + c_t \right) - a_{k,t} - a_t + p_t \\
&= \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} + \frac{(1-\delta)1}{1+\delta\varphi} c_t - \frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} + p_t.
\end{aligned}
$$

So the sectoral Phillips curve can be written as:

$$\pi_{k,t} = \beta E_t \pi_{k,t+1} + \frac{1-\alpha_k}{\alpha_k (1-\alpha_k\beta)^{-1}} \left[\begin{array}{c} \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} + \frac{1-\delta}{1+\delta\varphi} c_t - (p_{k,t} - p_t) \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} \end{array} \right].$$

Finally, note that:

$$-(p_{k,t} - p_t) = \frac{1}{\eta} (c_{k,t} - c_t) - \frac{1}{\eta} (d_{k,t} - \bar{d}_t).$$

Therefore, the sectoral Phillips curve can be alternatively written as:

$$\pi_{k,t} = \beta E_t \pi_{k,t+1} + \frac{1-\alpha_k}{\alpha_k (1-\alpha_k\beta)^{-1}} \left[\begin{array}{c} \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} + \frac{1}{\eta} c_{k,t} + \left(\frac{1-\delta}{1+\delta\varphi} - \frac{1}{\eta} \right) c_t \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} - \frac{1}{\eta} (d_{k,t} - \bar{d}_t) \end{array} \right]$$

If we are interested in the aggregate Phillips curve, we can obtain using the relation:

$$\pi_t = \sum_{k=1}^{K} n_k \pi_{k,t}.$$

F.5 Equilibrium conditions

We are interested in the dynamics of aggregate variables:

$$\{y_t, c_t, z_t, h_t, (w_t - p_t), \pi_t, i_t\},$$

and sectoral variables:

$$\{y_{k,t}, \pi_{k,t}, p_{k,t}\}.$$

Then the following equations are sufficient for determining the equilibrium dynamics:

$$\text{monetary policy} \quad : \quad i_t = \phi_\pi \pi_t + \phi_y c_t + \mu_t$$

$$or$$

$$m_t \;=\; exogenous\ stochastic\ process,$$

$$\text{IS: } c_t = E_t[c_{t+1}] - (i_t - E_t \pi_{t+1}) + (\gamma_t - E_t \gamma_{t+1}),$$

$$\text{agg. labor supply: } w_t - p_t = \varphi h_t + c_t,$$

$$\text{agg. production: } y_t = a_t + \sum_k n_k a_{k,t} + (1 - \delta) h_t + \delta z_t,$$

$$\text{agg. cost-min relation: } w_t - p_t = z_t - h_t,$$

$$\text{resource constraint: } y_t = (1 - \psi)c_t + \psi z_t,$$

$$\text{aggregate PC: } \pi_t = \beta E_t \pi_{t+1} + \sum_k n_k \frac{1 - \alpha_k}{\alpha_k (1 - \alpha_k \beta)^{-1}} \left[\begin{array}{c} \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} + \frac{1}{\eta} c_{k,t} + \left(\frac{1-\delta}{1+\delta\varphi} - \frac{1}{\eta} \right) c_t \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} - \frac{1}{\eta} \left(d_{k,t} - \bar{d}_t \right) \end{array} \right],$$

$$\text{sectoral PC: } \pi_{k,t} = \beta E_t \pi_{k,t+1} + \frac{1 - \alpha_k}{\alpha_k (1 - \alpha_k \beta)^{-1}} \left[\begin{array}{c} \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} + \frac{1}{\eta} c_{k,t} + \left(\frac{1-\delta}{1+\delta\varphi} - \frac{1}{\eta} \right) c_t \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} - \frac{1}{\eta} \left(d_{k,t} - \bar{d}_t \right) \end{array} \right],$$

$$\text{sectoral demand: } y_{k,t} - y_t = -\eta (p_{k,t} - p_t) + d_{k,t},$$

$$\text{Definition of inflation: } \pi_{k,t} = p_{k,t} - p_{k,t-1}.$$

Alternatively we could use $\pi_t = \sum_{k=1}^{K} n_k \pi_{k,t}$ instead of aggregate Phillips curve.

F.6 Alternative expression for equilibrium equations

When we estimate the model, we focus on the dynamics of:

$$\{i_t, h_t\}, \{c_{k,t}, \pi_{k,t}\}_{k=1}^{K}$$

Thus it is convenient to substitute out $\{y_{k,t}, y_t, p_{k,t}\}$ from the system we presented in the previous subsection. The following $6 + (2 \times K)$ linear difference equations characterizes the equilibrium dynamics of those variables in the model that we take to the data:

$$\text{monetary policy: } i_t = \phi_\pi \pi_t + \phi_y c_t + \mu_t,$$

$$\text{IS: } c_t = E_t [c_{t+1}] - (i_t - E_t \pi_{t+1}) + (\gamma_t - E_t \gamma_{t+1}),$$

$$\text{agg. labor supply: } w_t - p_t = \varphi h_t + c_t,$$

$$\text{agg. production: } (1 - \psi)c_t + \psi z_t = a_t + \sum_k n_k a_{k,t} + (1 - \delta) h_t + \delta z_t,$$

$$\text{agg. cost-min relation: } w_t - p_t = z_t - h_t,$$

$$\text{aggregate PC: } \pi_t = \beta E_t \pi_{t+1} + \sum_k n_k \frac{1 - \alpha_k}{\alpha_k (1 - \alpha_k \beta)^{-1}} \left[\begin{array}{c} \left(\frac{(1-\delta)\varphi}{1+\delta\varphi} + \frac{1}{\eta}\right) c_{k,t} + \left(\frac{(1-\delta)(1-\psi\varphi)}{1+\delta\varphi} - \frac{1}{\eta}\right) c_t + \frac{(1-\delta)\psi\varphi}{1+\delta\varphi} z_t \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} - \frac{1}{\eta} \left(d_{k,t} - \bar{d}_t\right) \end{array} \right],$$

$$\text{sectoral PC: } \pi_{k,t} = \beta E_t \pi_{k,t+1} + \frac{1 - \alpha_k}{\alpha_k (1 - \alpha_k \beta)^{-1}} \left[\begin{array}{c} \left(\frac{(1-\delta)\varphi}{1+\delta\varphi} + \frac{1}{\eta}\right) c_{k,t} + \left(\frac{(1-\delta)(1-\psi\varphi)}{1+\delta\varphi} - \frac{1}{\eta}\right) c_t + \frac{(1-\delta)\psi\varphi}{1+\delta\varphi} z_t \\ -\frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} - \frac{1}{\eta} \left(d_{k,t} - \bar{d}_t\right) \end{array} \right],$$

$$\text{sectoral demand: } \Delta (c_{k,t+1} - c_{t+1}) = -\eta (\pi_{k,t+1} - \pi_{t+1}) + \Delta \left(d_{k,t+1} - \bar{d}_{t+1}\right).$$