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Do Multisectoral New Keynesian Models Match Sectoral Data?

Philippe Andrade and Viacheslav Sheremirov

Abstract:
We document empirical regularities of disaggregated inflation and consumption and study whether multisectoral New Keynesian models can explain them. We focus on higher moments of the inflation and consumption growth distributions as well as on the contemporaneous comovement of these two variables. We find that the sectoral distributions of inflation and consumption growth are asymmetric, with inflation skewed negatively and consumption growth positively. Both distributions are highly leptokurtic. In the full sample, from the mid-1980s through 2021, sectoral inflation and consumption growth overall correlate negatively, indicating the prevalence of supply shocks over demand shocks. The negative correlation is robust across historical episodes during this period, except during the COVID-19 pandemic, when inflation and consumption growth comoved positively. While the baseline model can match some of these facts for a specific shock process, in its baseline setup the model struggles to match them simultaneously.

JEL Classifications: E12, E31, E32, E52
Keywords: disaggregated inflation, multisectoral models, idiosyncratic shocks

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1 Introduction

Recent influential papers study the consequences of introducing production networks and sectoral heterogeneity into macroeconomic models with nominal rigidities. These contributions show that adding these features to an otherwise standard New Keynesian model has important consequences for the sources of macroeconomic fluctuations (Baqaee and Farhi 2022, Guerrieri et al. 2022) as well as for the effectiveness and the design of stabilization policies (La'O and Tahbaz-Salehi 2022, Woodford 2022).

To date, however, these contributions are mostly theoretical, and there is relatively little assessment of how such models perform empirically. The existing empirical studies focus on the aggregate properties of these multisectoral models by assessing either how production networks and producer heterogeneity can amplify the effects of macroeconomic shocks or how sectoral shocks can contribute to aggregate fluctuations.[1] Their results emphasize the key role of heterogeneous price stickiness, as in Carvalho (2006) and Nakamura and Steinsson (2010).

In this paper, we investigate how well these multisectoral New Keynesian models can match some empirical properties of sectoral prices and quantities. We think of these properties as moments that can be used to discipline these models, which is needed to derive their quantitative implications for macroeconomic fluctuations and policies. More specifically, we consider two sets of statistics: (1) higher moments of the inflation and consumption growth cross-sectional distributions and (2) the contemporaneous comovement between these two variables.

Our interest in higher moments, namely skewness and kurtosis in the cross section of sectoral inflation and consumption growth, comes from the fact that deviations from normal distribution are a distinctive feature of models with production networks and heterogeneous producers (see Acemoglu et al. 2012, Baqaee and Farhi 2019). Moreover, kurtosis in the distribution of producer price changes has been shown to play an important role in the degree of monetary non-neutrality at the aggregate level (Alvarez, Le Bihan, and Lippi 2016). This gives us reasons to assess whether a calibrated multisectoral New Keynesian model can replicate these dimensions of the sectoral data.

[1] See Carvalho, Lee, and Park (2021), Pasten, Schoenle, and Weber (2020, 2021), Ghassibe (2021).

We focus on the contemporaneous comovement of sectoral inflation and consumption growth because this reduced-form indicator is informative about whether demand or supply shocks are the dominant driver of fluctuations at the sectoral level. We can use this relationship to verify that the shocks' processes in the model represent well those in the data. If they do, the reduced-form comovement in the model should match that in the data. Otherwise, the shocks in the model are likely imbalanced or come from different sectors than in the data.

We document that the benchmark multisectoral model is partially successful in matching these targets, but some important challenges remain. The model can generate positive kurtosis for both inflation and consumption distributions. The model also matches the contemporaneous comovement when sectoral sizes are taken into account. However, the model fails to generate asymmetry in the distributions, and quantitatively, kurtosis in the model is substantially smaller than in the data. Moreover, likely due to its symmetric features, the model struggles to match the comovement when all sectors are given an equal weight. Based on our results, we propose that multisectoral models incorporate distributional asymmetries of the kind observed in the data.

Specifically, using disaggregated personal consumptions expenditures (PCE) and prices for the 1983–2021 period, we compute disaggregated inflation and real consumption growth rates at a quarterly frequency. We examine the distributions of sectoral inflation and consumption growth and find that the inflation distribution is skewed negatively, while the distribution of consumption growth has positive skewness. Both distributions are highly leptokurtic, with the consumption distribution having larger kurtosis. These distributional properties remain when we remove sectoral and temporal fixed effects.

We also compute reduced-form comovement of inflation and consumption growth. We find that inflation and consumption growth overall comove negatively during the full sample period, indicating that supply shocks were dominant. We also examine historical episodes during this period and find that negative correlation is a robust feature of the data. The only episode during which the comovement of inflation and consumption growth was positive is the COVID-19 pandemic.

Next, we consider a multisectoral New Keynesian model from the recent literature that is shown to capture well many important aspects of macroeconomic dynamics following aggregate and idiosyncratic shocks. The model follows Carvalho, Lee, and Park (2021) and features heterogenous price stickiness, roundabout production, aggregate and sectoral demand and supply shocks, and heterogenous persistence and volatility, among other elements. We follow the original study but, in order to match our empirical sample, re-estimate the model's parameters using Bayesian methods for the sample period that includes 13 more years of data. We then use the model with the updated parameters to generate artificial data for sectoral consumption growth and inflation. We employ these model-generated data to conduct the same exercises as in our empirical analysis.

We document three main results. First, the model's ability to match comovement depends on the weighting scheme employed. The model comes close to the data when we use sectoral weights based on consumption shares. However, the model cannot match the raw comovement when each sector is assigned an equal weight. Hence, the model has only partial success, according to this metric. Second, the distributions of sectoral consumption growth and inflation in the model are inherently symmetric. Thus, not only does the model fail to match the skewness observed in the data, but it does not generate any skewness at all. Third, the model shows partial success in generating positive kurtosis but has some quantitative challenges. Similar to the data, the model produces leptokurtic distributions of inflation and consumption growth, with larger kurtosis for consumption growth. But kurtosis in the model is 1 to 1.5 orders of magnitude smaller than in the data.

Finally, we shed more light on the model's mechanism and its ability to match the data by examining sectoral inflation and consumption growth dynamics following isolated shocks. While the responses of sectoral inflation and consumption to aggregate shocks are heterogenous, they are symmetric and do not have fat tails. When we consider sectoral shocks, the dynamics of sectoral distributions depend crucially on the sector's characteristics, such as price stickiness, shock persistence, and its size. We find that idiosyncratic supply shocks stemming from the sectors with high price stickiness and low shock persistence have the potential to produce sectoral distributions with asymmetries, fat tails, and negative comovement of inflation and consumption growth. However, on the whole such shocks do not appear to drive the dynamics of the model.

In addition to the papers cited above, our work contributes to the literature assessing whether the granular origins of aggregate fluctuations, emphasized in Gabaix (2011), among other papers, is supported by the data. Boivin, Giannoni, and Mihov (2009), Foerster, Sarte, and Watson (2011), Andrade and Zachariadis (2016), Barrot and Sauvagnat (2016), Atalay (2017), Cesa-Bianchi and Ferrero (2021), and many others postulate identifying assumptions to tease out sectoral shocks and to assess how these shocks contribute to aggregate fluctuations. Unlike those studies, this paper does not impose any identifying restrictions. We emphasize some reduced-form moments of sectoral variables that a model with sectoral and aggregate shocks should be able to reproduce. We then study the contribution of sectoral shocks to the dynamics of aggregate inflation and consumption using this structural model.

The paper proceed as follows. Section 2 presents our empirical analysis. Section 3 describes the model. Section 4 covers parametrization of the model. In Section 5, we compare the properties of the model-generated data with those documented in the empirical section. Section 6 discusses the dynamics of sectoral variables in the model following aggregate and idiosyncratic demand and supply shocks. Section 7 concludes.

2 Empirical Analysis

2.1 Data and Measurement

We compile personal consumption expenditures (PCE) price and quantity indexes for 27 disaggregated categories. The list of consumption categories matches that in Carvalho, Lee, and Park (2021). We update the sample to include the period from 1983 through 2021 at a quarterly frequency. We compute disaggregated inflation rates ($\pi_{i,t}$) in consumption category i and quarter t as $\pi_{i,t} = P_{i,t}/P_{i,t-1} - 1$ and quarterly changes in consumption as $C_{i,t} = RPCE_{i,t}/RPCE_{i,t-1} - 1$, where $P_{i,t}$ and $RPCE_{i,t}$ are the disaggregated PCE price index and real personal consumption expenditures per capita, respectively.

2.2 Distributions of Sectoral Inflation and Consumption Growth

The distribution of price changes plays an important role in the workhorse models with price stickiness. Together with the distribution of sectoral Calvo rates, it determines the distribution of sectoral inflation rates. We examine this distribution, along with that for consumption growth rates, before we estimate the comovement of the two variables (Figure 1).

In Figure 1a, we show the distribution of quarterly changes (not annualized) in sectoral price and consumption indexes, using raw data.[2] The average quarterly inflation rate is 0.47 percent, and the median is 0.51 percent, both of which correspond to approximately a 2% annual inflation rate. The average consumption growth rate is slightly higher, at 0.66 percent per quarter, and the median is slightly lower (0.47 percent). The standard deviation of consumption growth is about twice as large as the standard deviation of inflation. While inflation is negatively skewed (long left tail), consumption growth is positively skewed. Both distributions are quite leptokurtic (have fat tails). We will use these moments, together with the contemporaneous comovement of the two variables, to assess the benchmark model.

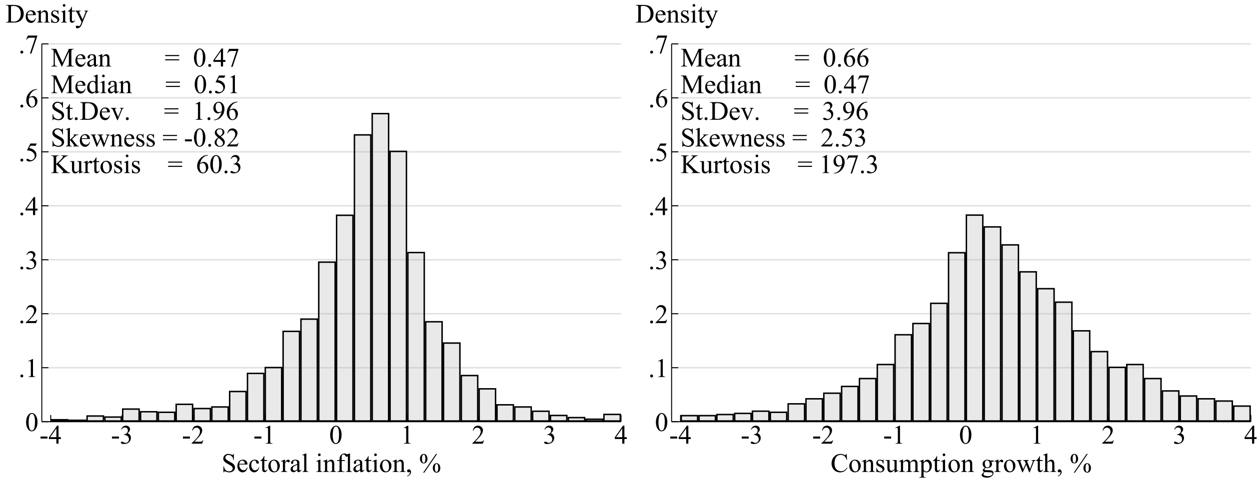
Because disaggregated prices and quantities may follow sectoral trends, which are not captured well by models, we next focus on deviations from sectoral means (Figure 1b). By construction, the means of these deviations are zero, and the medians are close to zero. Yet, the higher moments of these distributions are qualitatively similar to those based on raw data.

The inflation- and consumption-growth distributions considered above are affected by both aggregate and idiosyncratic shocks. In Figure 1c, we focus on the effects of sectoral shocks by partialling out sector and time fixed effects. Sectoral shocks account for 90.6 percent of the inflation variation and for 75.1 percent of the consumption-growth variation. The inflation distribution remains negatively skewed and the consumption distribution positively skewed. Both distributions are again highly leptokurtic.

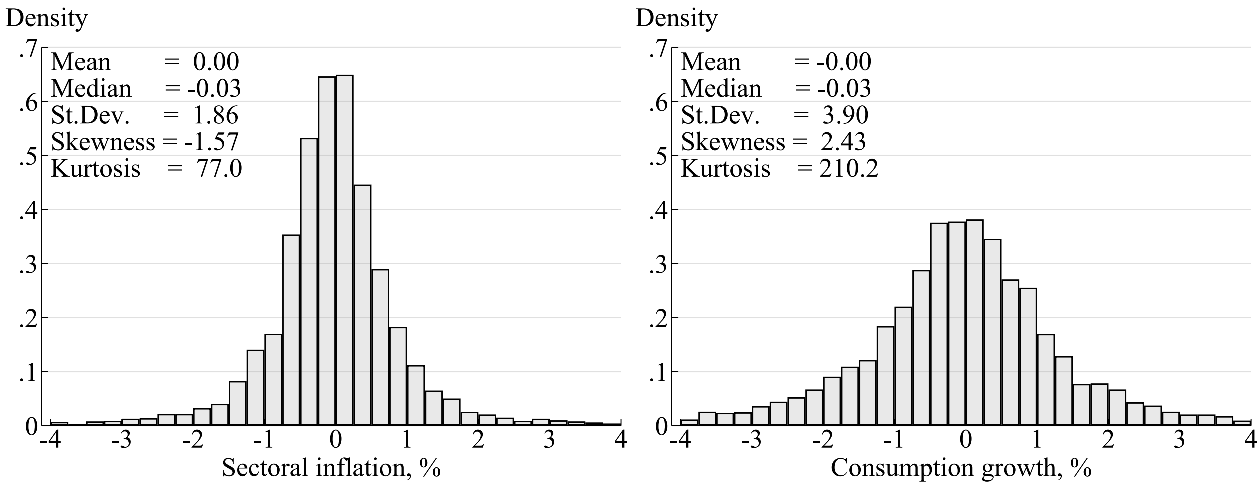
[2] For visibility, we cut the tails at 4 percent on both sides of each distribution. But we use all observations to compute the distributional moments.

Figure 1: The Sectoral Distributions of Inflation and Consumption Growth

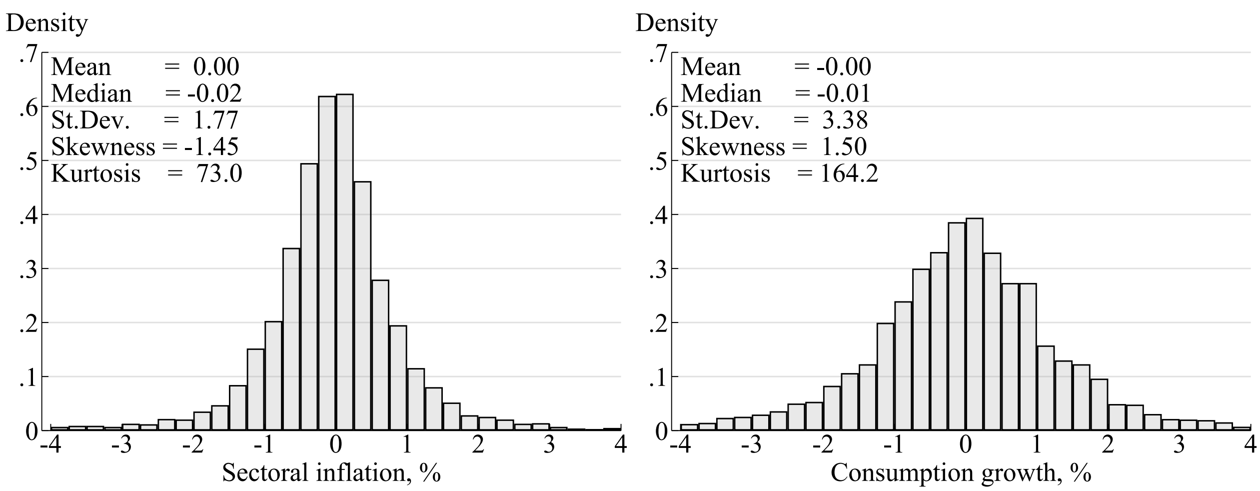
(a) Quarterly Changes



(b) Deviations from Sectoral Means



(c) Partialled-out Sector and Time Effects



Note: For visibility, values greater than 4 percent in magnitude are not shown but are included in calculation of the moments.

Source: All figures and tables in the empirical section are based on the authors' calculations using data from the U.S. Bureau of Economic Analysis.

2.3 Comovement

To determine the relative importance of demand and supply shocks during the sample period, we estimate the following model:

$$\pi_{i,t} = \alpha_i + \beta C_{i,t} + \gamma_t + \varepsilon_{i,t}, \tag{1}$$

where parameters α_i capture sectoral fixed effects, and parameters γ_t partial out the comovement due to aggregate shocks. Hence, when γ_t is not included in the model, the variation in consumption and inflation is driven by both aggregate and idiosyncratic shocks, whereas when it is included, the variation is driven solely by sectoral shocks. In the specification above, the coefficient β measures the overall comovement of prices and quantities. If $\beta > 0$, demand shocks dominate. If $\beta < 0$, supply shocks do.

The main advantage of specification (1) is its simplicity. Alternative approaches typically impose a structure to identify aggregate and idiosyncratic demand and supply shocks. The identification of such shocks, however, can pose significant challenges, and the results can differ across various identification methods. Our approach instead measures the contemporaneous comovement of sectoral prices and quantities, which plays a fundamental role in theory but is often overlooked in practice.[3]

We estimate Equation (1) for four combinations of fixed effects and for two alternative weighting schemes. Table 1 shows the results. In Panel (a), we employ equally weighted observations. In the full sample, the comovement is negative and statistically significant, suggesting that on the whole, supply shocks dominated. The only positive (and insignificant) coefficient is obtained in the specification where we do not control for time effects and use equal weights (column 2). This specification corresponds to the mixture of aggregate and idiosyncratic shocks.

In Panel (b), we use PCE weights to account for sectoral sizes.[4] With consumption weights, the comovement coefficient is consistently negative across various specifications. But in the case

[3] In a similar spirit, Sheremirov (2020) uses empirical comovement between inflation and price dispersion to differentiate across various models of price stickiness.

[4] As a baseline, we use time-varying weights. In the appendix, we show the results with fixed weights (Table A.1).

Table 1: Comovement of Inflation and Consumption Growth

	(1)	(2)	(3)	(4)
	(a) Equal Weights			
Slope	-0.020^{***}	0.006	-0.059^{***}	-0.025^{***}
	(0.007)	(0.007)	(0.008)	(0.008)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,185	4,185	4,185	4,185
	(b) Consumption Weights			
Slope	-0.053^{***}	-0.022^{**}	-0.084^{***}	-0.047^{***}
	(0.009)	(0.009)	(0.010)	(0.010)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,185	4,185	4,185	4,185

Notes: HAC standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of no time effects (column 2), the coefficient is smaller and somewhat sensitive to the choice of weighting scheme (see the appendix).

2.4 *Historical Episodes*

The relative importance of different types of shocks can differ across macroeconomic environments and historical episodes. While we find that supply shocks dominate in the full sample, it is not a priori clear how robust their dominance is across time. It turns out that this result is quite robust.

To show this, we split our baseline sample into five subsamples. The first one, the 1983–1991 period, covers the beginning of the Great Moderation. The second one, 1992 through 2006, covers the later Great Moderation period. Conventional wisdom holds that the slope of the Phillips curve declined in the early 1990s. The third episode, 2007 through 2015, corresponds to the Great Recession and the subsequent slow recovery. The 2016–2019 period is characterized by steady expansion, with falling unemployment and low inflation. The 2020–2021 period covers the COVID-19 pandemic.

Table 2 shows estimates of Equation (1) for each of these episodes. To save space, we focus on specifications that include sectoral fixed effects. While the economic environment has varied

Table 2: The Comovement across Historical Episodes

	(a) Equal Weights		(b) Consumption Weights	
Category effects	Y	Y	Y	Y
Time effects	N	Y	N	Y
	(1)	(2)	(3)	(4)
1983–1991	-0.068^{***}	-0.069^{***}	-0.062^{***}	-0.062^{***}
	(0.021)	(0.022)	(0.021)	(0.022)
1992–2006	-0.077^{***}	-0.078^{***}	-0.062^{***}	-0.058^{***}
	(0.018)	(0.019)	(0.018)	(0.019)
2007–2015	-0.236^{***}	-0.296^{***}	-0.257^{***}	-0.300^{***}
	(0.037)	(0.039)	(0.043)	(0.045)
2016–2019	-0.294^{***}	-0.314^{***}	-0.237^{***}	-0.256^{***}
	(0.050)	(0.051)	(0.049)	(0.051)
2020–2021	0.054^{***}	0.030	0.030^{*}	0.015
	(0.016)	(0.019)	(0.018)	(0.021)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

substantially over time, the correlation of inflation and consumption growth is negative in all but one episode. For the period before the Great Recession, the comovement coefficient varied from -0.078 to -0.058. After the Great Recession and up to the COVID-19 pandemic, the negative comovement increased in magnitude (to values in the range of -0.31 to -0.24). Finally, during the pandemic, the comovement turned positive, indicating that overall, demand shocks prevailed.[5]

Summary: In this section, we examined the comovement of sectoral inflation and consumption growth as well as their distributions. We documented four key results. First, sectoral consumption growth rates are about twice as dispersed as sectoral inflation, when measured by their standard deviations. Second, sectoral inflation has negative skewness, while sectoral consumption growth has positive skewness. Third, both distributions are highly leptokurtic, with consumption growth significantly more so. Fourth, in the baseline sample, the comovement of the two variables is overall negative, indicating prevalence of supply shocks during this period. The negative comovement is relatively stronger in response to sectoral shocks, with somewhat more ambiguous results for aggregate shocks.

[5]Additional analysis suggests that a positive comovement during this period was particularly strong in its early part (March 2020 through April 2021). Since April 2021, supply shocks have started to play a larger role. See Sheremirov (2021).

3 Model

We consider a standard multisectoral New Keynesian model recently studied in the literature (Carvalho, Lee, and Park 2021). This model features heterogeneous price stickiness à la Calvo (1983), roundabout production, aggregate and sectoral demand and supply shocks, and heterogenous persistence and volatility. Monetary policy is conducted according to a standard Taylor rule. Aggregate shocks include a productivity shock (supply), a preference shock (demand), and a monetary policy shock. Sectoral shocks include a sectoral productivity shock and a relative demand shock.

The economy comprises K sectors, indexed by k. The set of all firms in sector k, denoted by $\mathscr{I}_k$, has measure n_k. Each firm $i \in [0,\, 1]$ belongs to one—and only one—sector: $\bigcup_{k=1}^{K} \mathscr{I}_k = [0,1]$.

3.1 Households

A representative household maximizes utility,

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \Gamma_t \left(\log C_t - \sum_{k=1}^{K} \omega_k \frac{H_{k,t}^{1+\varphi}}{1+\varphi} \right) \right], \tag{2}$$

subject to the budget constraint:

$$P_t C_t + \mathbb{E}_t \left[Q_{t,t+1} B_{t+1} \right] = B_t + \sum_{k=1}^{K} W_{k,t} H_{k,t} + \sum_{k=1}^{K} \int_{\mathscr{I}_k} \Pi_{k,t}(i)\, \mathrm{d}i, \tag{3}$$

where C_t is aggregate consumption, $H_{k,t}$ is hours worked in sector k, P_t is the aggregate price level, B_t is a one-period nominal bond maturing in t, $Q_{t,t+1}$ is the price of the bond purchased in period t and maturing in $t+1$ (stochastic discount factor), $W_{k,t}$ is the nominal wage in sector k, and $\Pi_{k,t}(i)$ is the profits of firm i operating in sector k. Parameters β and φ are the discount factor and the inverse Frisch elasticity of labor supply, respectively. Parameters ω_k capture the disutility of labor in sector k. The aggregate demand shock, Γ_t, is modeled as a disturbance to the discount factor.

Consumption and prices are aggregated across the sectors using Dixit–Stiglitz aggregation:

$$C_t = \left(\sum_{k=1}^{K} \left(n_k D_{k,t} \right)^{\frac{1}{\eta}} C_{k,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{4}$$

$$P_t = \left(\sum_{k=1}^{K} n_k D_{k,t} P_{k,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}, \tag{5}$$

where η is the elasticity of substitution across sectors, n_k is the equilibrium size of sector k, and $D_{k,t}$ is the relative demand shock, constrained so that $\sum_{k=1}^{K} \left(n_k D_{k,t} \right) = 1$.

Aggregation within sectors is analogous, with the elasticity of substitution $\theta > \eta$:

$$C_{k,t} = \left(\left(\frac{1}{n_k} \right)^{\frac{1}{\theta}} \int_{\mathscr{I}_k} C_{k,t}(i)^{\frac{\theta-1}{\theta}} \, \mathrm{d}i \right)^{\frac{\theta}{\theta-1}}, \tag{6}$$

$$P_{k,t} = \left(\frac{1}{n_k} \int_{\mathscr{I}_k} P_{k,t}(i)^{1-\theta} \, \mathrm{d}i \right)^{\frac{1}{1-\theta}}. \tag{7}$$

3.2 Firms

Firms combine labor, $H_{k,t}(i)$, and intermediate inputs, $Z_{k,t}(i)$, to produce output, $Y_{k,t}(i)$, according to Cobb–Douglas production function, with the share of intermediate inputs δ:

$$Y_{k,t}(i) = A_t A_{k,t} H_{k,t}(i)^{1-\delta} Z_{k,t}(i)^{\delta}. \tag{8}$$

Here, A_t is the aggregate productivity shock, and $A_{k,t}$ is the sectoral productivity shock. Intermediate inputs are aggregated across and within sectors with the same elasticities of substitution η and θ, respectively.

$$Z_{k,t}(i) = \left(\sum_{\ell=1}^{K} \left(n_\ell D_{\ell,t} \right)^{\frac{1}{\eta}} Z_{k,\ell,t}(i)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

$$Z_{k,\ell,t}(i) = \left(\left(\frac{1}{n_\ell} \right)^{\frac{1}{\theta}} \int_{\mathscr{I}_\ell} Z_{k,\ell,t}(i,j)^{\frac{\theta-1}{\theta}} \, \mathrm{d}j \right)^{\frac{\theta}{\theta-1}}$$

Firms set prices à la Calvo with sector-specific stickiness parameters α_k. Hence, as usual, the price level in sector k depends on the price level in the preceding period and the optimal reset price $P^*_{k,t}$:

$$P_{k,t} = \left((1-\alpha_k)P^{*\,1-\theta}_{k,t} + \alpha_k P^{1-\theta}_{k,t-1}\right)^{\frac{1}{1-\theta}}. \tag{9}$$

The optimal reset price maximizes the expected present value of the firm's profit stream:

$$P^*_{k,t} = \text{argmax}_{P_{k,t}(i)}\, \mathbb{E}_t \sum_{s=0}^{\infty} \alpha_k^s \left(\prod_{r=t}^{t+s-1} Q_{r,r+1}\right) \Pi_{k,t+s}(i), \tag{10}$$

where the profit is

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

3.3 Monetary Policy

Monetary policy is conducted according to the Taylor rule:

$$\frac{I_t}{\bar{I}} = \left(\frac{I_{t-1}}{\bar{I}}\right)^{\rho_i} \left(\left(\frac{P_t}{P_{t-1}}\right)^{\phi_\pi} \left(\frac{C_t}{\bar{C}}\right)^{\phi_c}\right)^{1-\rho_i} \exp \mu_t, \tag{11}$$

where I_t is the gross nominal interest rate, and μ_t is a monetary policy shock. The bar over the variables indicates steady-state values. Parameters ϕ_π and ϕ_c govern the policy response to inflation and consumption gap, respectively, while ρ_i captures interest-rate smoothness.

3.4 Shocks

All shocks follow an AR(1) process, with persistence $\rho^{\cdot}$ and an innovation $\varepsilon^{\cdot}_t$, which has time-invariant volatility $\sigma^{\cdot}$. In particular, there are three aggregate shocks: supply (productivity, A_t), demand (preference, Γ_t), and monetary (μ_t):

$$\log A_t \equiv a_t = \rho^A a_{t-1} + \varepsilon_t^A, \tag{12}$$

$$\log \Gamma_t \equiv \gamma_t = \rho^\Gamma \gamma_{t-1} + \varepsilon_t^\Gamma, \tag{13}$$

$$\mu_t = \rho^\mu \mu_{t-1} + \varepsilon_t^\mu. \tag{14}$$

The model has $2k$ sectoral shocks, k supply shocks (productivity, $A_{k,t}$) and k demand shocks ($D_{k,t}$), with heterogenous persistence and volatility:

$$\log A_{k,t} \equiv a_{k,t} = \rho_k^A a_{k,t-1} + \varepsilon_{k,t}^A, \tag{15}$$

$$\log D_{k,t} \equiv d_{k,t} = \rho_k^D d_{k,t-1} + \varepsilon_{k,t}^D. \tag{16}$$

Finally, all innovations are normally distributed with zero means and shock-specific standard deviations:

$$\begin{pmatrix} \varepsilon_t^\mu \\ \varepsilon_t^\Gamma \\ \varepsilon_t^A \\ \varepsilon_{k,t}^A \\ \varepsilon_{k,t}^D \end{pmatrix} \sim \begin{pmatrix} \sigma^\mu \\ \sigma^\Gamma \\ \sigma^A \\ \sigma_k^A \\ \sigma_k^D \end{pmatrix} \odot \mathcal{N}(\mathbf{0}, \mathbf{I}),$$

where $\mathbf{0}$ is the 5x1 vector of zeros, $\mathbf{I}$ is the 5x5 identity matrix, and $\odot$ denotes Hadamard product. Because this model has been solved before, we relegate the description of its solution and equilibrium conditions to the appendix.

4 Parameterization

We follow the two-step approach of Carvalho, Lee, and Park (2021) to parameterize the model. First, we calibrate standard parameters such as the discount factor and the elasticities of substitution, using typical values or targets from the previous literature. Then, we estimate the remaining

Table 3: Calibrated Parameters

Parameter (1)	Value (2)	Description (3)	Source / Target (4)
β	0.99	Discount factor	$\bar{\imath} = 4\%$
φ	2	Inverse Frisch labor supply elasticity	Carvalho, Lee, and Park (2021)
θ	6	Elasticity of substitution across varieties	20% mark-up
η	2	Elasticity of substitution across sectors	Hobijn and Nechio (2019)
δ	0.7	Share of intermediate inputs	Carvalho, Lee, and Park (2021)
n_k	varies	Sectoral size	PCE expenditure weights

parameters using Bayesian methods. The model is parameterized at a quarterly frequency, with the estimation sample from 1983 through 2021.

Table 3 summarizes the calibrated parameters. The discount factor, β, is set to result in an equilibrium nominal interest rate of 4 percent per annum. The elasticity of substitution across varieties within a sector, θ, is set to result in a 20 percent equilibrium mark-up. The elasticity of substitution across sectors, η, follows Hobijn and Nechio (2019). The Frisch elasticity of labor supply and the share of intermediate goods are from Carvalho, Lee, and Park (2021). The relative sizes of K sectors, n_k, are calibrated to match the corresponding weights in the PCE data.

We estimate the price-stickiness and Taylor-rule parameters, as well as shock persistence and volatility, using Bayesian methods. Table 4 summarizes the posterior modes, the priors, and the distribution for these parameters. The prior means for the Taylor rule and the Calvo parameters are based on previous literature, whereas the priors for persistence and volatility are flat, which allows the estimation process to choose from a wide range of values. The estimated response to inflation, at 2.68, is greater than the prior mean (1.5), whereas the response to the consumption gap is lower than its prior (0.31 versus 0.5 annualized). The estimated interest-rate smoothness (0.75) is comparable to its prior. Prices are estimated to be less sticky than according to the prior. The weighted average Calvo rate is estimated at 0.56, while the raw average is 0.47, compared with 0.63 and 0.51 prior means, respectively. Finally, sectoral shocks appear to be quite persistent.[6] For instance, the median half-life of sectoral supply shocks is 17.3 quarters, which is far greater than

[6] Table A.2 in the appendix shows estimates of price stickiness by sector.

Table 4: Estimated Parameters

Parameter	Description	Posterior	Prior		Distribution
		Mode	Mean	SD	
(1)	(2)	(3)	(4)	(5)	(6)
Taylor rule					
ϕ_π	Response to inflation	2.68	1.5	0.25	Normal
ϕ_c	Response to consumption gap	0.31/4	0.5/4	0.05/4	Normal
ρ_i	Interest-rate smoothness	0.75	0.7	0.15	Beta
Price stickiness					
$\sum_{k=1}^{K} \alpha_k n_k$	Aggregate	0.56	0.63	0.1	Beta
$\sum_{k=1}^{K} \alpha_k / K$	Average	0.47	0.51	0.1	Beta
Sectoral supply shock persistence					
$-\log 2/\log \rho_k^A$	Median half-life	17.3	1.9	*	Beta

* The standard deviation of the underlying priors for ρ_k^A is 0.15.
Source: Authors' calculations.

the prior.[7]

5 Model versus Data

Using the model above, we simulate 10,000 artificial observations in each sector, with 2,000 additional burn-in observations. We then estimate Equation (1) using the simulated data and compare the comovement coefficients with those observed in the data. Note that we obtain a substantially larger number of points than observed in the data so that we can ignore sampling uncertainty. By construction, the resulting standard errors for the comovement coefficients are going to be small and not directly comparable with their empirical counterparts. We therefore focus on the slopes' magnitudes.

Table 5 shows the comovement of sectoral inflation and consumption growth in the model. Because the model is estimated on the demeaned data, the coefficients in column (1) are the counterpart of those in column (2) of Table 1, and the coefficients in column (2) should be compared with those in column (4) of Table 1. In the latter case, the coefficients account for idiosyncratic shocks only, whereas in the former they account for comovement due to both aggregate and id-

[7]We focus on the median half-life because the distribution of half-lives across sectors has a long right tail.

Table 5: Comovement of Inflation and Consumption Growth in the Model

Time effects	N	Y
	(1)	(2)
	(a) Equal Weights	
Slope	0.00387***	0.00387***
	(0.00049)	(0.00046)
	(b) Consumption Weights: Sample Average (1983–2021)	
Slope	−0.01838***	−0.01948***
	(0.00054)	(0.00047)
	(c) Consumption Weights: End of Period (2021)	
Slope	−0.02355***	−0.02542***
	(0.00056)	(0.00049)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: All tables and figures in this and the following section are based on the authors' calculations using model-simulated data.

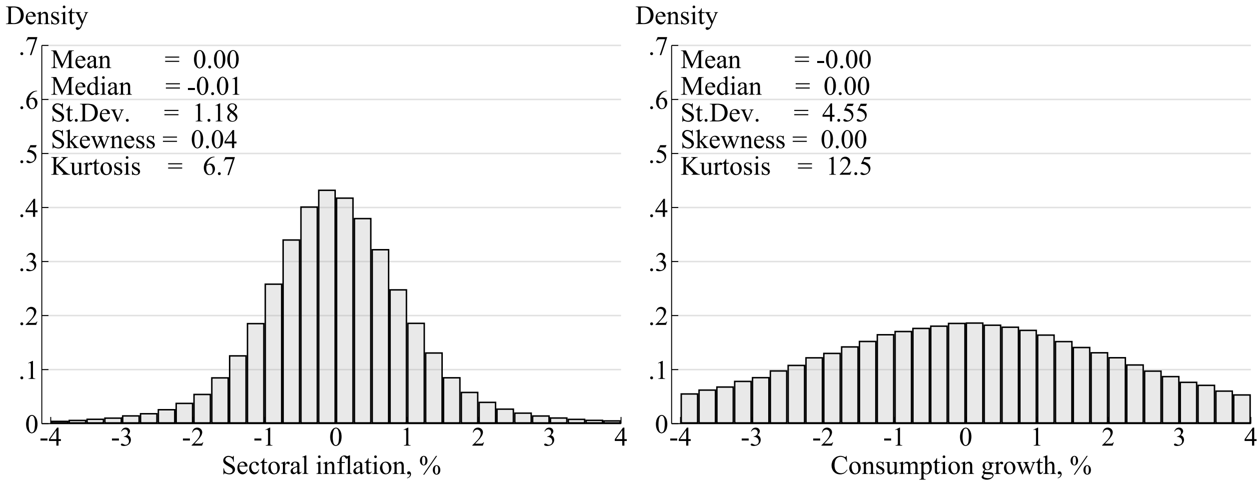
iosyncratic shocks.

Before comparing the model with the data, we note that there are two differences between the empirical and model-based specifications that may need to be accounted for. First, due to stochastic singularity, the model is estimated with one sector dropped, whereas the empirical results include all sectors. Second, in the data we can trace the weights across time, whereas in the model the sectoral weights are fixed in the steady state. Fortunately, these two discrepancies do not materially affect our conclusion. But to facilitate direct comparison, we re-estimate our empirical model with exactly the same sectoral composition and fixed weighting scheme as in the model-generated case. The results are shown in Table A.3 in the appendix.

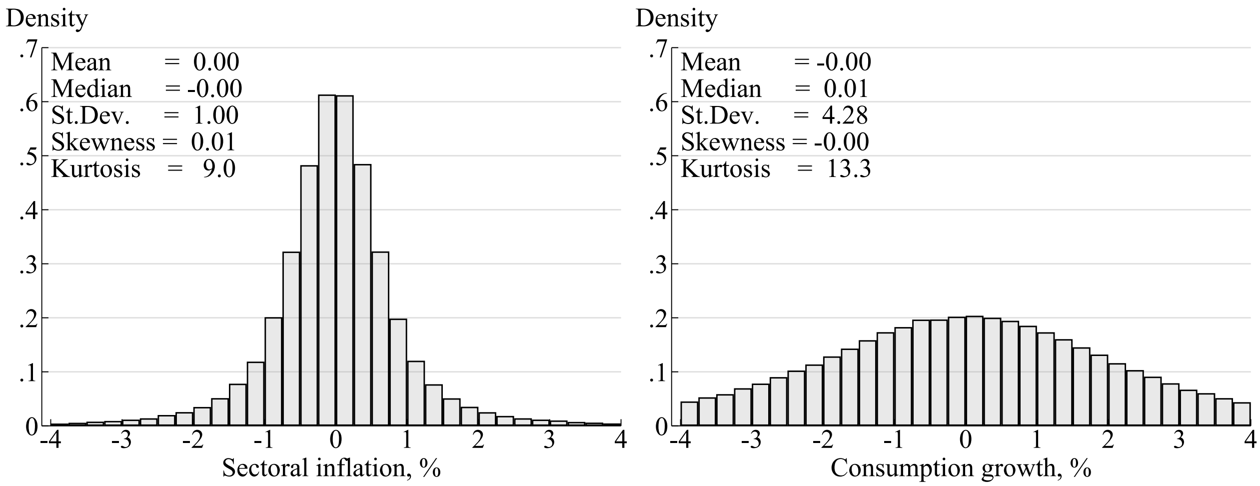
The key results of this exercise are threefold. First, when the sectors are equally weighted (Table 5, Panel a), the model does not capture well the dynamics of sectoral inflation and consumption growth due to idiosyncratic shocks. The comovement coefficient is positive for the model-generated data and negative for the actual data. Second, the model does somewhat better once aggregate shocks are not partialled out: The comovement in the model and in the data are both positive. But the coefficient is more than an order of magnitude larger in the data than in the model. Third, the model performs quite well when observations are weighted by their consumption

Figure 2: The Distributions of Inflation and Consumption Growth in the Model

(a) Deviations from Sectoral Means



(b) Partialled-out Sector and Time Effects



Note: For visibility, values greater than 4 percent in magnitude are not shown but are included in calculation of the moments.

shares (Panel b), especially for the case when the effects of aggregate shocks are partialled out.

Next, we compare the moments of individual distributions. The results are shown in Figure 2. Because the model is estimated on demeaned data, Figure 2a should be compared with Figure 1b and Figure 2b with Figure 1c. We document three important departures of the model from the data. First, inflation is substantially less dispersed and consumption growth is more dispersed in the model than in the data. Second, the model generates symmetric distributions across sectors. As we showed earlier, the distributional skewness is a salient feature of the data. Third, while the model generates leptokurtic distributions of inflation and consumption growth rates, kurtosis in the model is 1 to 1.5 orders of magnitude smaller than in the data. Yet, overall the model captures the fact that the consumption growth distribution has greater dispersion and greater kurtosis than the inflation distribution.

The model's inability to match the unweighted sectoral comovement of inflation and consumption growth as well as higher moments of their distributions is puzzling, as the model does quite well in matching the weighted comovement. The previous literature shows, for example, that the model can overall match the decomposition into aggregate and idiosyncratic shocks well, using methods such as factor-augmented vector autoregression (FAVAR). In this context, Carvalho, Lee, and Park (2021) show that it is important to get the distribution of sectoral Calvo rates right, while sectoral linkages play only a secondary role. However, based on our results, it is likely that more complex input-output linkages are important for generating a plausible comovement of inflation and consumption growth. Because such comovement plays a fundamental role in macroeconomic theory, models that can match it well should be better candidates for practical analyses of macroeconomic dynamics and policy evaluation.

6 Sectoral Responses to Aggregate and Idiosyncratic Shocks

While this model has some challenges matching the higher moments of the inflation and consumption growth distributions, in this section we illustrate the dynamics of sectoral variables in response to aggregate and idiosyncratic demand and supply shocks. We show that in many cases the responses have a consistent shape across sectors, with the scale depending on the sector's size and price stickiness. That could generally allow a matching of the average dynamics—and often the volatility—but there is rarely a case where the model produces the kind of asymmetric responses necessary to match the skewness and the kurtosis in the data. Hence, we argue that it is not just the composition of the shocks that the model fails to match but also the mechanism that gives rise to the asymmetries.

6.1 *Aggregate Shocks*

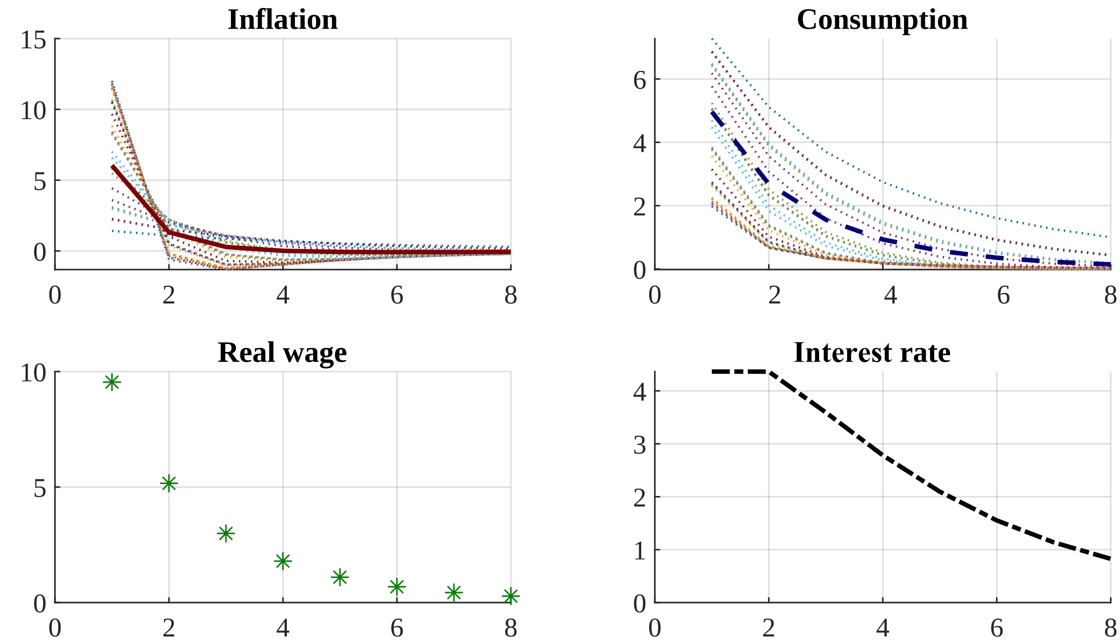
We start by examining the effects of aggregate shocks. Figure 3 shows the responses of inflation, consumption, the real wage, and the nominal interest rate to a preference shock, Γ_t, scaled to produce an aggregate inflation response of 6 percent on impact. For illustrative purposes, we consider a mildly persistent shock, with a half-life of two quarters.[8] The top panel shows the responses of inflation and consumption. The thick lines correspond to the aggregate variables, while the thin dotted lines show sectoral responses. Aggregate inflation returns to the steady state at the speed that matches the shock persistence, while the aggregate consumption response is more persistent due to the slower adjustment of relative prices resulting from heterogeneity in the Calvo rates. The responses of sectoral inflation illustrate this heterogeneity well. Inflation in the sectors with relatively flexible prices responds stronger on impact but then converges to the steady state from below. Inflation in the sectors with relatively sticky prices adjusts less on impact and takes longer to converge. The responses of consumption preserve their on-impact order. Consumption in the sticky-price sectors responds more than consumption in the flexible-price sectors during the entire period. As expected, in response to expansionary demand shocks, the real wage increases and monetary policy tightens (bottom panel).

Figure 4 shows the responses to an aggregate productivity shock, A_t, that would give rise to the same on-impact response of aggregate inflation as in the previous case. We consider a slightly more persistent supply shock, setting the half-life to four quarters.[9] Following this shock, inflation rises and consumption falls both in the aggregate and for each sector. Importantly, the relative responses of sectoral inflation and consumption follow a pattern similar to the one they follow in response to the aggregate demand shock. The bottom panel shows that the real wage decreases and monetary policy tightens.

[8]While this small-scale model lacks many ingredients necessary to analyze post-COVID macroeconomic dynamics, we scale the shock to roughly match the duration of the fiscal stimulus and inflation during this period. Over the entire sample, aggregate shocks are estimated to be more persistent. For instance, the estimated half-life of the preference shock is 11.2 quarters. Note also that because the impulse responses are deviations from the steady state, a 6 percent deviation would correspond to an 8 percent inflation in the data.

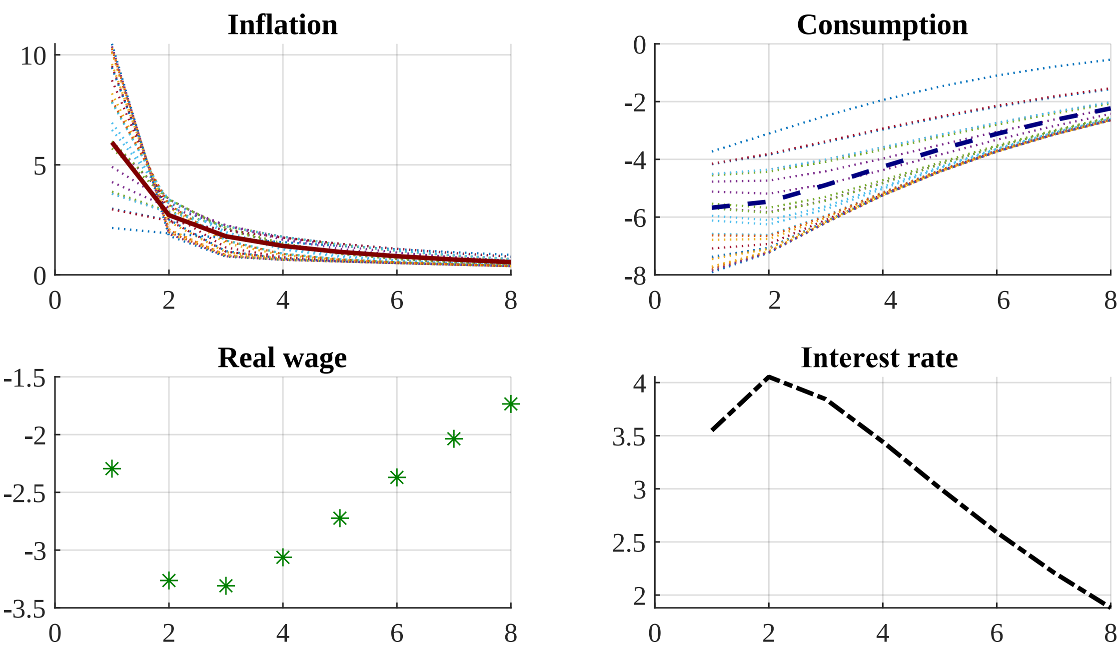
[9]One can think of this shock as reflecting supply-chain constraints lasting for two years.

Figure 3: Responses to an Aggregate Demand Shock



Notes: The figure shows the responses to a preference shock, Γ_t, with a half-life of two quarters scaled to generate a 6 percent aggregate inflation on impact. The responses are measured at an annualized quarterly rate. The thick solid and dashed lines in the top panel show the responses of aggregate inflation and aggregate consumption, respectively. The thin dotted lines show the responses of sectoral variables.

Figure 4: Responses to an Aggregate Supply Shock



Notes: The figure shows the responses to a aggregate productivity shock, A_t, with a half-life of four quarters scaled to generate a 6 percent aggregate inflation on impact. The responses are measured at an annualized quarterly rate. The thick solid and dashed lines in the top panel show the responses of aggregate inflation and aggregate consumption, respectively. The thin dotted lines show the responses of sectoral variables.

It is noteworthy that the effects of neither aggregate demand nor aggregate supply shocks can alone explain the post-COVID macroeconomic dynamics. The data during this period are characterized by high inflation, a mild increase in consumption, and a decline in real wages. Hence, both shocks are likely at play. In the appendix, we show the responses of key variables when both shocks are operational (Figure A.1). We choose the scale to roughly match the responses of both inflation and consumption. Even so, the model produces a counterfactual increase in the real wage. Another relevant mismatch between the model and the data is the scale of the interest-rate responses. One reason for this mismatch is that the estimated Taylor rule could be quite different from the ones that were relevant during the pandemic.[10] Another interpretation is that monetary policy during that period could have accommodated the aggregate shocks stemming from the pandemic. We consider the case of monetary accommodation in the appendix (Figures A.2 and A.3). Monetary accommodation affects the size of the responses but not their shape in the case of the preference shock, because the two demand shocks work in the same direction. In the case of the productivity shock, monetary accommodation again affects the scale but not the shape of the inflation and consumption responses, but it has a notable effect on real-wage dynamics. In this case, the real wage rises on impact, then declines for a few quarters, and then slowly converges from below.

The bottom line of our analysis of the effects of aggregate shocks is as follows. While aggregate demand and supply shocks can produce heterogenous responses for sectoral inflation and consumption, these responses are generally symmetric and tight around the aggregate response line. Thus, aggregate shocks in this model cannot produce the asymmetric distribution of inflation and consumption and the fat tails that we observe in the data. Therefore, does this asymmetry come mostly from sectoral shocks? We examine this question next.

6.2 Sectoral Shocks

We focus on the effects of sectoral supply shocks in three sectors: energy, new motor vehicles and parts, and used motor vehicles. We focus on a small number of sectors not only for practical

[10] Another possible explanation is that the response of the latent federal funds rate was much larger than that of the nominal rate, which could have been constrained by the zero lower bound during the early stage of the pandemic.

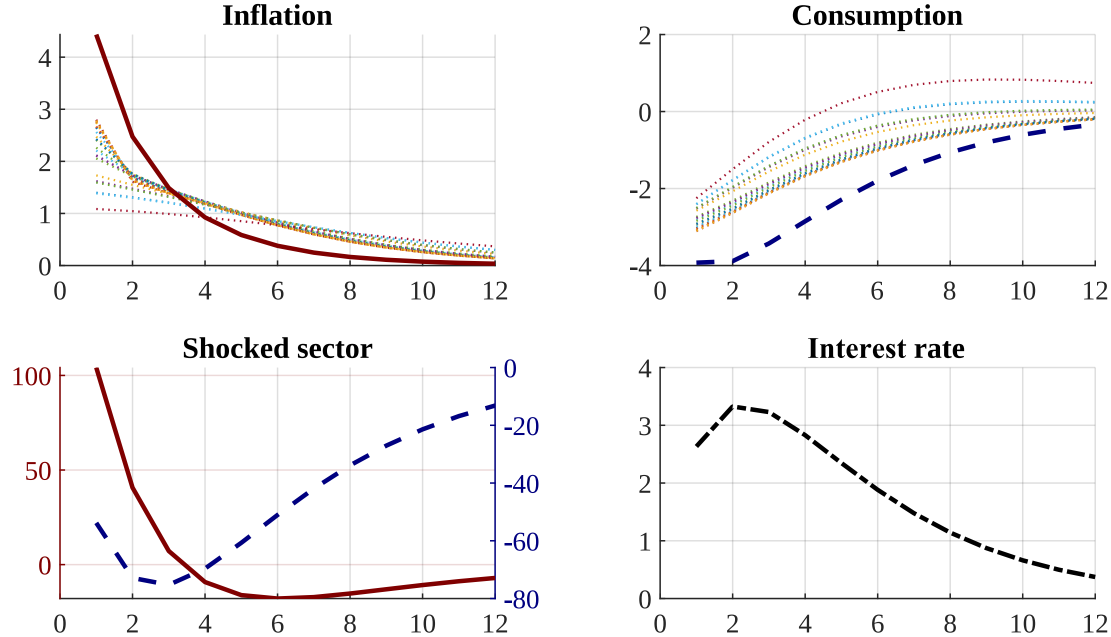
reasons but because in the model there are only three sector-specific parameters that govern the effects of sectoral supply shocks: price stickiness, shock persistence, and sector size. Hence, by considering sectors with relatively large and small values of these parameters, we can shed light on the sectoral effects in general. We focus on supply shocks because they tend to be more important at the sectoral level. The sectoral demand shocks, by construction, are relative demand shocks and hence have a limited effect on aggregate dynamics. We consider the energy sector because it has a particularly low estimated persistence of supply shocks and because it experienced a large shock recently. The new-cars sector is characterised by relatively large price stickiness, while the used-car sector has relatively flexible prices. Both automobile sectors are estimated to have significantly more persistent shocks than the energy sector.

Figure 5 shows the responses of key variables to an energy supply shock. The top panel shows the responses of inflation (left plot) and consumption (right plot) for the sectors other than energy (thin dotted lines) as well as the aggregate variables (thick solid and dashed lines). The bottom-left panel shows the responses of energy inflation (red solid line, left axis) and energy consumption (blue solid line, right axis). We scale the shock to match the sectoral inflation rate in 2021:Q1. The shock's persistence is based on the baseline structural estimate, which corresponds to a half-life of 2.6 quarters. Hence, this is a transitory energy shock.

The energy supply shock leads to a jump in inflation and a drop in consumption on impact, followed by a monotonic decline in inflation and a monotonic increase in consumption both in the aggregate and for all other sectors. It also produces an idiosyncratic response of energy inflation and energy consumption that is quite different from the aggregate response. Hence, a shock such as this could, in principle, explain the negative comovement of inflation and consumption as well as the asymmetric and leptokurtic distributions of the two variables found in the data. Here, the negative comovement stems from the other sectors, while the asymmetry and kurtosis are due to the shocked sector.

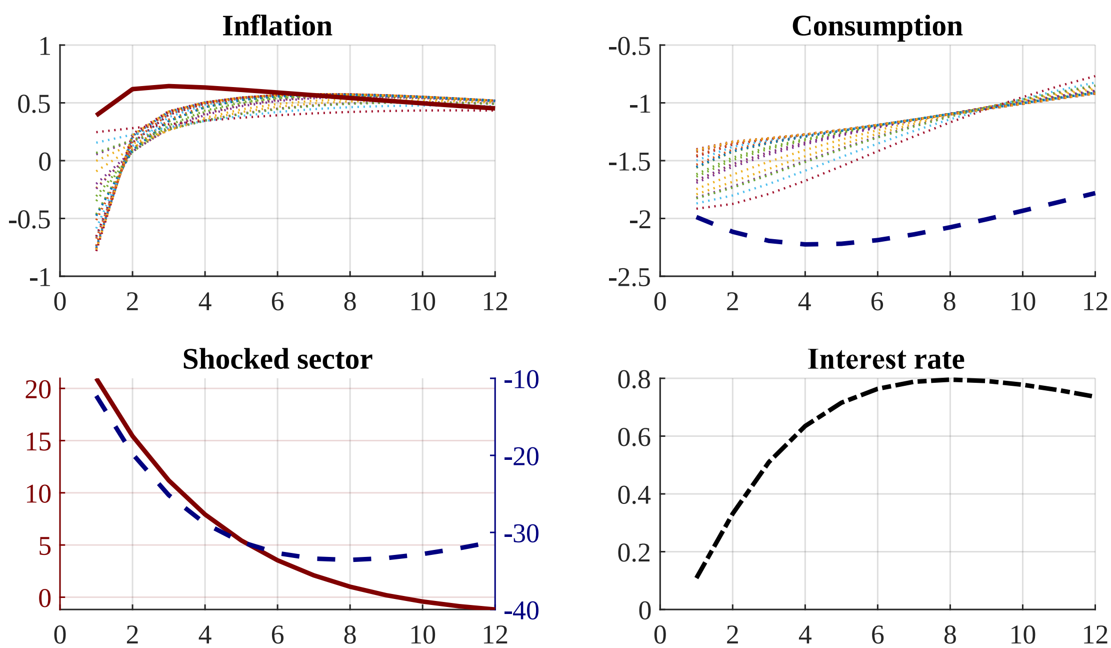
The dynamics appear to be quite different when we consider a supply shock for new motor vehicles and parts (Figure 6). This sector is characterized by significantly larger persistence as

Figure 5: Responses to a Supply Shock in the Energy Sector



Notes: The figure shows the responses to a sectoral productivity shock, $A_{k,t}$, for energy. The shock is scaled to produce on-impact sectoral inflation that matches the corresponding metric in the data in 2021:Q1. The shock's persistence corresponds to a half-life of 2.6 quarters, which is based on the structural estimation of the model. The thick solid and dashed lines in the top panel show the responses of aggregate inflation and aggregate consumption, respectively. The thin dotted lines in the top panel show the dynamics in the sectors other than energy. The bottom-left panel shows the responses of inflation (red solid line, left axis) and consumption (blue dashed line, right axis) in the energy sector.

Figure 6: Responses to a Supply Shock for New Motor Vehicles and Parts



Notes: See notes to the previous figure. The shock's persistence corresponds to a half-life of 14.2 quarters.

well as higher price stickiness. This shock leads to positive comovement between inflation and consumption that lasts for a long period, in part because its highly persistent effect on inflation leads to a robust interest-rate tightening. In the appendix (Figure A.5), we show the responses to a supply shock for used cars, a shock that has a similar persistence but much lower price stickiness. In response to that shock, the positive comovement of sectoral inflation and consumption is short-lived and quickly gives rise to a negative comovement. While the shock's effects can last for a considerable time, the sectoral distributions of inflation and consumption become tight relatively quickly and hence would not be able to match the empirical regularities observed in the data.

Summary: The main results of this section are twofold. First, aggregate demand and supply shocks in a workhorse multisectoral model cannot explain the regularities of the sectoral distributions of inflation and consumption. Aggregate demand shocks lead to a positive comovement between inflation and consumption, a metric that is, on average, negative in the data, while aggregate supply shocks cannot produce the skewness and kurtosis of the distributions. The effects of sectoral supply shocks are highly heterogeneous and depend on sectoral characteristics such as price stickiness and shock persistence. Some sectoral supply shocks can match disaggregated data qualitatively, but overall, we find important quantitative differences between the model and the data that need further examination and detailed explanation. The multisectoral model is capable of matching some important elements of sectoral dynamics in the data, especially in the middle of the distributions, but it struggles to explain the details.

Is it possible to get closer to moments in the data with this class of models? This section suggests that it may be so by putting more weight on sectors such as used cars and energy and less weight on sectors such as new cars. In this context, more weight could mean higher variance and higher kurtosis of the sectoral shocks and/or more asymmetries in the input-output network. Fat-tailed shocks and asymmetric sectoral linkages may engender a larger contribution of sectoral shocks to aggregate fluctuations than in symmetric models with Gaussian shocks.

7 Conclusion

This paper examines whether multisectoral New Keynesian models can match disaggregated data on inflation and consumption. We find that in the data, the distributions of sectoral inflation and consumption growth are asymmetric and highly leptokurtic. During the full sample period, sectoral inflation exhibits negative contemporaneous comovement with consumption growth, which can be consistent with the prevalence of supply shocks over demand shocks on the whole. This negative comovement depends on the economic environment, but it appears quite robust across the historical episodes considered. The workhorse multisectoral New Keynesian model generates distributions of sectoral inflation and consumption growth that lack the asymmetry observed in the data and have a significantly lower kurtosis. Moreover, the model struggles to generate a consistently negative comovement of inflation and consumption growth. We also examine how different types of shocks in the model affect these sectoral distributions. The sectoral dynamics engendered by aggregate shocks appear to be significantly different from those observed in the data. Yet, sectoral shocks with features such as high price stickiness and low shock persistence can generate asymmetries, kurtosis, and negative inflation–consumption comovement. Our results imply that while workhorse multisectoral models achieve success among many dimensions, they may still need some improvement to better match the properties of sectoral inflation and consumption distributions.

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Appendix

A Additional Results

Table A.1: Empirical Comovement: Robustness to Weighting

	(1)	(2)	(3)	(4)
(a) Fixed Weights: Sectoral Averages over the Sample				
Slope	-0.029^{***}	-0.003	-0.065^{***}	-0.032^{***}
	(0.008)	(0.008)	(0.010)	(0.009)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,185	4,185	4,185	4,185
(b) 2021 Consumption Weights				
Slope	-0.036^{***}	-0.005	-0.072^{***}	-0.033^{***}
	(0.008)	(0.008)	(0.009)	(0.009)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,185	4,185	4,185	4,185

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: All tables and figures in the appendix are based on the authors' calculations.

Table A.2: Estimates of Price Stickiness by Sector

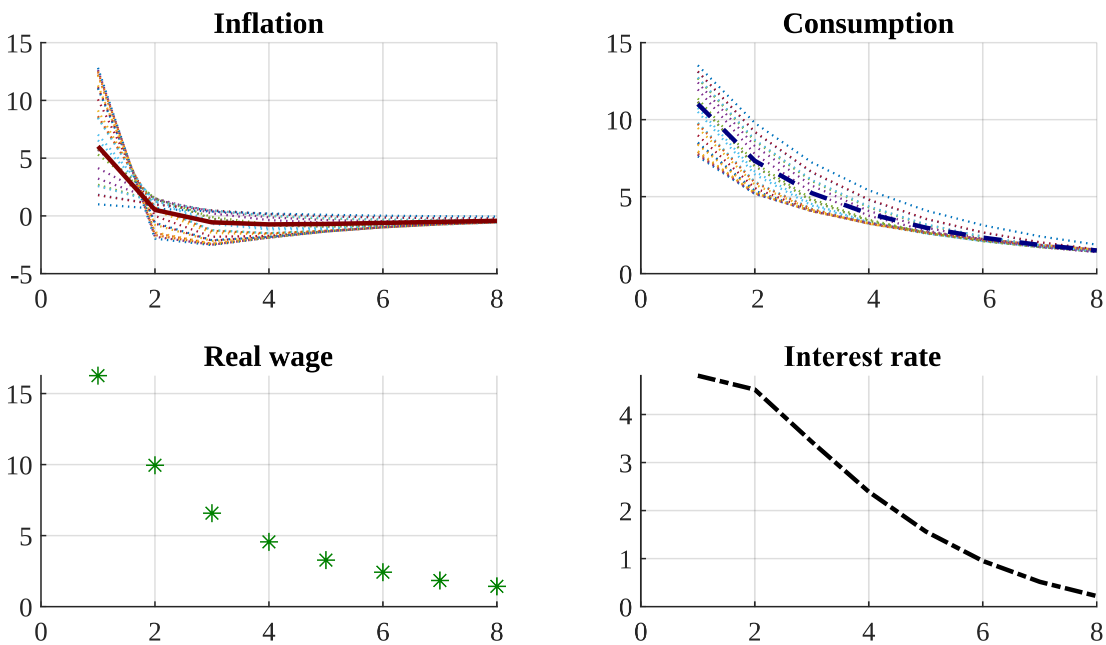
Sector	Price stickiness		
	Prior	Posterior	Weight, %
	(1)	(2)	(3)
New motor vehicles and parts	0.52	0.82	3.0
Used motor vehicles	0.12	0.17	1.6
Furnishing, appliances, tableware, tools	0.48	0.38	3.1
Video, audio, photo, information processing	0.46	0.58	2.2
Sporting goods, vehicles, recreational books, musical instruments	0.69	0.60	1.6
Other durables (jewelry, educational books, luggage, phones)	0.55	0.53	1.8
Food and nonalcoholic beverages off-premises	0.32	0.26	6.9
Alcoholic beverages off-premises	0.49	0.26	1.2
Garments	0.31	0.18	2.4
Other clothing, footwear	0.41	0.19	0.7
Gas and energy	0.12	0.67	2.4
Pharmaceuticals	0.61	0.57	3.9
Recreational items, magazines, newspapers	0.76	0.50	2.2
Personal care, household supplies	0.58	0.32	2.3
Tobacco	0.31	0.14	0.7
Housing	0.72	0.76	15.8
Utilities	0.21	0.25	2.5
Health care	0.86	0.73	16.7
Motor vehicle services	0.50	0.42	2.0
Public transportation	0.18	0.42	0.8
Recreational services	0.73	0.82	3.3
Food services	0.85	0.88	6.0
Accommodations	0.25	0.41	0.8
Financial services	0.78	0.16	8.3
Communication	0.31	0.16	1.7
Education	0.82	0.76	1.9
Other services	0.86	0.77	4.3

Table A.3: Empirical Comovement: Matching Sectoral Composition

	(1)	(2)	(3)	(4)
		(a) Equal Weights		
Slope	-0.020^{***}	0.006	-0.046^{***}	-0.012^{**}
	(0.005)	(0.004)	(0.005)	(0.005)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,030	4,030	4,030	4,030
		(b) Contemporaneous Consumption Weights		
Slope	-0.043^{***}	-0.013^{***}	-0.066^{***}	-0.029^{***}
	(0.005)	(0.004)	(0.006)	(0.005)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,030	4,030	4,030	4,030
		(c) Fixed Weights: Sectoral Averages over the Sample		
Slope	-0.029^{***}	-0.004	-0.051^{***}	-0.019^{***}
	(0.005)	(0.004)	(0.005)	(0.005)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,030	4,030	4,030	4,030
		(d) 2021 Consumption Weights		
Slope	-0.037^{***}	-0.006	-0.061^{***}	-0.022^{***}
	(0.005)	(0.004)	(0.006)	(0.005)
Category effects	N	Y	N	Y
Time effects	N	N	Y	Y
Observations	4,030	4,030	4,030	4,030

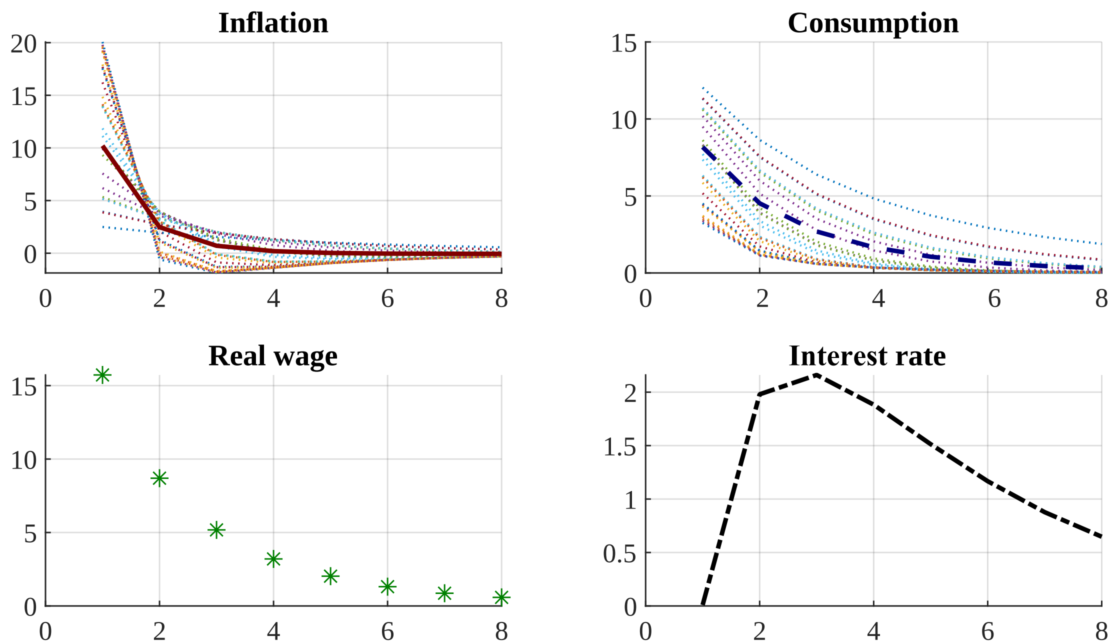
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.1: Responses to a Combination of Aggregate Demand and Aggregate Supply Shocks



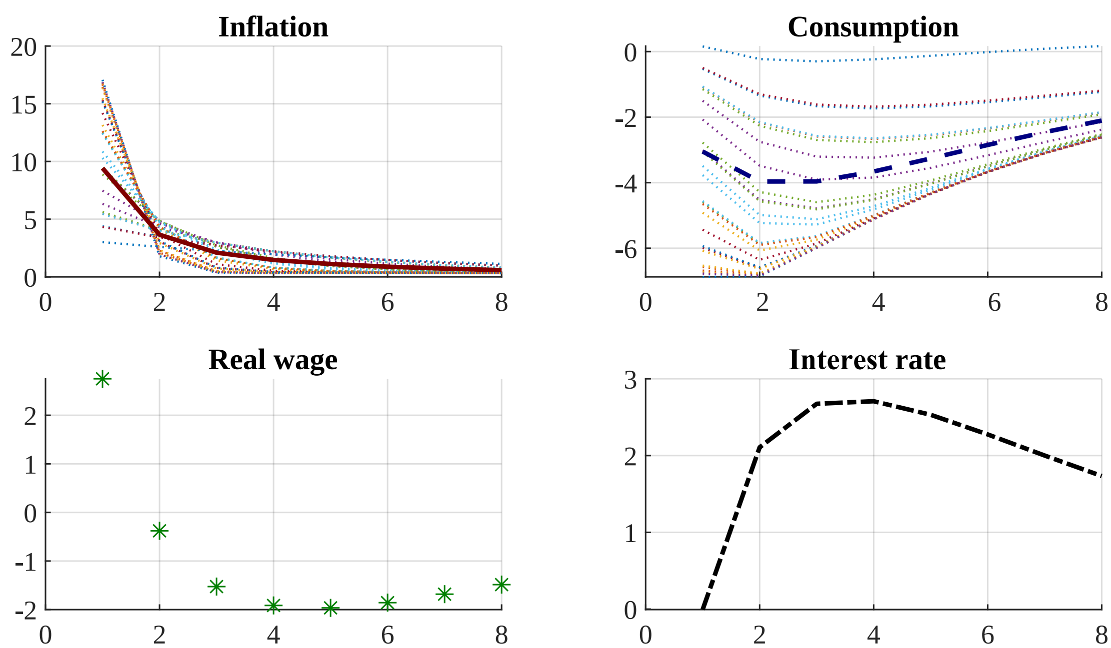
Notes: The figure shows the responses to a combination of the preference shock, Γ_t, with a half-life of two quarters and the aggregate productivity shock, A_t, with a half-life of four quarters scaled to generate a 6 percent aggregate inflation and an 11 percent consumption increase on impact.

Figure A.2: Responses to an Aggregate Demand Shock with Monetary Accommodation



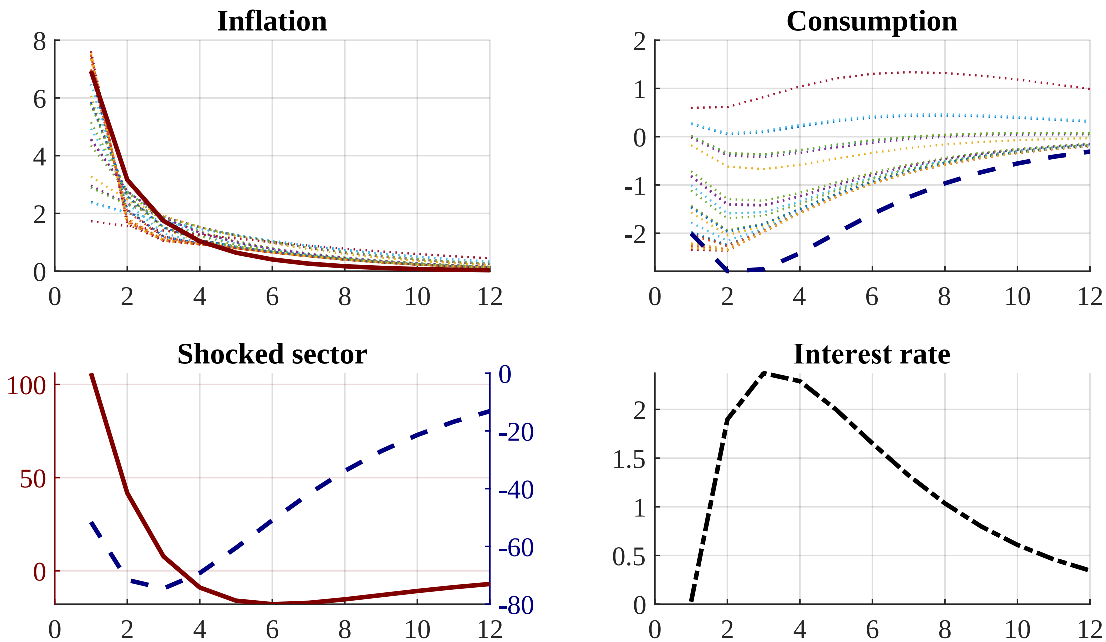
Notes: The figure shows the responses to a preference shock, Γ_t, with a half-life of two quarters of the same size as in Figure 3 with perfect monetary accommodation on impact.

Figure A.3: Responses to an Aggregate Supply Shock with Monetary Accommodation



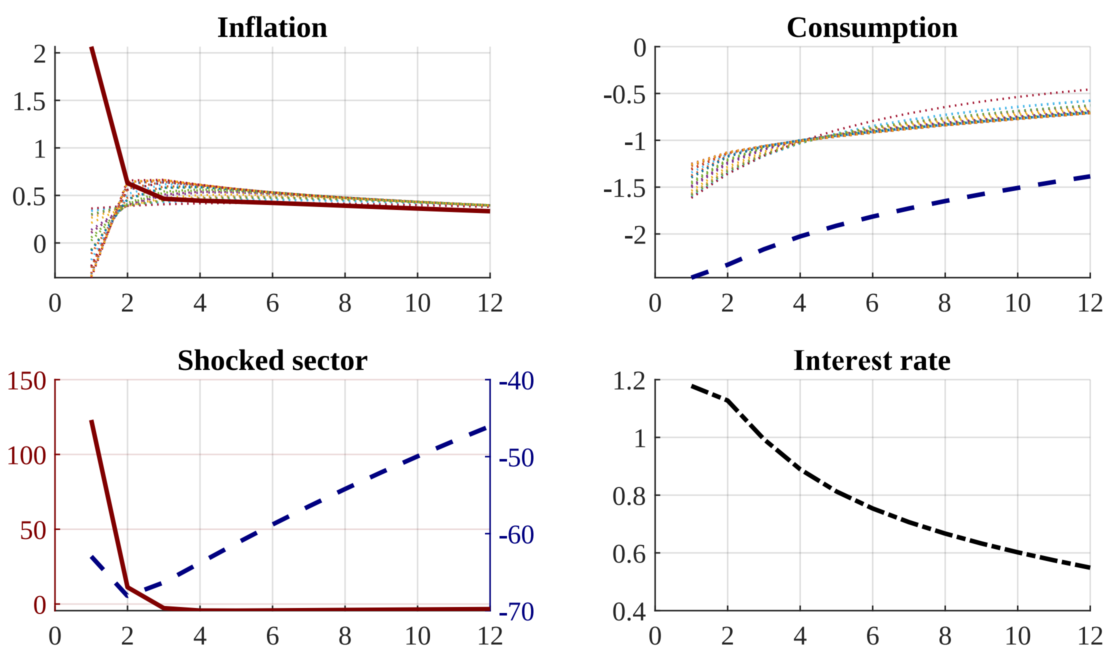
Notes: The figure shows the responses to a aggregate productivity shock, A_t, with a half-life of four quarters of the same size as in Figure 4 with perfect monetary accommodation on impact.

Figure A.4: Responses to a Supply Shock in the Energy Sector with Monetary Accommodation



Notes: The figure shows the responses to a sectoral productivity shock, $A_{k,t}$, for energy, with perfect monetary accommodation on impact. See notes to Figure 5.

Figure A.5: Responses to a Supply Shock for Used Motor Vehicles



Notes: See notes to Figure 5. The shock's persistence corresponds to a half-life of 17.0 quarters.

B Model's Equilibrium Conditions

This appendix presents equilibrium conditions for the baseline model.

B.1 Household's First-Order Conditions

The household's optimization problem results in three equilibrium conditions:

(1) stochastic Euler equation,

$$Q_{t,t+1} = \beta \frac{\Gamma_{t+1}}{\Gamma_t} \frac{C_t}{C_{t+1}} \frac{P_t}{P_{t+1}}; \tag{1}$$

(2) intratemporal condition,

$$\frac{W_{k,t}}{P_t} = \omega_k H_{k,t}^{\varphi} C_t; \tag{2}$$

(3) optimal demand,

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

$$C_{k,t}(i) = \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} C_{k,t}. \tag{4}$$

B.2 Demand for Intermediate Inputs

Firms' demand for intermediate inputs is obtained using first-order conditions for the cost-minimization problem, where prices and wages are taken as given. The resulting conditions comprise three equations:

$$Z_{k,t}(i) = \frac{\delta}{1-\delta} \frac{W_{k,t}}{P_t} H_{k,t}(i), \tag{5}$$

$$Z_{k,\ell,t}(i) = n_\ell D_{\ell,t} \left(\frac{P_{\ell,t}}{P_t} \right)^{-\eta} Z_{\ell,t}(i), \tag{6}$$

$$Z_{k,\ell,t}(i,j) = \frac{1}{n_\ell} \left(\frac{P_{\ell,t}(j)}{P_{\ell,t}} \right)^{-\theta} Z_{k,\ell,t}(i). \tag{7}$$

B.3 Profit Optimization

The first-order condition for firms' optimization problems, which determines the optimal reset price, is as follows:

$$\mathbb{E}_t \sum_{s=0}^{\infty} \alpha_k^s \left(\prod_{r=t}^{t+s-1} Q_{r,r+1} \right) \left(\frac{P_{k,t}^*}{P_{k,t+s}} \right)^{-\theta} \left(\frac{P_{k,t+s}}{P_{t+s}} \right)^{-\eta} Y_{t+s} \left(P_{k,t}^* - \frac{\theta}{\theta - 1} \mathscr{M}_{k,t+s} \right) = 0, \tag{8}$$

where

$$\mathscr{M}_{k,t+s} = A_{t+s}^{-1} A_{k,t+s}^{-1} \frac{1}{1-\delta} \left(\frac{\delta}{1-\delta} \right)^{-\delta} P_{t+s}^{\delta} W_{k,t+s}^{1-\delta}.$$

B.4 Market-Clearing Conditions

Finally, there are three types of market-clearing conditions:

(1) markets for goods,

$$Y_{k,t}(i) = C_{k,t}(i) + \sum_{\ell=1}^{K} \int_{\mathscr{I}_\ell} Z_{\ell,k,t}(j,i)\, \mathrm{d}j, \tag{9}$$

(2) labor markets,

$$H_{k,t} = \int_{\mathscr{I}_k} H_{k,t}(i)\, \mathrm{d}i, \tag{10}$$

(3) financial market,

$$B_t = 0. \tag{11}$$