# Relative Price Shocks and Inflation*

Francisco Ruge-Murcia[†] and Alexander L. Wolman[‡]

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**Abstract**

Inflation is determined by interaction between monetary policy and real factors, including shocks to supply and demand for different components of the consumption basket. We construct a 15-sector New Keynesian model with a production network and heterogeneity in price rigidity, in the volatility of sectoral shocks, and in the trend rates of productivity growth across sectors to quantify the contributions to inflation from sectoral supply and demand shocks, monetary policy shocks, and aggregate real shocks. The model is estimated by maximum likelihood on U.S. data from 1995 through 2019, when the policy regime appeared to be stable. We find that relative price shocks were major contributors to the inflation deviations from target and the inflation surge after the pandemic.

*JEL classification*: E31, E52, E58
*Key Words*: Monetary policy, production network, sectoral shocks, gasoline shocks, inflation shortfall, inflation surge, COVID-19.

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[†]Department of Economics, McGill University. Email: francisco.ruge-murcia@mcgill.ca
[‡]Federal Reserve Bank of Richmond. Email: alexander.wolman@rich.frb.org

# 1. Introduction

This paper quantifies the influence of real factors and monetary policy on U.S. inflation under the stable policy regime in place since 1995 and in specific episodes like the shortfall of inflation from target in 2012-2019 and its surge starting in 2021. By real factors, we mean not only aggregate shocks, but the sectoral supply and demand shocks that drive relative price changes across consumption categories. Following Reis and Watson (2010) we refer to these shocks as relative price shocks and provide model-based evidence that motivates this label: sectoral shocks lead to large movements in the relative price of goods produced by the sector affected by the shock, and smaller responses in the relative price of other goods. The analysis is based on an estimated multi-sector New Keynesian model with 15 consumption categories from the Personal Consumption Expenditures (PCE) price index. The model features a production network with input-output (I-O) interactions, and heterogeneity in price rigidity, in the volatility of sectoral productivity and demand shocks, and in the trend rates of productivity growth across sectors.

Monetary policy in our model could in theory offset real factors and perfectly stabilize inflation, but in practice we observe equilibrium fluctuations in inflation. This motivates our objective of quantifying the relative contributions of monetary policy and relative price shocks, along with other shocks, to the behavior of U.S. inflation. The issue is important because central banks are accountable to the public and called to explain sustained deviations from stated price-stability policies. Providing such explanations requires an economic model that can causally establish to what extent inflation deviations arise from shocks outside the control of the central bank or from monetary policy itself. This is the task we undertake here.[1]

Our paper makes three contributions to the literature. The first contribution involves the basic analysis of inflation and relative prices. We construct and estimate a model that addresses the empirical observations that the mean and standard deviation of sectoral price changes are different across consumption categories. The model accounts for the first observation by allowing different rates of productivity growth across categories, and it accounts for the second observation by postulating different shock volatility and price adjustment costs across categories. The production of goods in each category involves other goods as inputs. However, compared with most of the previous literature that studies the transmission of monetary policy in production networks (for instance, Bouakez, Cardia, and Ruge-Murcia (2009), Pasten, Schoenle, and Weber (2024), Rubbo (2023), and Afrouzi and Bhattarai (2025)), we allow for long-run growth at the sectoral level and derive the balanced growth path of the economy. We show that this extension is empirically important because sectoral price indexes have different trends and aggregate inflation is, by construction, a weighted average of sectoral rates of price changes.[2]

[1] The Federal Reserve Act requires the Federal Reserve Board to submit semi-annually a written *Monetary Policy Report* to Congress with discussions on "the conduct of monetary policy and economic developments and prospects for the future." The possible causes of the inflation surge were amply discussed in the press and in speeches by central bankers.

[2] Related work by Wolman (2011) studies optimal inflation in an economy with trending relative prices but without input-

We estimate the model on monthly data from 1995-2019 by maximum likelihood and decompose inflation into the contribution of monetary policy shocks, aggregate productivity and demand shocks, and shocks to productivity and demand in each of the consumption categories. Over the sample, inflation was low and stable, but nonetheless exhibited substantial month-to-month volatility. One way we evaluate the model fit is through its ability to match the historical relationship between the monthly inflation rate and the distribution of relative price changes. From 1995 to 2019 there was a negative relationship between the monthly inflation rate and the share of consumption expenditures exhibiting relative price increases. Our model reproduces that relationship and thus—within the context of the model—we can explain what causes the relationship to arise. Previous literature that studies the effect of sectoral shocks on inflation generally focuses on the distinction between core and overall inflation. There are at least two drawbacks to this approach. First, consumers care about overall inflation. Second, while food and especially energy are the source of most large relative price shocks, they are not the only source.

The second contribution is to decompose the shortfall of inflation from target in the 2012-2019 period. According to this decomposition, which uses the smoothed estimates of the structural shocks of the model, the largest contributors to the cumulative shortfall of the price level from the 2% trend implied by the Federal Reserve's target were relative price shocks, notably to gasoline and energy goods. A limited, but consistent, part of the inflation shortfall is attributable to monetary policy and, hence, we conclude that U.S. monetary policy was mildly restrictive during this period. Note that we describe a causal effect. Without a model, when one analyzes inflation and category price changes, it is only possible to describe the extent to which the price change in a particular category accounts for inflation.[3] Instead, working with an estimated structural model, we are able construct measures of the extent to which particular shocks caused the inflation shortfall.

The third contribution is an out-of-sample analysis of the high inflation episode that began around the spring of 2021 during the pandemic. As with the inflation shortfall, we decompose inflation into contributions from each of the shocks. Here, however, the smoothed estimates of the model's shocks use out-of-sample data, as our estimation sample ends in January, 2020. In conducting local analysis around the model's (trending) steady state, we assume that the same policy rule remained in place during this high inflation episode and that the economy remained in the rational expectations equilibrium characterized by that local analysis. Under these assumptions, we find that monetary policy played a limited role in the inflation surge. Instead aggregate demand shocks and relative price shocks account for most of the inflation surge. In contrast, monetary policy (along with aggregate and sectoral demand shocks) appear to be the main drivers of the persistent above-target inflation in 2024-2025.

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output interactions.

[3]Exercises of this nature are standard in the monetary policy reports produced by the Federal Reserve, the Bank of England, and other central banks. While mechanically breaking down inflation into its components can be helpful, this exercise does not allow one to evaluate the role of monetary policy or the relative contribution of sectoral supply and demand shocks in generating the current inflation rate.

Related work that brings some theory to bear on the relationship between relative prices and inflation include Ball and Mankiw (1995), who note that there is an empirical relationship between the level of inflation and measures of asymmetry in the distribution of relative price changes; Balke and Wynne (2000), who argue that the pattern identifed by Ball and Mankiw can be explained without relying on sticky prices and assume instead completely flexible prices; and Smets, Tielens, and Hove (2019), who focus on the role of production bottlenecks. Another related literature studies how the Phillips curve can appear to flatten when policy is conducted optimally so as to stabilize inflation. McLeay and Tenreyro (2020) is a leading example of that research. While we model policy as following an exogenous rule rather than being determined as the solution to an optimization problem, in practice the Federal Reserve did stabilize inflation from 1995-2019 and this is embodied in our estimated model. We emphasize that the remaining small fluctuations in inflation tend to be associated with variation in relative prices across categories, as opposed to Phillips curve channels. Borio, Disyatat, Xia, and Zakrajsek (2021) also emphasize that in a stable monetary policy regime, sector-specific factors can play a major role in driving inflation.

The paper proceeds as follows. Section 2 describes the model and its balanced growth path. Section 3 describes our empirical approach and reports parameter estimates. Section 4 presents the basic analysis of inflation and relative price shocks. Section 5 focuses on three inflation episodes. Section 7 concludes. An appendix explains our filtering strategy for extracting the contribution of each shock starting from the state-space representation of the model solution and taking into account the indirect effect of the shocks via the endogenous state variables.

# 2. The Model

The economy consists of a representative household, continua of firms in a finite number of sectors, and a monetary authority. Within each sector, firms are monopolistic competitors and produce differentiated goods used for final consumption by households and as materials input by other firms. There are exogenous shocks to aggregate and sectoral productivity, aggregate and sectoral demand, and monetary policy.

## 2.1 Households

The representative household maximizes

$$E_\tau \sum_{t=\tau}^{\infty} \beta^{t-\tau} \left( \ln C_t + \varphi \frac{(1-N_t)^{1-\chi}}{1-\chi} \right), \tag{1}$$

where $E_\tau$ denotes the conditional expectation as of time $\tau$, $\beta \in (0,1)$ is the discount factor, $C_t$ is consumption, $N_t$ is hours worked, and $\varphi$ and $\chi$ are positive preference parameters. Consumption is a Cobb-Douglas aggregate of goods produced in different sectors $s = 1, 2, \ldots, S$,

$$C_t = \prod_{s=1}^{S} (\xi_s)^{-\xi_s} (c_{s,t} - u_t - u_{s,t})^{\xi_s}, \tag{2}$$

where $\xi_s \in (0,1)$, $\sum_{s=1}^{S} \xi_s = 1$, $c_{s,t}$ is consumption of goods produced in sector $s$, and $u_t$ and $u_{s,t}$ respectively denote aggregate and sectoral preference shocks. These shocks resemble a subsistence level of consumption for any good in sector $s$ and will act as demand shocks. Within each sector, there is a continuum $[0,1]$ of monopolistically-competitive firms that each produce a differentiated good. The household's preferences for these goods are represented by the CES aggregator

$$c_{s,t} = \left( \int_0^1 (c_{s,t}(i))^{(\theta-1)/\theta} di \right)^{\theta/(\theta-1)}, \tag{3}$$

where $c_{s,t}(i)$ is consumption of the good produced by firm $i$ in sector $s$ and $\theta > 1$ is the elasticity of substitution between goods produced in the same sector.

The household's time endowment is normalized to be one. Hours worked is the sum of hours worked in all firms in all sectors,

$$N_t = \sum_{s=1}^{S} \int_0^1 n_{s,t}(i) di, \tag{4}$$

where $n_{s,t}(i)$ is hours worked in firm $i$ in sector $s$. Labor is perfectly mobile across firms and sectors and, consequently, wages will be the same in equilibrium. In every period, the household faces the budget constraint,

$$P_t C_t + B_t \leq P_t w_t N_t + R_{t-1} B_{t-1} + D_t, \tag{5}$$

where $P_t$ is the aggregate price index, $B_t$ is nominal bonds, $w_t$ is the real wage, $R_t$ is the gross nominal interest rate, and $D_t$ are dividends.

The solution to the household's maximization problem shows that the optimal labor supply satisfies

$$\frac{\varphi (1 - N_t)^{-\chi}}{C_t^{-1}} = w_t, \tag{6}$$

meaning that the marginal rate of substitution between leisure and consumption equals the real wage. Optimal total consumption satisfies the intertemporal Euler equation,

$$C_t^{-1} = \beta R_t E_t \left( C_{t+1}^{-1} / \pi_{t+1} \right), \tag{7}$$

where $\pi_{t+1} = P_{t+1}/P_t$ is the gross inflation rate. Optimal consumption of the sectoral composite good is

$$c_{s,t} = \xi_s \frac{P_t}{P_{s,t}} C_t + u_t + u_{s,t}, \tag{8}$$

where

$$P_t = \prod_{s=1}^{S} P_{s,t}^{\xi_s} \tag{9}$$

is the counterpart of the Personal Consumption Expenditure (PCE) price index in our model. Optimal consumption of the individual differentiated good is

$$c_{s,t}(i) = \left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-\theta}\left(\xi_s \frac{P_t}{P_{s,t}} C_t + u_t + u_{s,t}\right), \tag{10}$$

where

$$P_{s,t} = \left(\int_0^1 P_{s,t}(i)^{1-\theta} di\right)^{1/(1-\theta)}. \tag{11}$$

is a sectoral consumer price index. In equilibrium, where $P_{s,t}(i) = P_{s,t}$, demand shocks will disturb the sectoral consumption shares so that they are not constant despite the assumption of a Cobb-Douglas aggregator in (2).

## 2.2 Firms

Firm $i \in (0,1)$ in sector $s$ produces output, $y_{s,t}(i)$, using the decreasing returns to scale technology,[4]

$$y_{s,t}(i) = (e^{z_t} e^{z_{s,t}} (n_{s,t}(i))^{\alpha} (M_{s,t}(i))^{1-\alpha})^{\nu}, \tag{12}$$

where $e^{z_t}$ and $e^{z_{s,t}}$ are, respectively, aggregate and sectoral productivity factors, $n_{s,t}(i)$ is labor input, $M_{s,t}(i)$ is materials, and $\alpha, \nu \in (0,1)$ are parameters. In the special case where $\nu \to 1$, the production function (12) is constant returns to scale. Labor is completely mobile across firms and sectors. Materials input used by firm $i$ in sector $s$ is a Cobb-Douglas aggregate of intermediate goods produced in different sectors, $m^j_{s,t}(i)$, for $j = 1, 2, \ldots, S$,

$$M_{s,t}(i) = \prod_{j=1}^{S} \left(\kappa^j_s\right)^{-\kappa^j_s} \left(m^j_{s,t}(i)\right)^{\kappa^j_s}, \tag{13}$$

where $\kappa^j_s \in (0,1)$ are weights such that $\sum_{j=1}^{S} \kappa^j_s = 1$, and $m^j_{s,t}(i)$ is the quantity purchased from firms in sector $j$. Note that the weights depend only on the sector and not on the firm. Hence, all firms in the same sector use the same combination of materials to produce their output and, thus, sectoral data from the U.S. Input-Output accounts can be used to calibrate the values of $\kappa^j_s$.

The quantity of intermediate goods purchased from firms in sector $j$ is given by the CES aggregator,

$$m^j_{s,t}(i) = \left(\int \left(m^j_{s,t}(i,l)\right)^{(\theta-1)/\theta} dl\right)^{\theta/(\theta-1)}, \tag{14}$$

where $m^j_{s,t}(i,l)$ is the quantity that firm $i$ in sector $s$ purchases from firm $l$ in sector $j$. The elasticity of substitution between intermediate goods produced in the same sector ($\theta$) is the same as in the consumption aggregator (3). Thus, the markup in the market for intermediate goods will be the same as in the market for final goods and, hence, the price of the good will be the same regardless of its final use.

[4] Decreasing returns is important for our analysis because it allows demand shocks to affect relative prices. Under constant returns to scale and in the baseline case where prices are flexible, relative prices are equal to the inverse of relative sectoral productivity and invariant to demand shocks.

Each firm incurs a price-adjustment cost which is assumed to be quadratic in the size of the nominal price adjustment (Rotemberg (1982)). The per-unit cost is

$$\Phi_{s,t}(i) = \Phi\left(P_{s,t}(i), P_{s,t-1}(i)\right) = \frac{\phi_s}{2}\left(\frac{P_{s,t}(i)}{\pi_s P_{s,t-1}(i)} - 1\right)^2, \tag{15}$$

where $\phi_s \geq 0$ and $\pi_s$ is the steady-state gross rate of sectoral price changes. This specification implies complete indexation to the trend sectoral rate of price changes.[5] The adjustment cost is incurred in units of (own) sectoral output, $y_{s,t}$. This means that 1) the firm implicitly demands the sectoral good $s$ for the purpose of covering its price adjustment costs (see below), and 2) the total nominal adjustment cost for firm $i$ in sector $s$ is $P_{s,t}\Phi_{s,t}(i)y_{s,t}$.

The firm chooses output, inputs, and the price of its good to maximize profits. Revenue are sales to consumers and to firms in all sectors. Costs comprise the the costs of labor, materials, and price adjustment. The optimal choice of labor and the material composite, $M_{s,t}(i)$, equates their marginal product and price,

$$W_t = \alpha\nu\Omega_{s,t}(i)\left(e^{z_t}e^{z_{s,t}}\right)^{\alpha\nu}\left(\frac{n_{s,t}(i)}{M_{s,t}(i)}\right)^{(\alpha-1)\nu}\left(n_{s,t}(i)\right)^{\nu-1} \tag{16}$$

and

$$Q_{s,t} = (1-\alpha)\,\nu\Omega_{s,t}(i)\left(e^{z_t}e^{z_{s,t}}\right)^{\alpha\nu}\left(\frac{n_{s,t}(i)}{M_{s,t}(i)}\right)^{\alpha\nu}\left(M_{s,t}(i)\right)^{\nu-1}, \tag{17}$$

where $W_t$ is the nominal wage, $\Omega_{s,t}(i)$ is the nominal marginal cost, and $Q_{s,t}$ is the price of $M_{s,t}(i)$. These equations imply that with decreasing returns to scale (i.e., $\nu \in (0,1)$), the marginal cost is firm-specific. That is, taking as given the wage, the price of the sectoral intermediate input, and the sectoral level of productivity, the firm's marginal cost is increasing in the firm's inputs.[6] Moreover, one can write

$$\Omega_{s,t}(i) = \left(\frac{1}{\alpha\nu}\right)\left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha} e^{-\alpha(z_t+z_{s,t})}W_t^{\alpha}\left(Q_{s,t}\right)^{1-\alpha} y_{s,t}(i)^{(1-\nu)/\nu}, \tag{18}$$

which shows that the elasticity of the firm's marginal cost with respect to its output is $(1-\nu)/\nu) > 0$. Thus, the firm's marginal cost is increasing in the firm's output. In contrast, with constant returns to scale (i.e., $\nu = 1$), the marginal cost is only a function of input prices.

The optimal choice of the composite sectoral good, $m^j_{s,t}(i)$, and the good produced by firm $l$ in sector $j$ are

$$m^j_{s,t}(i) = \kappa^j_s\left(\frac{P_{j,t}}{Q_{s,t}}\right)^{-1} M_{s,t}(i), \tag{19}$$

and

$$m^j_{s,t}(i,l) = \left(\frac{P_{j,t}(l)}{P_{j,t}}\right)^{-\theta} m^j_{s,t}(i). \tag{20}$$

[5]In an earlier version of this paper (Ruge-Murcia and Wolman (2022)), we assumed indexation to a convex combination of the sectoral rate of price changes and the aggregate inflation rate. However, we found that the coefficients of this combination were poorly identified. The specification we adopt here has the advantage that the adjustment costs are zero in the deterministic steady state.

[6]This result follows from the observations that 1) with a unit elasticity of substitution, $n_{s,t}(i)/M_{s,t}(i)$ depends only on the ratio of input prices, but 2) the above equations contain an additional input term with exponent $\nu - 1 < 0$. Thus, everything else equal, an input increase involves an increase in marginal cost.

Finally, the demand for own-sector goods to cover price adjustment costs is

$$\Phi_{s,t}(i,k) = \left(\frac{P_{s,t}(k)}{P_{s,t}}\right)^{-\theta} \Phi_{s,t}(i), \tag{21}$$

where $k$ denotes a firm in sector $s$.

The optimal price choice takes as given the total demand. Total demand comprises the demand from households (as final goods), from all firms in all sectors (as intermediate inputs), and from firms in the own sector to cover their price adjustment costs. This optimal choice satisfies

$$\begin{aligned}
0 = {} & (1-\theta)\left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-\theta} y_{s,t} + \frac{\theta}{\nu}\left(e^{z_t}e^{z_{s,t}}\right)^{-\alpha}\frac{W_t}{P_{s,t}\,(i)}\left(\frac{1-\alpha}{\alpha}\frac{W_t}{Q_{s,t}}\right)^{\alpha-1}\left(\left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-\theta} y_{s,t}\right)^{1/\nu} \\
& + \frac{\theta}{\nu}\left(e^{z_t}e^{z_{s,t}}\right)^{-\alpha}\frac{Q_{s,t}}{P_{s,t}\,(i)}\left(\frac{1-\alpha}{\alpha}\frac{W_t}{Q_{s,t}}\right)^{\alpha}\left(\left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-\theta} y_{s,t}\right)^{1/\nu} \\
& - \phi_s \frac{P_{s,t}}{\pi_s P_{s,t-1}(i)}\left(\frac{P_{s,t}(i)}{\pi_s P_{s,t-1}(i)} - 1\right)\left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-\theta} y_{s,t} + \theta\frac{\phi_s}{2}\left(\frac{P_{s,t}(i)}{\pi_s P_{s,t-1}(i)} - 1\right)^2\left(\frac{P_{s,t}(i)}{P_{s,t}}\right)^{-(1+\theta)} y_{s,t} \\
& + \phi_s E_t\left(\frac{1}{R_{t+1}\pi_s}\left(\frac{P_{s,t+1}(i)}{P_{s,t}(i)^2}\right)^2\left(\frac{P_{s,t+1}(i)}{\pi_s P_{s,t}(i)} - 1\right)\left(\frac{P_{s,t+1}(i)}{P_{s,t+1}}\right)^{-\theta} y_{s,t+1}\right).
\end{aligned} \tag{22}$$

Compared with the standard pricing equation in the literature based on constant returns to scale, (22) makes clear that when the firm changes its price, thereby changing the input quantities demanded, it also changes its marginal cost.

## 2.3 Shock Processes

Sectoral productivity follows a random walk with drift,

$$z_{s,t} = (1-\rho_s)\mu_s + z_{s,t-1} + \rho_s(z_{s,t-1} - z_{s,t-2}) + \epsilon_{s,t}, \tag{23}$$

where $\mu_s$ is the drift, $\rho_s \in (-1,1)$, and $\epsilon_{s,t}$ is an independently and identically distributed innovation drawn from a Normal distribution with mean zero and variance $\sigma^2_{z,s}$. We allow for different drifts across sectors so that our model can account for observed trends in relative prices. To see that trends in relative prices are a key feature of the data, consider Figure 1, which plots the price indexes for selected PCE consumption categories, along with the PCE index, for the period 1995M1 to 2020M1. The figure shows that 1) the rate of price changes across consumption categories is systematically different across categories and, consequently, 2) relative prices (i.e., relative to the PCE) feature long-run trends. Our model will account for these features as arising from long-run, stochastic trends in productivity along the balanced growth path and taking into account the network structure of the economy.[7]

[7]For a version of this model where productivity trends are deterministic functions of time, see the working paper version of this article (Ruge-Murcia and Wolman (2022)).

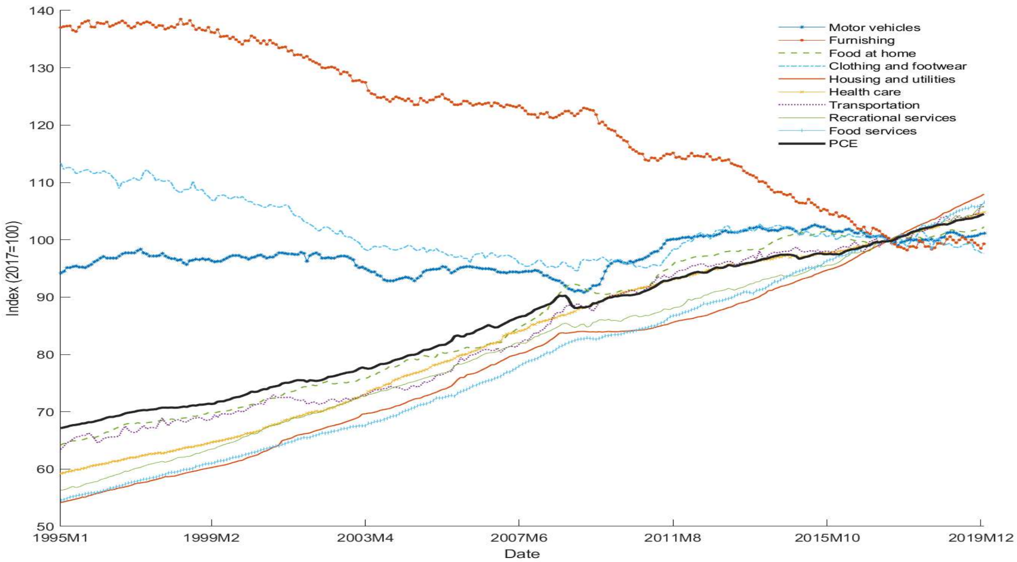


Figure 1: Trends in relative prices for selected PCE consumption categories.

Aggregate productivity follows the process,

$$z_t = (1-\rho)\mu + z_{t-1} + \rho(z_{t-1} - z_{t-2}) + \epsilon_t, \tag{24}$$

where $\mu$ is drift, $\rho \in (-1, 1)$, and $\varepsilon_t$ is an i.i.d. innovation drawn from a Normal distribution with mean zero and variance $\sigma_z^2$. Without loss of generality, we normalize $\mu = 0$, but allow for nonzero $\mu_s$. Results would be unchanged if we were to allow an non-zero stochastic trend in aggregate productivity—for instance, equal to the growth rate of aggregate output and with sectoral trends adjusted accordingly. The maintained assumption in this paper is that the trends in relative prices observed in the data are driven by productivity growth differentials across consumption categories. Since productivity shocks have (stochastic) trends, demand shocks must also have particular trends because otherwise they will either become irrelevant or else will come to dominate consumption along the growth path. Thus, we assume

$$u_t = e^{az_t}\vartheta_t, \tag{25}$$

$$u_{s,t} = e^{b_s z_{s,t}}\vartheta_{s,t}, \tag{26}$$

where $a$ and $b_s$ are constant coefficients and $\vartheta_t$ and $\vartheta_{s,t}$ are disturbance terms. The disturbance terms follow the stationary processes

$$\vartheta_t = \varrho\vartheta_{t-1} + \varepsilon_t, \tag{27}$$

$$\vartheta_{s,t} = \varrho_s\vartheta_{s,t-1} + \varepsilon_{s,t}. \tag{28}$$

where $\varrho, \varrho_{s,t} \in (-1, 1)$ and $\varepsilon_t$ and $\varepsilon_{s,t}$ are i.i.d. innovations drawn from Normal distributions with mean zero and variances $\sigma^2_\vartheta$ and $\sigma^2_{\vartheta,s}$, respectively. Intuitively, we are assuming that productivity and demand shocks are co-integrated and grow proportionally to each other. The parameters $a$ and $b_s$ are the coefficients of their co-integrating vector and the disturbance terms represent temporary deviations from their long-run relation. One can show that the unique values of $a$ and $b_s$ in (25) and (26) that are consistent with a balanced growth path are

$$a = \alpha\nu/(1 - \nu(1 - \alpha)),$$
$$b_s = \nu\alpha L_s.$$

## 2.4 Monetary Policy

The monetary authority sets the nominal interest rate following the rule,

$$\ln(R_t/R) = \delta \ln(R_{t-1}/R) + (1 - \delta)\left(\lambda_\pi (\pi_t - \pi) + \lambda_y (\ln(v_t) - \ln(v_{t-1}) - \gamma_v)\right) + \eta_t. \tag{29}$$

where $v_t$ is real value added, $\delta \in (-1, 1)$, $\lambda_\pi$, and $\lambda_y$ are policy parameters that respectively represent responsiveness to the lagged interest rate, inflation, and the deviation of the growth rate of value added from its steady state (denoted $\gamma_v$), $\pi$ is the inflation target expressed in gross terms, $R$ is the nominal interest rate in the steady state, and $\eta_t$ is a disturbance that represents unexplained movements in the interest rate. This disturbance is assumed to be i.i.d. and drawn from a Normal distribution with mean zero and variance $\sigma^2_\eta$.

The definition of value added in (29) follows the National Income and Product Accounts (NIPA), meaning that value added is gross output minus expenditures on intermediate goods from all sectors,

$$V_t = \sum_{s=1}^{S} \left(P_{s,t} y_{j,t} - Q_{s,t} M_{j,t}\right). \tag{30}$$

Then, real value added measured in terms of units of consumption goods is

$$v_t = V_t/P_t. \tag{31}$$

## 2.5 Equilibrium and Market Clearing

The equilibrium of the model is symmetric within sectors and asymmetric across sectors. That is, all firms within a sector are identical and make exactly the same choices (labor input, price, and output), but firms in different sectors make different choices. In particular, firms in different sectors choose different prices and, hence, rates of price change will differ across sectors.

Since $P_{s,t}(i) = P_{s,t}$ for all $t$, we drop the firm-specific $i$ subscripts in (22) to obtain the sectoral Phillips curve,

$$\frac{P_{s,t}}{P_t} = \left(\frac{\theta}{\theta-1}\right)\left(\frac{\Omega_{s,t}}{P_t}\right) - \left(\frac{\phi_s}{\theta-1}\right)\frac{P_{s,t}}{P_t}\frac{\pi_{s,t}}{\pi_s}\left(\frac{\pi_{s,t}}{\pi_s}-1\right)$$
$$+\left(\frac{\theta}{\theta-1}\right)\frac{\phi_s}{2}\frac{P_{s,t}}{P_t}\left(\frac{\pi_{s,t}}{\pi_s}-1\right)^2 + \left(\frac{\phi_s}{\theta-1}\right)E_t\left(\frac{\pi_{s,t+1}}{R_{t+1}}\frac{\pi_{s,t+1}}{\pi_s}\frac{P_{s,t}}{P_t}\left(\frac{\pi_{s,t+1}}{\pi_s}-1\right)\frac{y_{s,t+1}}{y_{s,t}}\right).$$

where $\pi_{s,t} = P_{s,t}/P_{s,t-1}$. As in previous literature that derives sectoral Phillips curves in multi-sector economies (e.g., Imbs, Jondeau, and Pelgrin (2011)), the slope of the linearized Phillips curve is heterogeneous across sectors, in our case as a result of heterogeneity in price rigidity.

Goods market clearing in each sector implies that sectoral gross output equals final consumption by households, intermediate consumption by firms in all sectors, and price adjustment costs (which are incurred in terms of sector $s$ output). That is,

$$y_{s,t} = c_{s,t} + \sum_{j=1}^{S} m_{j,t}^{s} + \Phi_{s,t} y_{s,t}, \tag{32}$$

for $s = 1, ..., S$. Finally, labor market clearing for the economy as a whole is,

$$N_t = \sum_{s=1}^{S} n_{s,t}. \tag{33}$$

## 2.6 Balanced Growth Path

An important contribution of this paper is that it incorporates differential rates of productivity growth across sectors into a production network and derives their implications for inflation and monetary policy.[8]

Using the production function and the properties of the productivity shocks write

$$\left(\frac{y_{s,t}}{y_{s,t-1}}\right)^{1/\nu} = e^{\alpha\mu_s}\left(\frac{M_{s,t}}{M_{s,t-1}}\right)^{1-\alpha} = e^{\alpha\mu_s}\left(\prod_{j=1}^{S}\left(\frac{m_{s,t}^{j}}{m_{s,t-1}^{j}}\right)^{\kappa_j^j}\right)^{1-\alpha}. \tag{34}$$

Thus, along the balanced growth path, the growth rate of the material input $m_{s,t}^{j}$ is the same as the growth rate of sectoral output. Denoting the former by $\gamma_j$ and the latter by $\gamma_s$, write

$$e^{\gamma_s/\nu} = e^{\alpha\mu_s}\left(\prod_{j=1}^{S} e^{\gamma_j \kappa_s^j}\right)^{1-\alpha},$$

which implies

$$\gamma_s = \nu\left(\alpha\mu_s + (1-\alpha)\sum_{j=1}^{S}\kappa_s^j\gamma_j\right), \tag{35}$$

[8]The full derivation of the balanced growth path is available in a technical appendix available from the authors upon request. In this section, we focus on the most relevant variables for the subsequent empirical analysis.

for $s = 1, 2, ..., S$. Thus, sectoral output growth is a convex combination of the exogenous productivity growth and the endogenous growth of materials input, and proportional to the extent of decreasing returns to scale. Along the balanced growth path, sectoral output growth is the same as sectoral consumption growth. In vector notation,

$$\begin{bmatrix} \gamma_1 \\ \gamma_2 \\ ... \\ \gamma_S \end{bmatrix} = \alpha\nu \begin{bmatrix} \mu_1 \\ \mu_2 \\ ... \\ \mu_S \end{bmatrix} + \nu\left(1-\alpha\right) \begin{bmatrix} \kappa_1^1 & \kappa_1^2 & . & . \\ \kappa_2^1 & . & . & . \\ . & . & . & . \\ . & . & . & \kappa_S^S \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ ... \\ \gamma_S \end{bmatrix}, \tag{36}$$

and solving explicitly for sectoral output growth,

$$\Gamma = \alpha\nu \left(I - \nu\left(1-\alpha\right) K\right)^{-1} \Upsilon, \tag{37}$$

where $I$ is an $S \times S$ identity matrix, $\Gamma = [\gamma_1\ \gamma_2\ ...\ \gamma_S]'$ and $\Upsilon = [\mu_1\ \mu_2\ ...\ \mu_S]'$ are $S \times 1$ column vectors, and the $S \times S$ matrix,

$$K = \begin{bmatrix} \kappa_1^1 & \kappa_1^2 & . & . \\ \kappa_2^1 & . & . & . \\ . & . & . & . \\ . & . & . & \kappa_S^S \end{bmatrix},$$

is the model counterpart of the an input-output matrix with rows denoting the consuming sector and columns denoting the producing sector.

The matrix $\left(I - \nu\left(1-\alpha\right) K\right)$ in (37) is the Leontief matrix with $\nu\left(1-\alpha\right) \in (0,1)$ being an adjustment factor. As in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), the adjustment factor is proportional to the share of intermediate inputs in production, but in their paper the coefficient of proportionality is 1 because they assume constant returns to scale $(\nu = 1)$ , while in this paper the coefficient is less than 1 because our model features decreasing returns to scale. Denote the inverse of the Leontief matrix by

$$L = \left(I - \nu\left(1-\alpha\right) K\right)^{-1}, \tag{38}$$

and note that the individual sectoral output growth rates are linear combinations of the sectoral productivity growth rates,

$$\gamma_s = \alpha\nu L_s \Upsilon, \tag{39}$$

where $L_s$ denotes the $sth$ row of $L$. In special case where there are no input-output interactions and all materials used by sector $s$ are produced in sector $s$, $K$ is an identity matrix and the growth rate of sector $s$ is $\alpha\nu/(1-(\nu(1-\alpha)))\mu_s$. That is, the growth rate of sector $s$ depends only on its own productivity growth. Instead, with input-output interactions, the growth rate of $s$ depends on the productivity growth of the producers of its material inputs in a manner determined by the production network.

The definition of the consumption aggregator implies that the growth rate of consumption along the balanced path is

$$\gamma_C = \sum_{s=1}^{S} \xi_s \gamma_s = \xi' \Gamma, \tag{40}$$

where $\xi = [\xi_1 \; \xi_2 \; ... \; \xi_S]'$. That is, the growth rate of consumption is the weighted average of the growth rates of sectoral output with weights given by their respective consumption shares. Likewise, the definition of the aggregate price index implies that aggregate inflation along the balanced path is the weighted average of the rates of sectoral prices changes,

$$\pi_t = \sum_{s=1}^{S} \xi_s \pi_{s,t}. \tag{41}$$

In line with notion that the price index is a consumption price index (like the PCE), the weights are the respective consumption expenditure shares.

Finally, after some algebra one can show that the trend growth (or decline) in sectoral relative prices is determined entirely by a real factor, namely sectoral relative productivity growth:

$$\pi_{s,t} - \pi_t = \alpha\nu \left(\xi' L - L_s\right) \Upsilon. \tag{42}$$

In order to shed some light on this relation, consider the case with no input-output interactions where $K$ is an identity matrix. In that case,

$$\pi_{s,t} - \pi_t = \left(\frac{\alpha\nu}{1-\nu(1-\alpha)}\right) \left(\sum_{j=1}^{S} \xi_j \mu_j - \mu_s\right). \tag{43}$$

Thus, if productivity growth in sector $s$ is higher than that of the economy as a whole, the sector will feature a rate of sectoral price growth below the aggregate inflation rate and, thus, a decreasing relative price. In the international trade literature, this mechanism underpins the celebrated Balassa-Samuelson effect whereby different rates of productivity growth in the tradable good sector compared with the non-tradable good sector can induce a trend in the real exchange rate (see Balassa (1964) and Samuelson (1964))). We stress that while sectoral relative prices can move around temporarily because of monetary policy shocks (and other shocks, of course), the trend in relative prices is invariant to monetary policy and to parameters representing price stickiness.

Ngai and Pissarides (2007) study balanced growth in multi-sector economies with structural change. For a model without materials, they find that the rate of change of the relative price of two goods is equal to the difference between the growth rates of their total factor productivity (see their Proposition 1 in p. 432). This result would allow a researcher to make inferences about the relative productivity growth in two sectors based on the rate of change of their relative price. However, for the case with materials, (42) implies that for any two sectors $s$ and $j$,

$$\pi_{s,t} - \pi_{j,t} = \alpha\nu \left(L_j - L_s\right) \Upsilon. \tag{44}$$

That is, the rate of change in relative prices depends on the difference between the linear combination of the productivity growth of the suppliers of material inputs, with coefficients given by the respective rows of the inverse of the Leontieff matrix.[9] Thus, everything else equal, a sector $j$ that uses intensively a good produced by a sector with high productivity growth may feature a declining relative price compared with another sector $s$ that does not use this good as production input. In Section 3.2, we construct estimates of productivity growth for 15 sectors of the U.S. economy using (42), that is, using the rate of price changes across sectors, but taking into account input-output interactions as well.[10]

The model is solved using a first-order perturbation, with the rational-expectation solution of the linearized system found using the approach in Klein (2000).

# 3. Empirical Analysis

In this section, we describe the data, including the construction of an input-output table based on sectoral consumption data, outline the estimation method, report the parameter estimates, and evaluate the fit of the model.

## 3.1 Data

The data used to estimate the model are monthly observations of the rates of nominal price change and real per-capita consumption growth for fifteen consumption expenditure categories of the U.S. economy from 1995M1 to 2020M1. The use of both price and quantity data helps us identify the demand and productivity (i.e., supply) shock processes. The sample starts around the time that we view the FOMC as having settled on implicitly targeting an inflation rate of 2% per year. The average annualized inflation rate over the sample period was 1.8%. The inflation target was officially adopted in January 2012 and applies to the personal consumption expenditures (PCE) price index.

The choice of sample period is geared to confront the issue of monetary policy regimes. At one extreme, if there is a stable underlying monetary policy regime, then the tools of rational expectations and local approximation of dynamic stochastic general equilibrium models may be appropriate. At another extreme, clearly identified breaks in regime can be the source of facts against which theories are evaluated, but the researcher must decide how to model information sets of private agents and the policy-maker. The assumption in this paper is that from January 1995 to December 2019 the United States was in a stable, well-understood monetary policy regime and that it is appropriate to use a locally approximated model with

[9]A similar point is made by Ngai and Samaniego (2009) in a growth accounting exercise, but their concern is structural change and they do not examine either the empirical implications of this result or its role in aggregate inflation and monetary policy.

[10]Foerster, Hornstein, Sarte, and Watson (2022) follow an alternative approach and compute the growth rates of total factor productivity for 16 sectors using KLEMS (capital, labor, energy, materials, services) data from of the Bureau of Economic Analysis and the Bureau of Labor Statistics integrated industry-level production accounts. These author then examine the implications of sectoral trends for the trend growth in aggregate output in a model with a production network similar to ours.

rational expectations to study that period. This assumption is not directly testable, but the stability of both actual inflation and long-term inflation expectations is consistent with it.[11]

The fifteen categories comprise all of the PCE except for the final consumption expenditures of nonprofit institutions serving households, which we exclude from our analysis; this category accounted for 2.6% of the PCE during the sample period. The sectors are listed in Table 1. The raw data used to construct the sectoral price changes are seasonally adjusted price indices from the Bureau of Economic Analysis (BEA) Tables 2.4.4 and 2.4.5. The raw data used to construct the sectoral consumption growth rates are monthly nominal expenditures produced by the BEA. The consumption and price series correspond exactly to the same categories. The consumption series are converted into real per-capita terms by dividing by their corresponding seasonally-adjusted price index and by the mid-month U.S. population estimate produced by the BEA. The latter series was obtained from the website of the Federal Reserve Bank of St. Louis.

Descriptive statistics for the thirty series (expressed in percentages at an annual rate) are reported in Table 1. These statistics show the following. First, there is substantial heterogeneity in the mean and standard deviation of the rate of price changes and real consumption growth across PCE consumption categories. Second, a number of consumption categories—mostly durable goods—feature a negative rate of price changes meaning that their nominal price has *decreased* on average over the sample period. In contrast, the rate of price changes for service categories is positive and above to the rate of PCE inflation. Third, except for motor vehicles, consumption growth of durable goods is larger than aggregate consumption growth. Fourth, except for health care, consumption growth of services is smaller than aggregate consumption growth. Fifth, the standard deviation of the rate of price changes for gasoline and energy goods is larger by one order of magnitude than that of other consumption categories. Finally, the standard deviation of consumption growth of motor vehicles is the largest among consumption categories, followed by gasoline and energy goods, other durable goods, and clothing and footwear.

The heterogeneity in Table 1 motivates our modeling strategy, which accounts for the heterogeneity in means by allowing different rates of productivity growth across consumption categories along the balanced growth path, and accounts for heterogeneity in standard deviations by postulating different volatility in sectoral shocks and price adjustment costs across categories.[12] Prior to the structural estimation of the model, all series are demeaned to make them consistent with the model solution, which describes the dynamics of price and quantity growth rates in deviations from their steady state values, which in this case coincides with their mean.

[11]Monthly PCE inflation averaged 1.8% at an annual rate from January 1995 to December 2019, with a standard deviation of 2.3%, compared to 5.2% and 3.2%, respectively, in the prior 25 years. The measure of 10-year-ahead inflation expectations produced by the Federal Reserve Bank of Cleveland has a mean of 2.3% over our sample period, with a standard deviation of 0.56%.

[12]In unreported work we performed Augmented Dickey-Fuller tests of the null hypothesis of a unit root in each series against the alternative of a stationary autoregression with a constant intercept. In all cases and for a number of lags ranging from zero to six, the hypothesis could be rejected at standard significance levels.

For the construction of the input-output (I-O) table in our model, we use the PCE Bridge table produced by the BEA. This table reports the commodity composition of all consumption categories in the PCE index. We use the 2007 detailed version of this table, which contains information at the highest level of disaggregation available. (The detailed table is not available before 2007.) The table reports both producers' and purchasers' values in million of current U.S. dollars. Purchasers' values differ from producers' values in that they include transportation costs and retail margins. We report results based on purchasers' values to be consistent with PCE data collection, which measures prices paid by the final consumer, but the estimate of I-O table based on producers' values is very similar. We exclude commodities associated with international travel (e.g., expenditures in the United States by nonresidents),[13] expenditures by nonprofit institutions, government-provided services (except for postal services), scrap (which enter in the table with a negative sign), and used and second-hand goods.[14] The final sample consists of 254 commodities. We use data from the North American Industry Classification System (NAICS) to assign commodities to the producing sectors in our model. This assignment involves subjective judgment but we obtain similar estimates of the I-O table when using other reasonable assignments.[15] Figure 2 plots the I-O table expressed in terms of expenditure shares and shows that it features large diagonal entries, but with some sectors being quantitatively important inputs in the production of other sectors. For instance, other nondurable goods is a large input to food at home and other durable goods, and other services is larger input to transportation services. The finding that the I-O table has large diagonal entries and smaller off-diagonal ones is well known is the literature, but Kamepalli, Ng, and Ruge-Murcia (2025) show that the near-sparsity of the I-O table need not imply low connectivity across sectors.

For the estimation of the model, we treat the nominal interest rate as a latent, rather than an observable, variable. We acknowledge that this choice is not standard in the literature, but it is motivated by two factors. First, over the sample period inflation was low and stable, but there was a secular decline in the nominal rate. This decline has been widely documented and studied in previous literature (see, for example, Laubach and Williams (2016)) and is generally attributed to a persistent decrease in the natural real rate. Rather than

[13]Some of these items—e.g., passenger fares for foreign travel—are included in the calculation of the PCE. However, since the amounts involved are relative small, our estimates of the shares that enter the I-O table are robust to including these items.

[14]We exclude second-hand goods for two reasons: First, commodities in our model are produced and consumed within the period (i.e., there are no second-hand goods in our model). Second, except for motor vehicles, second-hand goods are a relatively small proportion of household expenditures in other categories, for instance 5.4% in furniture and 6.6% in dishes and flatware. Second-hand cars and light trucks constitute 32.6% of expenditures in that category. Treating second-hand autos as newly produced goods has minor effects on the estimated I-O table. For example, the share of expenditures on motor vehicles and parts used to produce that consumption category rises from 0.90 to 0.92.

[15]The BEA industry codes assigned to each PCE consumption category are as follows: motor vehicles and parts = 3361MV; furnishings and household durables = 335 and 337; recreational goods = 334 and 3364OT; other durable goods = 21, 23, 321, 327, 331, 332, 333, and 339; clothing and footwear = 313TT and 315AL; gasoline and other energy goods = 324;, other nondurable goods = 11, 311, 322, 323, 325, 326, 3121, and 3122; housing and utilities = 22 and 53; health care = 62;, transportation services = 48TW; recreation services = 51 and 71; food services and accommodations = 72; financial services and insurance = 52; and other services = 44RT, 54, 55, 56, 61, 81, and 491000. Food at home is treated as a purely final good and not an input in the production of any other consumption category. The list excludes government services, scrap and second hand goods, non-comparable imports, and rest-of-the-world adjustments. The final list consists of 381 commodities, but only the 254 commodities in the Bridge table enter into our computation of our I-O table.

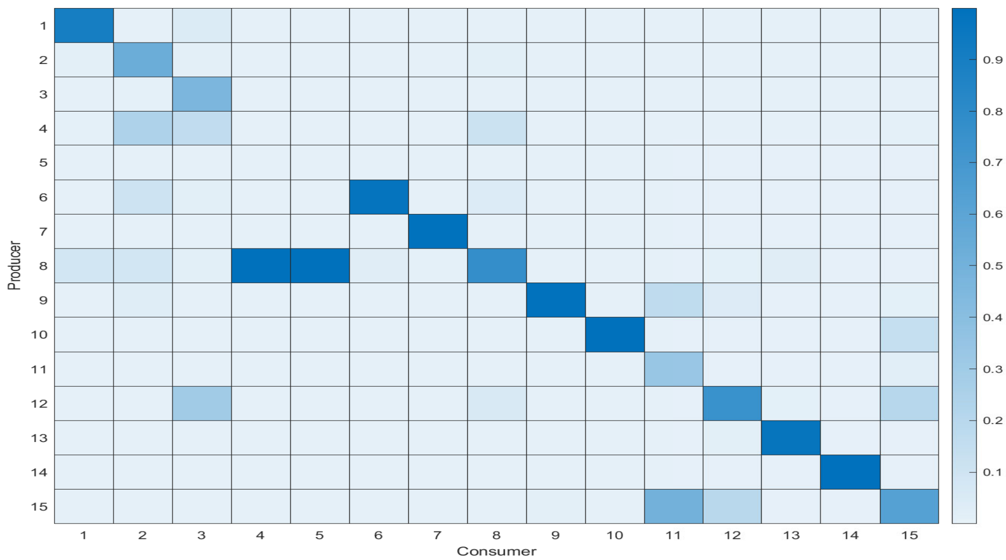


Figure 2: Input-output table with 1 = motor vehicles, 2 = furnishings and household durables, 3 = recreational goods, 4 = other durable goods, 5 = food at home, 6 = clothing and footwear, 7 = gasoline and energy goods, 8 = other nondurable goods, 9 = housing and utilities, 10 = health care, 11 = transportation services, 12 = recreation services, 13 = Food services and accommodation, 14 = financial services and insurance, and 15 = other services)

attempting to either explicitly model the natural rate (e.g., by introducing demographics into our model) or statistically recover the cyclical component of the interest rate (e.g., by means of a detrending procedure), we take an agnostic view here and treat this cyclical component as latent.[16] Second, we explored a number of modeling alternatives in preliminary work—including a shock to the discount rate, the introduction of a convenience yield to bond holding, and an exogenous shock to the Euler equation—, but the fundamental problem is that the nominal interest rate is nonstationary during our sample period and, hence, standard statistical inference is invalid.[17] We stress that modeling the policy instrument as latent does not impede the identification of the parameters of the Taylor rule. The reason is that we pursue here the structural estimation a fully-specified, rational-expectations model, and the cross equation restrictions imposed by the model lead to identification.

[16] The working paper version (Ruge-Murcia and Wolman (2022)) reports results based on quadratically detrending the nominal interest rate and using the residual as an estimate of the cyclical interest rate component. The conclusions drawn from that version of the model are similar to those reported here.

[17] The null hypothesis of a unit root in the nominal interest rate cannot be rejected at standard significance levels against the alternative that it follows a stationary autoregression with a constant intercept with number of lags from zero to six. The same conclusion is obtained when the alternative is a trend stationary model with number of lags from zero to six.

## 3.2 ML Estimation

The model is estimated by maximum likelihood (ML) using the Kalman filter to evaluate the likelihood function. The state equation of the state-space representation of the model solution is the joint process for exogenous and predetermined variables,

$$X_{t+1} = HX_t + \vartheta_{t+1}, \tag{45}$$

where $X_t$ and $\vartheta_t$ are $(4S+5) \times 1$ vectors with $S$ being the number of sectors, and $H$ is a $(6S+6) \times (6S+6)$ matrix with the parameters of the exogenous shock processes and the coefficients of the decision rules of the endogenous predetermined variables. The observation equation is

$$Y_t = GX_t, \tag{46}$$

where $Y_t$ is a $2S \times 1$ vector and $G$ is a $2S \times (4S+5)$ matrix whose elements are the coefficients of the decision rules for sectoral price changes and sectoral rates of consumption growth. The coefficients of the decision rules are nonlinear functions of the structural parameters. As is well known, this estimation approach is equivalent to using a Bayesian estimation strategy with diffuse priors. Hansen and Sargent (2013) show that the ML estimator obtained by applying the Kalman filter to the state-space representation of dynamic linear models is consistent and asymptotically efficient. Standard errors are estimated by the square root of the diagonal elements of $(T\mathcal{I})^{-1}$ where $T$ is the sample size and $\mathcal{I}$ is the information matrix, which is computed using the outer product of the scores at the maximum.

A difficulty that we face in estimating this model is that the steady state has to be computed numerically in every iteration of the algorithm that maximizes the likelihood function. Given the relatively large size of our model, this computation is time-consuming. In order to address this challenge, we first fix the parameters that determine the steady state and, with these parameters set, we estimate the parameters that determine the dynamics of the model by ML. The parameters that determine the steady state are fixed as follows. The weight of leisure in the utility function ($\varphi$) is set to 1.8, such that households work 1/3 of the time in steady state. The preference parameter $\chi$ is set to 1, which implies a Frisch labor supply elasticity of 1. The parameter that determines the elasticity of substitution between goods from the same sector ($\theta$) is set to 10. This implies a mark-up of approximately 10%. The elasticity parameter in the production function ($\alpha$) is set to 0.30 and the returns to scale parameters ($\nu$) is set to 0.75. The discount rate ($\beta$) is set to 0.998. Sensitivity analysis shows that results are reasonably robust to similarly plausible values of these parameters. The shares in the I-O table, which also determine the steady state, were fixed to values reported in Figure 2. Following the literature, the consumption weights are computed using the consumption expenditure shares in each sector,

$$\xi_s = \frac{P_{s,t}c_{s,t}}{P_tC_t},$$

where $P_{s,t}c_{s,t}$ are expenditures in sector $s$ and $P_tC_t$ are total consumption expenditures. Estimates of $\xi_s$ for each sector are reported in Column 1 of Table 2.

Finally, to estimate the drift in sectoral productivity, we solve the simultaneous system of equations (40) and (42), which delivers unique values of $\mu_1$, $\mu_2$, . . ., $\mu_S$. Because aggregate inflation is a linear combination of sectoral price changes, the system (42) alone does not pin down the absolute levels of sectoral productivity growth but only their relative levels. Basically, one of the equations in (42) is redundant. However, including the growth rate of aggregate consumption (40) allows us to determine the level and uniquely estimate $\mu_i$ for $i = 1, ...S$. These estimates are reported in Column 2 of Table 2. Our estimates imply that durable goods feature the largest rate of productivity growth in the U.S. economy. Within durables, recreational goods (which includes commodities like personal computers, tablets and peripheral equipment, audio equipment, etc.) have the highest productivity growth rate. The latter observation accounts for the persistent decrease of the nominal price of this category at the rate of 0.5% per month, or about 6% per year (see Table 1). Like us, Foerster, Hornstein, Sarte, and Watson (2022) find that the durable goods sector has the largest growth rate of total factor productivity and report relatively low growth rates for services sectors. A decrease in the relative price of equipment capital has been widely documented in the literature; for example, Gordon (1990) reports an annual rate of decline of more than 3%. In line with Balassa (1964) and Samuelson (1964), the sectors with the highest productivity growth produce tradable goods, while the sectors with the lowest productivity growth produce non-tradable goods (services). In summary, our model-based strategy to compute sectoral productivity growth on the basis of trends in relative price changes delivers estimates qualitatively consistent with those reported elsewhere in the literature and obtained using a variety of empirical strategies.

### 3.3 Parameter Estimates

Maximum likelihood estimates of sector-specific parameters—that is, price rigidity and the standard deviation of innovations of sectoral productivity and demand shocks—are reported in Table 3. Remaining ML estimates, including the parameters of the Taylor rule, are reported in Table 4.

Note in Table 3 that there is substantial heterogeneity in price rigidity across sectors and the null hypothesis that price rigidity is the same in all sectors is rejected by the data (see the $p$-value of the Wald test reported in the last row of Table 3). Heterogeneity in price rigidity across product categories has been documented by previous literature using highly disaggregated components of the consumer price index (CPI) (see, among others, Bils and Klenow. (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008)) and estimated multi-sector dynamic equilibrium models (see, e.g., Bouakez, Cardia, and Ruge-Murcia (2014)). In line with that literature, we find that price adjustment costs are generally higher in services than in other sectors. Two exceptions are transportation services, and financial services and insurance, which feature quantitatively small price rigidity parameters. Moreover, the null hypothesis that their cost parameter is zero (i.e., $\phi = 0$), and thus their prices are flexible, cannot be rejected at the 5% level. The prices of most categories of durables and nondurable goods are also rigid in the sense that the hypothesis $\phi = 0$ can be rejected at standard levels (e.g., food at home and recreational goods). Note that the price rigidity parameter for gasoline and energy goods is quantitatively small and not statistically significant, meaning that their prices are flexible. Quantitatively, the largest price rigidity parameters are those of motor vehicles and parts (an exception to the rule that goods have lower price adjustment costs), other services, housing and utilities, and food services and accommodations. In terms of the expenditure shares, 84% of consumption by U.S. households may be considered to have rigid prices.

The autoregressive coefficient of the first-difference of sectoral productivity shocks is quantitatively small and not statistically significant: $-0.050$ with standard error 0.033.[18] There is large heterogeneity in the standard deviation of productivity innovations and the hypothesis that they are the same in all sectors is rejected by the data. The largest standard deviation is that of gasoline and energy goods, followed by that of motor vehicles and parts. In general, the standard deviation is larger in durable and nondurable goods than in services. The standard deviation of aggregate productivity innovations in Table 4 is one and two orders of magnitude smaller than that the sectoral productivity shocks.

The autoregressive coefficient of sectoral demand shocks is 0.981 (0.003), where the figure in parenthesis is the standard error. Table 3 shows that there is large heterogeneity in the standard deviation of demand innovations and the hypothesis that they are the same in all sectors is rejected by the data. The largest standard deviations are those for motor vehicles and parts, and gasoline and energy goods.

The finding that the standard deviations of both supply and demand shocks to motor vehicles and parts are large explains why the observed frequency of price adjustments for these goods in microeconomic data is high despite the fact that we estimate their price rigidity parameter to be large and statistically significant. For example, Bils and Klenow. (2004) report that in their 1995-1997 sample the estimated average monthly frequency of price changes for new cars and trucks, which are the largest components of the motor vehicles and parts category, are 39.1 and 37.7, respectively, much higher than the frequency for the average good. Price adjustment costs may be substantial but the large volatility of sectoral shocks may nevertheless induce firms to optimally adjust prices frequently. It follows that heterogeneity in the frequency of price adjustments documented in earlier literature may be partly driven by heterogeneity in sector-specific shocks. So, in addition to heterogeneity in price rigidity, it is important to include other forms of heterogeneity—in particular, heterogeneity in the volatility of idiosyncratic shocks—in multi-sector New Keynesian models.

[18] In preliminary work, we estimated separate autoregressive coefficients for each sectoral demand and supply shock. However, for both supply and demand shocks, estimates of the autoregressive coefficients were quantitatively similar across sectors. Imposing the restrictions $\varrho_s = \varrho$ and $\rho_s = \rho$ for all $s$ is, thus, in rough agreement with the data and reduces the number of parameters to be estimated from 82 to 54 with a substantial gain in computational and statistical efficiencies.

In Table 4, the autoregressive coefficient of the demand shock is 0.996, and the standard deviation of its innovations is comparable to that of some sectoral demand shocks. Regarding the estimates of the monetary policy rule, the smoothing parameter is large (0.990), and statistically significant. The coefficients of inflation and output are positive and precisely estimated: 1.503 (0.263) and 0.934 (0.169), respectively.

## 3.4 Model Evaluation

In this section we evaluate the fit of the model in three ways. First, by comparing the means of sectoral consumption growth along the balanced growth path predicted by the model with those from the U.S. data. As described in Section 3.2, the sectoral rates of productivity growth were estimated using sectoral price changes and, by construction, the model fits the means of sectoral price changes exactly. However, our model also generates precise quantitative predictions about the means of sectoral consumption growth (see, for example, (35)). We evaluate these predictions by comparing actual and predicted means of sectoral consumption growth. Second, by comparing the standard deviation and auto-correlation of inflation and sectoral price changes predicted by the model with those of the U.S. data. In contrast to method of moments estimators (e.g., GMM), our ML estimation procedure does not explicitly target these moments.[19] Third, we examine the model fit of annual aggregate inflation, computed based on the smoothed inference about the state vector obtained using the Kalman filter. This is important because a key part of this project involves the decomposition of (fitted) inflation into the components due to each structural shock and this exercise is only meaningful if the model accurately fits the actual U.S. inflation rate.

Columns 1 and 2 of Table 5 report the mean sectoral consumption growth rates predicted by the model and estimated from the U.S. data. The predicted means are the theoretical values implied by the model along the balanced growth path, namely $\gamma_s$. As the trends in relative prices, those of sectoral consumption are driven by trends in sectoral productivity alone and invariant to monetary policy. The empirical counterparts of $\gamma_s$ are the sample means of the real, per-capita, consumption growth in each sector. The table shows that the predicted means closely track the actual means. In particular, the model accounts for the high consumption growth of durable goods and the low consumption growth of gasoline and energy goods. The correlation between actual and predicted series is high (0.956) and the model explains 92% of the variance of the variance of this series.

Columns 3 and 4 report the standard deviation of sectoral price changes predicted by the model and estimated from the U.S. data. The former are estimated as the sample average of standard deviations obtained using 1000 simulations with number of observations equal to the sample size, $T = 301$ and the parameter values reported in Tables 2 through 4. The data used to compute these statistics are percentages

[19]As it is well known, ML is the special case of GMM where the moment condition concerns the score vector (i.e., the gradient of the log-likelihood function with respect to the parameters). Thus, in the language of the calibration strategy frequently used in macroeconomics, the standard deviations and auto-correlations are "untargeted" moments.

at an annual rate. The table shows that our model captures the heterogeneity in the volatility of sectoral price changes—notably the large standard deviation of price changes for gasoline and other energy goods—, but over-predicts the standard deviation of price changes for motor vehicles and parts. Still, the correlation between actual and predicted series is high (0.976) and the model explains 95% of the variance of this series.

Columns 5 and 6 report the autocorrelation of sectoral price changes predicted by the model and estimated from the U.S. data. In general, the model over-predicts these autocorrelations, in part because input-output interactions act as a strong mechanism to transmit sectoral shocks from one sector to others *via* the consumption and materials aggregators (see (2) and (13), respectively), and also because we assume identical autoregressive coefficients for each sectoral demand and supply shock. Nonetheless, the model roughly preserves the ranking of autocorrelations observed in the data, meaning that sectors with a high (resp. low) autocorrelation in the data, also feature a high (resp. low) autocorrelation in the estimated model. In addition, the correlation between actual and predicted series is moderately high (0.517) and the model explains 27% of the variance of this series.

The results from Table 5 are reported in an alternative manner in Figure 3, which graphically compares the moments predicted by the model (vertical axis) with those computed from U.S. data (horizontal axis). If the model were to exactly match the moments of the data, all dots would lie on the blue 45-degree line.

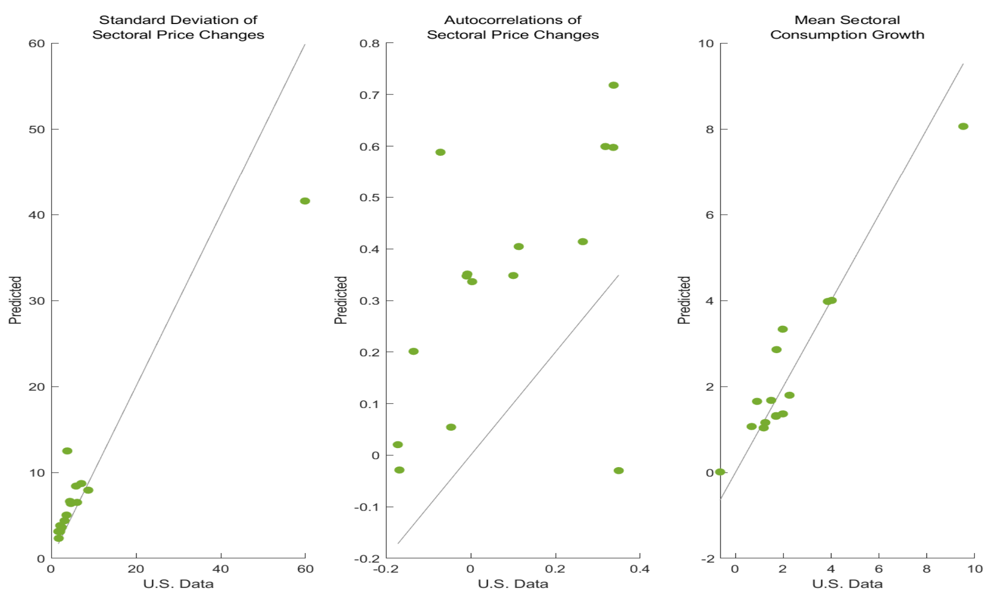


Figure 3: Comparison of actual and predicted sectoral moments.

Finally, Figure 4 plots the annual U.S. inflation rate measured by the PCE index (thick line) and the fit of the model obtained using the smoothed inference of the state vector computed using the Kalman filter (dash line). This figure shows that our estimated model closely tracks U.S. inflation. The $R^2$ of the fit is high and equal to 0.968. The $R^2$ of the fit based on the filtered inference (not reported) is basically the same up to the fourth decimal. These results underpin our analysis in Sections 5 and 6, where we decompose the fitted inflation rate into the contributions of each exogenous shock.

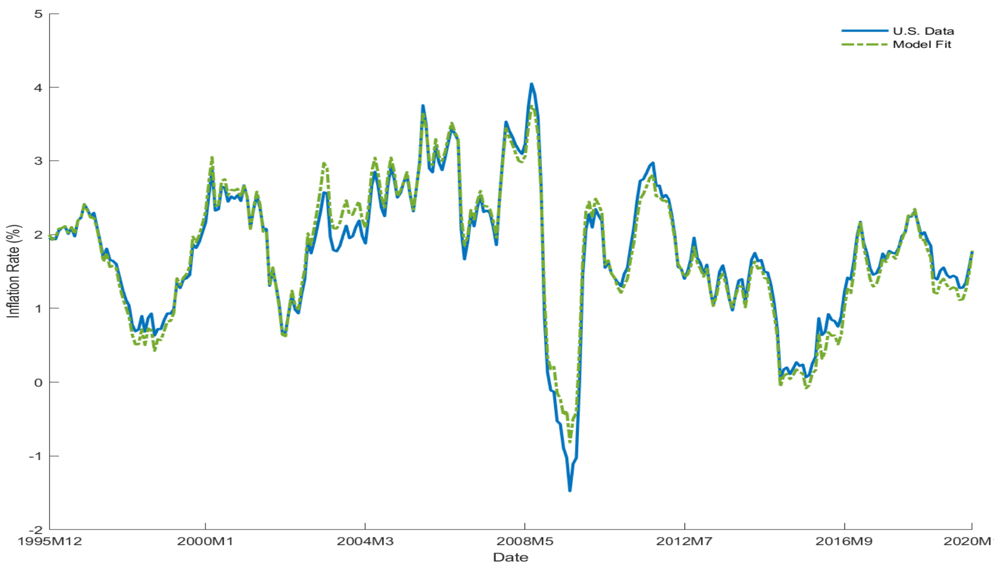


Figure 4: Actual U.S. Inflation (continuous line) and model fit (dotted line) computed using the smoothed inference of the state vector.

# 4. Relative Price Shocks and Inflation over the Entire Sample

With parameter estimates in hand, we can now turn to the model's implications regarding the role of relative price shocks in driving inflation dynamics. We begin with impulse response analysis and variance decompositions. Then we focus on a summary statistic for the distribution of relative price changes that has not—to our knowledge—previously been examined in the literature.

## 4.1 Impulse Responses

Figure 5 reports the responses of the rates of sectoral price changes to a negative productivity shock in each sector. For example, Panel A reports the response of the rate of price changes in motor vehicles (thick blue line) and in other sectors (thin black lines) to a negative productivity shock in the motor vehicles sector. The size of the shock is one standard deviation of the productivity innovation, $\sigma_{z,s}$ (see (23)). The effects on the rate of price changes in the sector that receives the shock are generally one order of magnitude larger than the effect on the rates in the other 14 sectors. The later are so similar quantitatively that in some cases that they appear as a single black line in Figure 5.

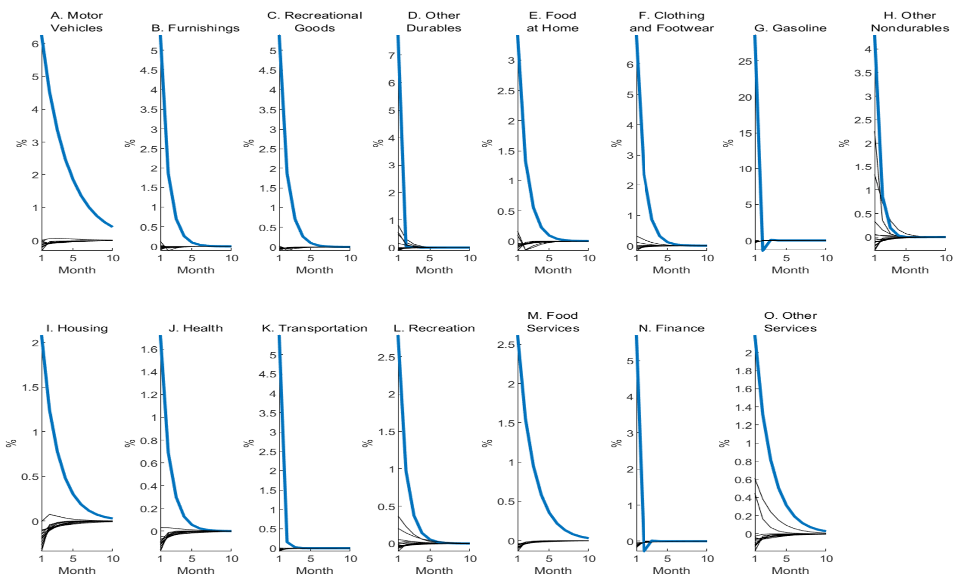


Figure 5: Response of the rates of sectoral price changes to a negative productivity shock in each sector.

Figure 6 reports the responses of the rates of sectoral price changes to a negative demand shock in each sector, with the size of the shock equal to one standard deviation of the demand innovation. In all panels, the demand shock leads to a large and persistent decrease in the rate of price changes of the good produced in that sector (dashed line). This decrease is generally one or more orders of magnitude larger than the rate for goods produced by the other 14 sectors (thin lines). Again, these 14 impulse responses are similar and sometimes appear as a single black line in Figure 6. The results in Figures 5 and 6 show that sectoral productivity and demand shocks yield a large response in the relative price of its own good and only a mild response in other relative prices, reinforcing our interpretation of sectoral shocks as relative price shocks. Put differently, our framework provides a structural interpretation—sectoral productivity and demand shocks—to the notion of relative price shocks employed by previous literature. (e.g., Reis and Watson, 2010).

Figure 7 plots the response of aggregate inflation to aggregate shocks (Panels A through C) and sectoral shocks (Panels D through R). The horizontal axis is months and the vertical axis is the inflation deviation from its steady state, expressed in percentage points at an annual rate. The dotted red lines are responses to demand shocks and the continuous blue lines are responses to productivity shocks. In all cases, the size of the shock is equal to one standard deviation of the innovations to its respective time-series process. Consequently, the scale of the vertical axis is different across panels.

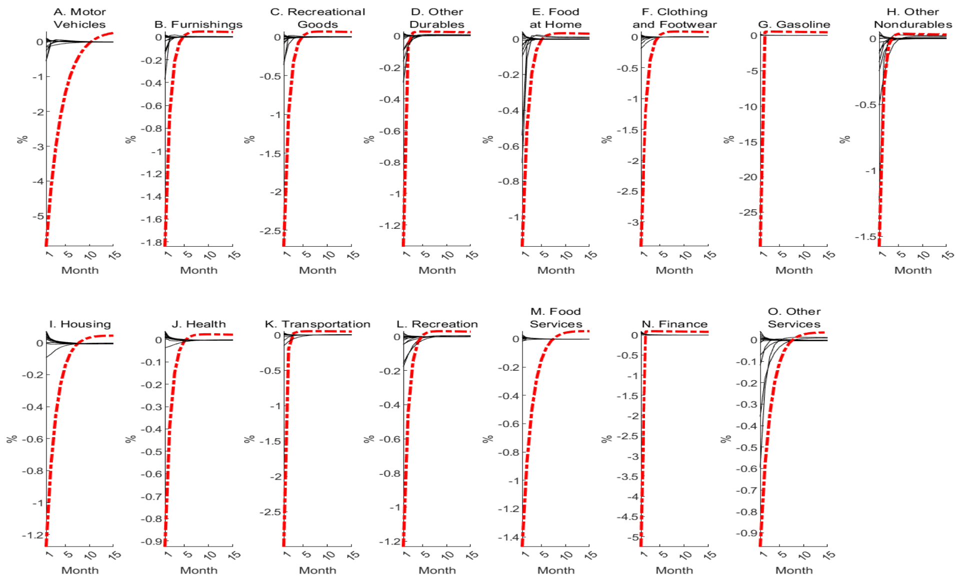


Figure 6: Response of the rates of sectoral price changes to a negative demand shock in each sector.

Concerning aggregate shocks, Panel A reports the response to a negative aggregate productivity shock. The response involves an initial increase of 0.39 pps above the steady state, after which inflation returns monotonically to its long-run value. Panel B reports the response to a negative aggregate demand shock and shows that inflation decreases initially by 0.44, but returns relatively quickly to its steady state. Finally, Panel C reports the response to a monetary policy shock that reduces the nominal interest rate and induces an initial increase in inflation of 0.52 pps, followed by a monotonic decrease to the steady state.

The remaining panels report the inflation response to sectoral shocks and show substantial heterogeneity across shocks. As expected negative productivity shocks lead to an increase in inflation, while negative demand shocks lead to a decrease in inflation, the only exception being the negative demand shock to other services. Regarding sectoral productivity shocks, the largest effects on inflation are associated with shocks to gasoline and energy goods (0.67 pps), other nondurable goods (0.41 pps), and financial services and insurance (0.36 pps). To shed light on the sources of heterogeneity, we regress the initial inflation response (i.e., the one corresponding to month 1 in Figure 7) on a constant, the price rigidity parameter, the standard deviation of the shock, the consumption weight, and the diagonal terms of the inverse Leontieff matrix. Results are reported in Columns 1 and 2 of Table 6. The negative coefficient of the price rigidity parameter means that sectors with more flexible prices (i.e., a smaller price rigidity parameters) react more to productivity shocks and induce a larger increase in aggregate inflation. Large negative shocks (e.g., to gasoline), shocks to sectors with a larger consumption share (e.g., housing), and shocks to sectors with a large entry along the

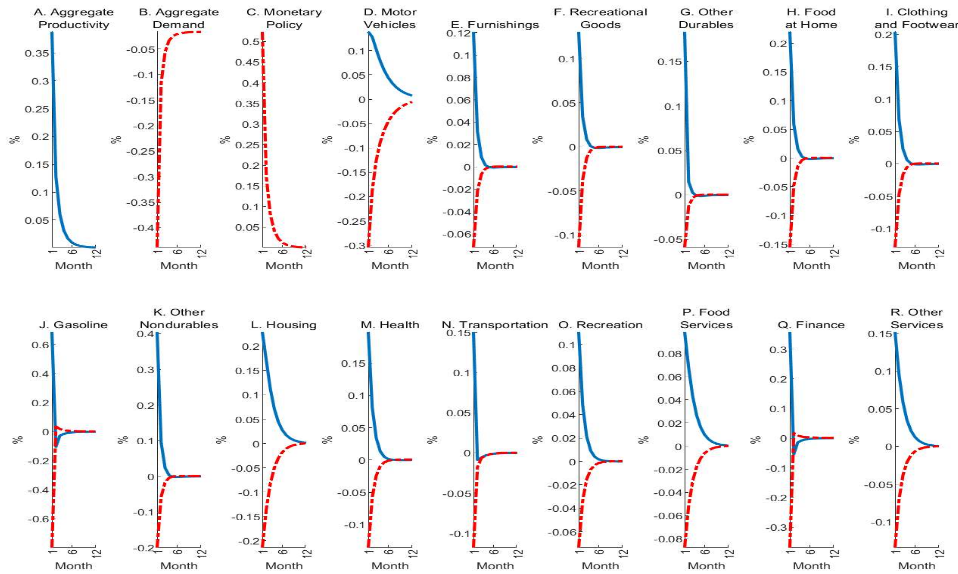


Figure 7: Response of aggregate inflation to negative aggregate, sectoral productivity, and sectoral demand shocks.

inverse Leontieff matrix also induce a larger increase in aggregate inflation. Afrouzi and Bhattarai (2025) derive an analytical expression for the effect of sectoral shocks on aggregate inflation with a direct effect proportional to the expenditure weight (i.e., our $\xi$) and an indirect effect through the network. In particular, these authors show that input-output relations amplify the effects of sectoral shocks *via* the inverse Leontief matrix and increase the pass-through of these shocks on impact. All together the variables in Table 6 jointly explain 77% of the variance of the inflation responses to productivity shocks.

Regarding demand shocks, the largest effects on inflation are associated with shocks to gasoline and energy goods ($-0.80$ pps), financial services and insurance ($-0.37$ pps), and motor vehicles ($-0.30$). Results of a regression of the initial inflation response to sectoral demand shock on a constant, the price rigidity parameter, the standard deviation of the shock, the consumption weight, and the diagonal terms of the inverse Leontief matrix are reported in Columns 3 and 4 of Table 6. The positive coefficient of the price rigidity parameter means that sectors with more flexible prices react more to demand shocks and induce a larger decrease in aggregate inflation. Large negative shocks and shocks to sectors with a larger consumption share also induce a larger decrease in aggregate inflation. The coefficient of the entries of the inverse Leontieff matrix is not statistically significant. Thus, we conclude, that input-output interactions are important for the transmission of supply shocks to inflation, but not for the transmission of demand shocks. All together these variables jointly explain 94% of the variance of the inflation responses to productivity shocks.

## 4.2 Accounting for the Variance of Inflation

Figure 8 plots the variance decomposition for the aggregate inflation rate at horizons from one to 20 months. The horizontal axes are months and the vertical axes are percentages. The dotted lines correspond to demand shocks and the continuous lines correspond to productivity shocks. Table 6 reports the unconditional variance decomposition obtained as the horizon increases without bound.

Panel A in Figure 8 and Column 1 in Table 6 show that the aggregate productivity shock accounts for 5.4% of the variance of the inflation forecast error at the one-month horizon and unconditionally, while the aggregate demand shock accounts for 6.9% at the one-month horizon and 7.6% unconditionally. Panel B and Column 1 show that the monetary policy shock accounts for 9.8% of the variance of the inflation forecast error at the one-month horizon and unconditionally, but this effect is not monotonic and reaches 10% at the two-month horizon before declining to its unconditional value. In summary, the three aggregate shocks in the model account for roughly 22% of the variance of aggregate inflation at all horizons.

Panel C and Columns 2 and 3 show that relative price shocks—productivity and demand—jointly account for about 78% of the variance of inflation at all horizons and almost equally split between both shock types. The finding that relative price shocks account for a large proportion of the unconditional variance of inflation is consistent with results in Reis and Watson (2010) who report that 76% of the movements in inflation are accounted for by a relative-price index.[20] A similar result is reported by Smets, Tielens, and Hove (2019) who find that sectoral shocks, by way of pipeline pressures, are an important contributor to the variance and persistence of headline inflation.

The remaining panels in Figure 8 (D through R) report the contribution of relative price shocks in each sector to the variance of the inflation forecasts error. Columns 2 and 3 in Table 6 report the unconditional variance decomposition accounted for by each shock. The figure and table support the following conclusions. First, shocks to gasoline and energy goods account for 40% of the variance of inflation at the one-month horizon and 35% unconditionally, with the demand shock accounting for a somewhat larger proportion than the productivity shock. Second, relative price shocks to finance and insurance, motor vehicles and parts, other nondurable goods, and housing and utilities substantially contribute to the unconditional variance of aggregate inflation—$8.4\%, 6.9\%, 6.8, \%$ and 5.6%, respectively—, with the demand shock relatively more important for motor vehicles, the supply shock relatively more important for other nondurable goods, and both shocks equally important for finance and insurance, and housing and utilities.

Research based on dynamic factor models (e.g., Boivin, Giannoni, and Mihov (2009)) usually finds that aggregate factors are the main driver of inflation. Using a structural model with input-output interactions, Onatski and Ruge-Murcia (2013) show that macroeconomic shocks can indeed be considered factors in that

[20]Note, however, that the structural interpretation of their index, which is based on a model of price setting under imperfect information, is different from our relative-price shocks because their index includes, for instance, the unanticipated component of the rate of money growth, which is an aggregate variable.

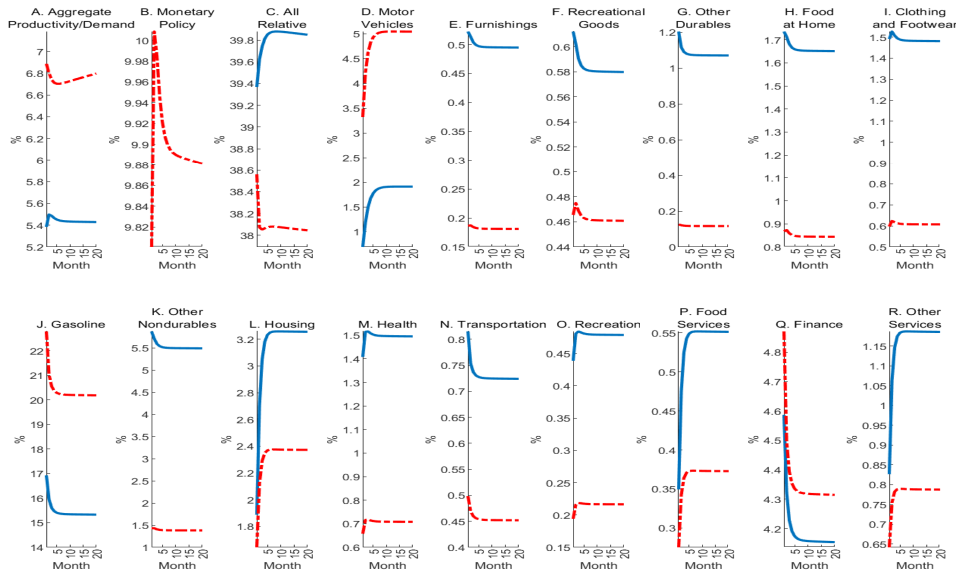


Figure 8: Variance decomposition of aggregate inflation. Aggregate and sectoral productivity shocks are plotted in continuous lines. Aggregate and sectoral demand shocks (including monetary policy) are plotted in dotted lines.

they nontrivially affect most variables in the model. However, principal components analysis has a hard time replicating the macroeconomic factor space because sectoral shocks can act as aggregate shocks when input-output interactions are present.[21] Another related literature examines the role of oil shocks in driving inflation expectations (e.g., Coibion and Gorodnichenko (2015) and Binder (2018)) and short-run inflation fluctuations (e.g., Clark and Terry (2010) and Kilian and Zhou (2022)). In line with that research, we find that gasoline shocks are among the most volatile relative price shocks and quantify their contribution to the variance of inflation. But, in addition, we show that in any given period, other categories (e.g., motor vehicles and parts, and finance and insurance) may also experience large shocks that account for sizable movements in aggregate inflation.[22]

Table 8 reports the contribution to the unconditional variance of each sectoral price change from the "own" relative price shocks, distinguishing between productivity (Column 1) and demand (Column 2) shocks; the aggregate productivity shock (Column 3); the aggregate demand shock (Column 4); and the monetary policy

[21] Boivin, Giannoni, and Mihov (2009) also emphasize the differential responses of sectoral prices to aggregate and sectoral shocks. Carvalho, Lee, and Park (2021) show how adding input-output linkages and labor market segmentation can help a multi-sector New Keynesian model match these patterns.

[22] There is also a literature that studies causality in the opposite direction—that is, from inflation to the variability of relative prices—with a focus on the 1970s and 1980s when inflation was not stable (for example, see Parks (1978)). In principle, our model can have inflation (i.e., policy) affect relative price variability but in practice that channel is weak, as one would expect in a stable policy regime like the one we consider

shock (Column 5). The table shows that the own productivity shock usually accounts for most of the variance of all sectoral price changes. The contribution of the own demand shock is also substantial, especially in gasoline and energy goods, and financial services and insurance. The contribution of the aggregate shocks varies across sectors, but it is generally very small. The contributions from other sectors' productivity and demand shocks are also small.[23] The finding that sector-specific shocks account for most of the variance of sectoral price changes is consistent with results in Boivin, Giannoni, and Mihov (2009) and Mackowiak, Moench, and Wiederholt (2009) based on estimated dynamic factor models: the former report that 85% percent of the monthly disaggregated price-change fluctuations are attributable to sector-specific shocks, while the latter report that the proportion of the variance in sectoral price changes due to sector-specific shocks in their median sector is 90% with a 90% confidence interval ranging from 79% to 95%. In our sample, sector-specific shocks account for between 52.1% of the variance of price changes for health care and 99.9% for gasoline and other energy goods.

## 4.3 Inflation and the Distribution of Relative Price Changes

Hornstein, Ruge-Murcia, and Wolman (2024) have shown that during our sample period there was a close relationship between monthly inflation and the share of relative price increases in the cross-sectional distribution. This is a natural benchmark for any model that builds up inflation from a distribution of disaggregated price changes. Panel A in Figure 9 displays the monthly PCE inflation rate rate on the vertical axis against the share of relative price increases—or equivalently, the share of nominal price increases greater than the inflation rate—from 1995 through 2019. There is a close negative relationship between the two variables.[24] Panel B in the same figure plots the same relationship but based on artificial data simulated from our estimated model. Because our estimated model closely matches the behavior of category price changes, it can account for this feature of the data.

We now provide some intuition for Figure 9 from the perspective of the model. To begin, note that there is a simple relationship between (i) the shares of relative price increases and decreases and (ii) the average sizes of relative price increases and decreases. Because the average relative price change is zero, the ratio of the share of relative price increases to the share of relative price decreases is identical to the ratio of the average relative price decrease to the average relative price increase,

$$\Gamma\left(\Upsilon^{+}\right) - (1-\Gamma)\left(\Upsilon^{-}\right) = 0,$$

which implies

$$\Gamma/(1-\Gamma) = (\Upsilon^{-})/(\Upsilon^{+}),$$

[23] These figures are not reported to save space, but their sum can be computed by subtracting the contributions in Table 8 from 100% for each sector.

[24] This empirical relationship is discussed in Wolman (2023) and examined in more detail by Hornstein, Ruge-Murcia, and Wolman (2024).

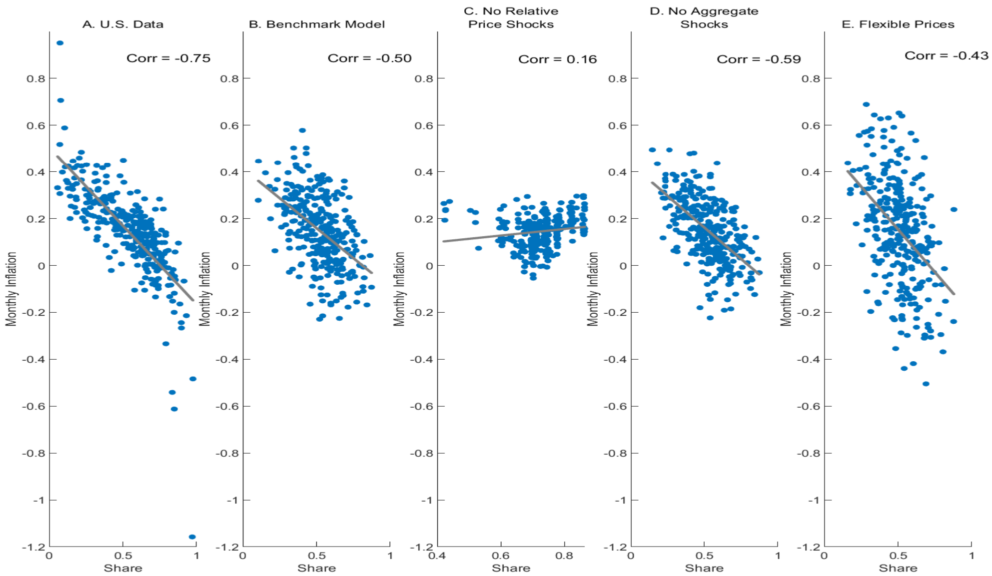


Figure 9: Relation between the inflation rate and the share of relative price increases in the data and in different versions of the model.

where $\Gamma$ is the share of relative price increases, and $\Upsilon^+$ and $\Upsilon^-$ are the average relative price increase and decrease, respectively. Note that the way we have written these equations, the average relative price decrease is a positive number.

The key point here is that monetary policy responds—in the model and generally in the data—to economy-wide aggregates, as opposed to sectoral price changes. When a relative price shock hits a particular sector, the desired relative price change is accomplished mainly by a nominal price change of the same sign for that sector, so that inflation moves in the same direction. In theory, it would be possible for monetary policy to perfectly stabilize inflation, or even to generate an upward sloping relationship between the share of relative price increases and the inflation rate. But either of these cases would require that in the face of a large relative price shock for just one sector, monetary policy generates large nominal price changes for all other sectors in the opposite direction. This is not what we see in the data.[25]

When the share of relative price increases is large, it is associated with a small share of sectors experiencing large positive productivity shocks (or large negative demand shocks), and choosing large *nominal* price decreases, which results in low inflation. When the share of relative price increases is small, it is associated

[25]Additionally, in New Keynesian models such as the one we employ, it is generally not optimal to stabilize the price level in response to large relative price shocks, unless those shocks hit sectors in which nominal rigidities are especially large. Goodfriend and King (1997) first made this general point; Aoki (2001) provided analytical results in a two-sector model; and Eusepi, Hobijn, and Tambalotti (2011) conducted quantitative analysis in a model similar to ours. See Woodford (2022) for an analysis of optimal policy in the context of sectoral shocks such as those associated with the COVID-19 pandemic.

with a small share of sectors experiencing large negative productivity shocks (or large positive demand shocks), and choosing large *nominal* price increases, which results in high inflation. The systematic behavior of monetary policy delivers these relationship between nominal and real variables as an equilibrium outcome: it is optimal for sectors experiencing changes in their desired relative price to move their nominal price in the same direction, and for other sectors to respond very little.

In order to better understand the model features that drive these results, we perform a comparative static exercise to examine the roles of sectoral and aggregate shocks and of price rigidity. Panel C in Figure 9 plots the relationship between the monthly PCE inflation rate rate and the share of relative price increases based on data simulated from a version of the model with no relative price shocks. Conversely, Panel D plots the relationship based on a version of the model with no aggregate shocks. These two panel show that sectoral (i.e., relative price) shocks are essential for the model to account for the empirical fact reported in Panel A.

Panel E plots the relationship based on a version of the model where all prices are flexible. That is, all parameters $\phi_s$ are set to zero while the remaining parameters are those reported in Tables 2 through 3. The close relationship between the two variables remains and we conclude that the relationship is not closely related to price stickiness or the heterogeneity in price stickiness across sectors. Compared with Ball and Mankiw (1995), whose explanation for the relationship between relative price changes and inflation relies on price stickiness, Balke and Wynne (2000) consider a flexible-price model with three central elements to their analysis. First, they point out that in a flexible price model, properties of the distribution of sectoral productivity growth would be reflected in the distribution of relative price changes. Second, they provide evidence that the distribution of productivity changes in fact had much in common with the distribution of sectoral price changes. These two elements are also present in our model in a more general setup where the data are allowed to determine the extent of price rigidity in each sector. Finally, they show that in a calibrated multi-sector model with flexible prices, basic properties of the empirical relationship between inflation and the distribution of relative price changes are replicated when the model is driven by an estimated sectoral productivity process.

# 5. Episodes

Our analysis thus far has described summary statistics and dynamics for the estimated model, where the estimation sample covered 1995 through 2019. We now use the model to decompose the behavior of inflation in three episodes, one within the estimation sample and two outside it.

## 5.1 Inflation Shortfall 2012-2019

From 2012 to 2019, PCE inflation averaged only 1.39%, well below the target of 2% announced by the Federal Reserve in January 2012. While this shortfall may seem minor in the context of the high inflation starting in

2021, it received significant attention at the time. For instance, in one of the key documents from the FOMC's review of its monetary policy framework in 2019-2020, the authors point out that "Inflation has persistently fallen short of the Committee's 2 percent inflation goal" (see Altig, Fuhrer, Giannoni, and Laubach (2020)). A theoretical explanation for the shortfall is that it resulted from the interaction between the effective bound on nominal interest rates and the Federal Reserve's implicit policy rule (see, for example, Bianchi, Melosi, and Rottner (2021)). Instead, our empirical approach exploits the state-space representation of the model to decompose inflation into the contributions from the various estimated shocks and determines causally to what extent the shortfall arose from shocks outside the control of the central bank or from monetary policy itself. The shocks are the smoothed estimates obtained using the Kalman filter. An important issue is that some variables in the state equation are endogenous, though ultimately a function of the exogenous shocks. In Appendix A, we propose a strategy to perform this decomposition so that the indirect effect of the shocks via the endogenous state variables is taken into account.

Figure 10 presents three panels that will guide our understanding of the contribution of key shocks to the U.S. inflation rate during this period. The horizontal axis is months from January 2012 to December 2019. The vertical axis is the inflation rate in percentage at the annual rate.

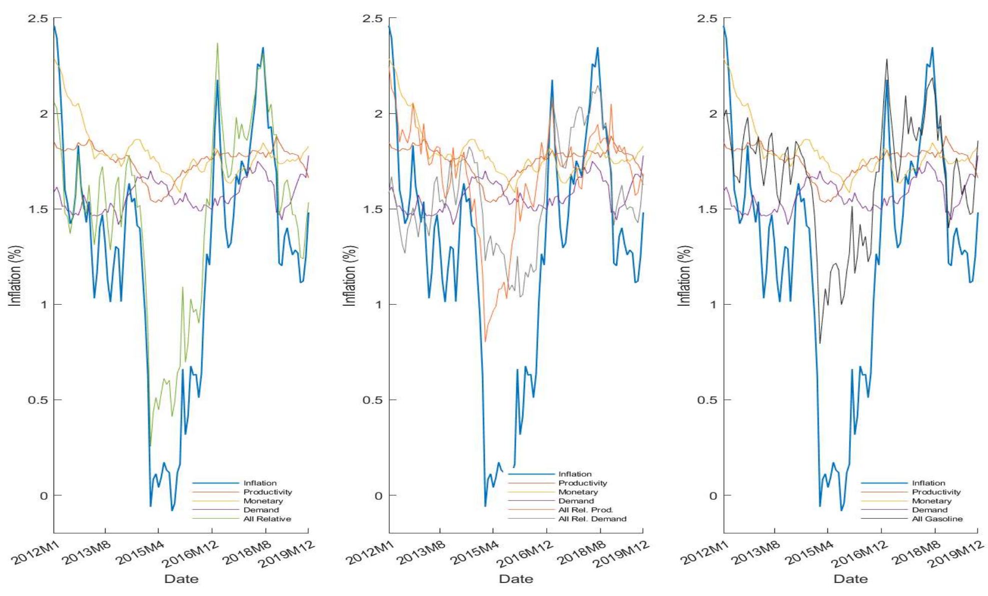


Figure 10: Contribution of structural shocks to the inflation shortfall.

Panel A reports the contribution of the aggregate productivity shock, the aggregate demand shock, the monetary policy shock, and the sum of all relative price shocks to the inflation shortfall. An important observation from Panel A is that monetary policy played a limited, but consistent, role in the shortfall.

Quantitatively, however, the aggregate demand shock and all relative price shocks played a much larger role, with the latter accounting for most of the shortfall in 2014-2016, when the shortfall was the largest. Panel B differs from Panel A in that it separately reports the sum of all sectoral productivity shocks and the sum of all sectoral demand shocks, in addition to all aggregate shocks. This panel shows that both productivity and demand relative-price shocks contributed in almost equal measure to the inflation shortfall.

Finally, Panel C attempts to shed some light on the contribution of gasoline and energy goods to the shortfall by reporting the part due to both productivity and demand shocks for this sector.[26] The figure shows that a substantial part of the inflation shortfall can be attributed to shocks to gasoline and energy goods. Relatedly, there was a large drop in oil prices between June 2014 and February 2016, when the barrel of West Texas Intermediate (WTI) went from $106 to $32. A mix of demand and supply considerations appear to have been at play. Prest (2018) argues that this price decline was driven by weakening global economic conditions and demand for commodities, including oil. Kanzig (2021) notes the large effect of the announcement by the Organization of the Petroleum Exporting Countries (OPEC) that it was leaving oil production levels unchanged despite calls from poorer OPEC members to lower quotas. The subsequent increase in oil prices up to 70$/barrel in July 2018 is contemporaneous with the increase of U.S. inflation up to its targeted value of 2%.

In summary, most of the inflation shortfall in 2012-2019, and in particular in the period 2014-2016 when the shortfall was the largest, is attributable to relative price shocks, notably to gasoline and other energy goods. A limited portion of the shortfall is attributable to monetary policy, but its contribution was stable over time, including during the period when the Federal Reserve was raising rates. While that rate increase was gradual by historical standards, according to our estimated model it represented contractionary policy.

### 5.2 Inflation Surge 2021-2023

We now use our estimated model to interpret the behavior of U.S. inflation in the period immediately after our estimation sample; that period corresponds to the COVID-19 pandemic and its aftermath, when inflation was at first volatile and then consistently far above the Federal Reserve's 2% target.

Because it interprets the data through the lens of the estimated model, our analysis assumes that the U.S. economy has remained in a rational expectations equilibrium involving local fluctuations around a steady state with a fixed inflation target. One might respond skeptically that we are assuming the answer to the most important question: has the U.S. economy remained in that equilibrium, or has the Fed's behavior deviated from its previous rule to such an extent that private agents no longer perceive that rule to be in place? We do not dispute the importance of that question, and in fact see our work as contributing to an answer: under the assumption that inflation has remained anchored, we provide estimates of the contributions to observed

[26]In preliminary work, we also computed the contribution of shocks to other categories, but they are quantitatively smaller than those to gasoline and are not reported to avoid cluttering the figure.

inflation from monetary policy and sectoral shocks. An evaluation of those estimates based on independent information can then help in assessing whether inflation has in fact remained anchored.

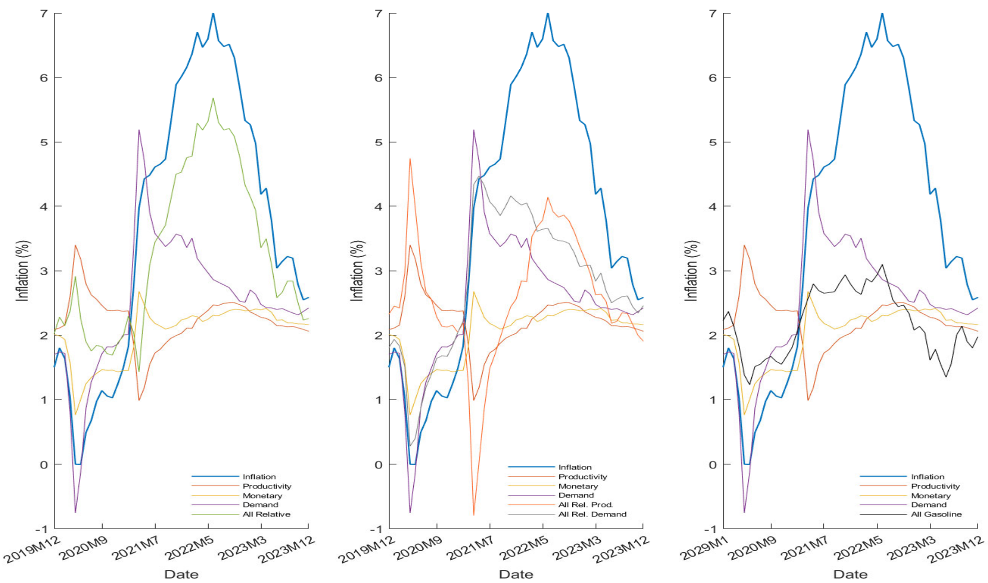


Figure 11: Contribution of structural shocks to the inflation surge.

As before, we decompose observed inflation into the contributions of the various shocks. The data is now outside our estimation sample, but the procedure is otherwise identical. Each component represents the counter-factual of what inflation would have been if only that one shock had been operative. Figure 11 presents selected elements of the decomposition of the inflation surge. The figure plots the period from January 2020 through December 2023 and, thus, captures the onset of the pandemic and the high inflation months that followed. As before, the figure presents three panels where the horizontal axis is months and the vertical axis is annual inflation in percent.

Panel A reports the contribution of the aggregate productivity shock, the aggregate demand shock, the monetary policy shock, and the sum of all sectoral productivity and sectoral demand shocks to inflation. Regarding the first year of the pandemic (up to March 2021), inflation fell well below target with most of the decline attributable to the aggregate demand shock, and to a lesser extent to the monetary policy shock despite the large asset purchase programs implemented by the Federal Reserve during this period. The effect of the negative aggregate productivity shock and all relative price shocks was to moderate the decline in inflation. This result is consistent with the view that negative supply shocks decrease output and increase inflation as illustrated in Figure 7.

Starting April 2021, the picture changes substantially with the contribution of the aggregate demand shock increasing substantially with monetary policy roughly consistent with the inflation target. This timing is contemporaneous with the lifting of mandates and capacity restrictions in the second quarter of 2021. Substantial fiscal stimulus programs were enacted as well: the Coronavirus Aid, Relief, and Economic Security (CARES) Act for $2.2 trillion in March 2020, the Paycheck Protection Program and Health Care Enhancement Act for $484 billion in April 2020, and the American Rescue Plan Act for $1.9 trillion in March 2021. In the subsequent months, most of the inflation surge is accounted for by relative price shocks and the persistent, but declining effect, of the aggregate demand shock. At its peak, inflation was 5 pps above target but monetary policy accounts for little of this surge. Instead, most of the surge is attributable to relative price and aggregate demand shocks.

Panel B distinguishes between productivity and demand relative price shocks. The panel shows that the substantial contribution of sectoral demand shocks to the surge, with sectoral productivity shocks becoming more important later in mid-2022. Panel B can be interpreted as providing our model's counterpart to Shapiro's (2022) decomposition of inflation into supply-driven and demand-driven components by means of a structural vector autoregression. Finally, Panel C shows that gasoline and energy goods accounts for a substantial part of the surge, contemporaneous with Russian invasion of Ukraine in February 2022. However, comparing Panels C and A indicates that the sum of relative-price shocks to the other sectors is just as important as those to gasoline. The latter include supply-chain disruptions, like the shortage of semiconductors that affected vehicle production, and transportation bottlenecks.

In related work, Guerrieri, Marcussen, Reichlin, and Tenreyro (2023) provide a wide-ranging analysis of COVID-era inflation, with special emphasis on energy price shocks and heterogeneity in the transmission of those shocks to prices of other goods and services. Gagliardone and Gertler (2023) perform a decomposition of inflation into the contributions of sectoral and aggregate shocks in an estimated DSGE model with two sectors, oil and non-oil. Ferrante, Graves, and Iacoviello (2023) analyze the pandemic as a shock that reallocates demand from services to goods using a 66-sector model with an input-output structure. Literature that studies the contribution of supply constraints to inflation include Comin, Johnson, and Jones (2023) and Bai, Fernández-Villaverde, Li, and Zanetti (2024).

Other research on pandemic-era inflation, while not considering explicit supply constraints, impose nonlinear aggregate Phillips curves that have a similar flavor. Harding, Lindé, and Trabandt (2023) and Benigno and Eggertsson (2023) construct one-sector models with nonlinear Phillips Curves; in the former case the nonlinearity is rooted in the goods market and in the latter case in the labor market. Bernanke and Blanchard (2023) empirical analysis also finds that sectoral shocks were important contributors to the high inflation episode that started in 2021. Ball, Leigh, and Mishra (2022) construct an empirical decomposition of the inflation surge into movements in core inflation arising from the labor market, delayed pass-through into core inflation of shocks to headline inflation, and shocks to headline inflation. The role of fiscal policy in the inflation surge is studied, for instance, by Hale, Leer, and Nechio (2025).

Finally, Gao and Nicolini (2023) examine the inflation surge through the lens of the quantity theory and argue that it primarily reflects shocks outside the control of the monetary authority. While our framework is quite different—there is no money in our model—our conclusions have the same flavor. We find that the inflation surge that started in 2021 is explained mainly by sectoral supply and demand shocks, with monetary policy shocks playing a modest role.

## 5.3 Stubborn Above-Target Inflation 2024-2025

Although inflation declined from its peak after the surge, it has remained well above target. We apply the same decomposition employed above to the period from January 2024 to December 2025 and report results in Figure 12. Inflation has been on average 0.40 pps above target and the figure shows that the excess of inflation over its target is primarily driven by demand factors: the aggregate and sectoral demand shocks and monetary policy. In particular, monetary policy appears to be relatively loose compared with the targeted 2% rate. Interestingly, in contrast to our previous decomposition, shocks to gasoline and eneryg goods appear to play no role on excess inflation in this period.[27]

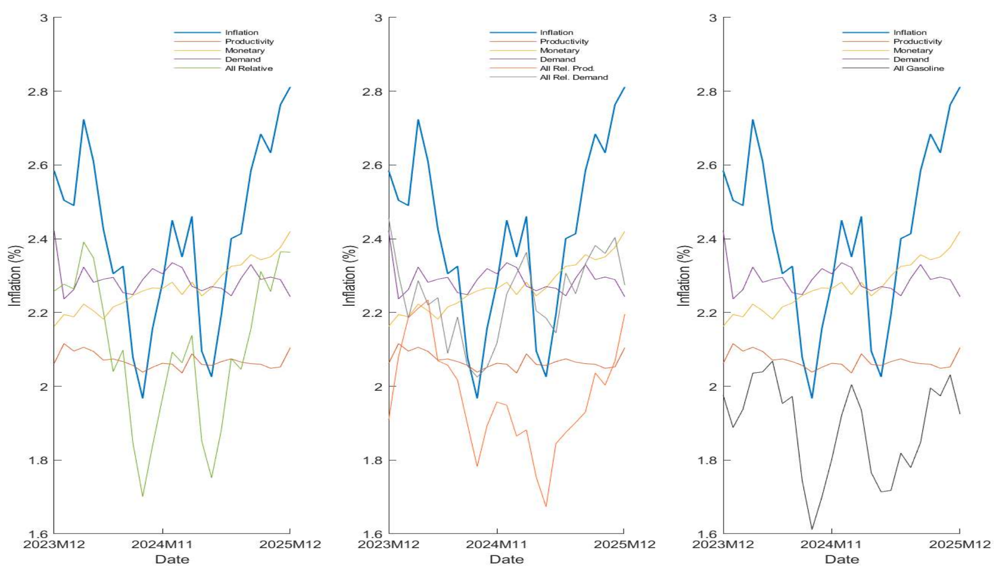


Figure 12: Contribution of structural shocks to the above-target inflation.

[27]Since our sample period ends in December 2025, we cannot shed light on the inflationary effects of the Iran war starting in February 2026 but intend to do so in future work.

## 6. Conclusions

Inflation is an equilibrium outcome that reflects the interaction of monetary policy with real factors in the economy, including shocks to the demand and supply for particular categories of consumption goods and services. In a purely classical model those “relative price shocks” would be irrelevant for the behavior of inflation. In reality, the distribution of relative price changes is correlated with the inflation rate. We quantify the contribution of relative price shocks, monetary policy shocks, and other shocks to the behavior of U.S. inflation from 1995 to 2019 by estimating a 15-sector New Keynesian model featuring a network structure with long-run growth and heterogeneity across sectors in the variance of shocks, in the degree of price stickiness and in the trend rates of productivity growth across sectors.

In addition to quantifying the contributions of the various shocks to inflation, we also decompose the behavior of inflation during three recent episodes. First, the inflation shortfall from 2012 to 2019, second, the inflation surge the pandemic, and third, the persistent above-target inflation in 2024-2025. The latter two episodes are outside our estimation sample, and our analysis is conducted under the maintained assumption that the economy remained in the same policy regime with rational expectations that we estimated on pre-COVID data. One of many areas for future research suggested by our analysis is to evaluate the extent to which the regime stability is an appropriate modeling assumption. In our summary analysis and in the three specific episodes, we find that relative price shocks are quantitatively important determinants of inflation. For example, over the full sample, relative price shocks account for 71 percent of the variance of inflation. Whether one uses a theoretical model or reduced form empirical analysis, it follows that during a stable policy regime the behavior of inflation cannot be understood without taking into account the behavior of relative prices.

**Table 1. Descriptive Statistics**

| Sector | Rate of Price Changes | | Consumption Growth | |
|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D |
| | (1) | (2) | (3) | (4) |
| Motor vehicles and parts | 0.296 | 3.801 | 1.715 | 53.286 |
| Furnishings and household durables | −1.272 | 4.639 | 4.022 | 12.749 |
| Recreational goods | −6.039 | 4.439 | 9.520 | 16.308 |
| Other durable goods | −0.872 | 7.116 | 3.861 | 16.075 |
| Food at home | 1.855 | 3.162 | 0.900 | 7.886 |
| Clothing and footwear | −0.605 | 5.867 | 1.974 | 15.892 |
| Gasoline and other energy goods | 3.619 | 59.865 | −0.644 | 19.743 |
| Other nondurable goods | 1.615 | 3.617 | 2.256 | 9.067 |
| Housing and utilities | 2.763 | 1.691 | 0.674 | 7.089 |
| Health care | 2.306 | 1.776 | 1.981 | 3.335 |
| Transportation services | 2.031 | 6.099 | 1.490 | 11.031 |
| Recreation services | 2.528 | 2.507 | 1.691 | 8.470 |
| Food services and accommodations | 2.671 | 2.135 | 1.246 | 8.711 |
| Financial services and insurance | 2.861 | 8.746 | 7.942 | 7.912 |
| Other services | 2.446 | 2.122 | 1.699 | 8.283 |
| Aggregate | 1.772 | 2.278 | 1.808 | 4.254 |

Notes: The statistics were computed using monthly series between 1995M1 and 2020M1 and expressed in percentages at an annual rate.

**Table 2. Sectoral Consumption Weights and Productivity Trends**

| Sector | Consumption Weight | Productivity Trend $\times 10^2$ |
|---|---|---|
| | (1) | (2) |
| Motor vehicles and parts | 0.0450 | 0.5159 |
| Furnishings and household durables | 0.0280 | 0.7660 |
| Recreational goods | 0.0321 | 2.0184 |
| Other durable goods | 0.0165 | 1.1240 |
| Food at home | 0.0802 | 0.2628 |
| Clothing and footwear | 0.0361 | 0.5933 |
| Gasoline and other energy goods | 0.0298 | 0.0001 |
| Other nondurable goods | 0.0822 | 0.2557 |
| Housing and utilities | 0.1876 | 0.1873 |
| Health care | 0.1595 | 0.2396 |
| Transportation services | 0.0346 | 0.3485 |
| Recreation services | 0.0397 | 0.2304 |
| Food services and accommodations | 0.0651 | 0.2007 |
| Financial services and insurance | 0.0775 | 0.1822 |
| Other services | 0.0862 | 0.2278 |

Notes: Consumption weights are the average shares of consumption expenditures from 1995M1 to 2020M1.

**Table 3. ML Estimates of Sectoral Parameters**

| | Price Rigidity | | S.D. Innovations to Productivity $\times 10^2$ | | S.D. Innovations to Demand $\times 10^4$ | |
|---|---|---|---|---|---|---|
| Sector | Estimate | s.e. | Estimate | s.e. | Estimate | s.e. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Motor vehicles and parts | 91.339* | 21.905 | 4.947* | 0.303 | 9.911* | 0.730 |
| Furnishings and household durables | 9.432* | 3.622 | 2.365* | 0.294 | 1.349* | 0.068 |
| Recreational goods | 9.803* | 2.722 | 2.502* | 0.226 | 2.223* | 0.110 |
| Other durable goods | 0.669 | 0.884 | 2.912* | 0.249 | 0.750* | 0.056 |
| Food at home | 15.847* | 4.600 | 2.284* | 0.241 | 1.918* | 0.047 |
| Clothing and footwear | 7.522* | 2.155 | 2.062* | 0.208 | 2.018* | 0.104 |
| Gasoline and other energy goods | 0.010 | 0.221 | 5.190* | 0.314 | 9.082* | 0.470 |
| Other nondurable goods | 3.879* | 1.170 | 1.244* | 0.119 | 1.824* | 0.083 |
| Housing and utilities | 35.928* | 8.962 | 1.086* | 0.108 | 2.690* | 0.159 |
| Health care | 11.001* | 2.722 | 0.582* | 0.061 | 1.175* | 0.063 |
| Transportation services | 0.935 | 0.580 | 1.839* | 0.104 | 1.673* | 0.052 |
| Recreation services | 8.867* | 2.404 | 1.035* | 0.100 | 1.149* | 0.060 |
| Food services and accommodations | 33.507* | 8.274 | 1.298* | 0.148 | 1.819* | 0.091 |
| Financial services and insurance | 0.017 | 0.273 | 1.040* | 0.057 | 2.544* | 0.129 |
| Other services | 40.414* | 13.033 | 1.489* | 0.209 | 2.189* | 0.066 |
| Wald test ($p$-value) | $< 0.001$ | | $< 0.001$ | | $< 0.001$ | |

*Note*: S.D. stands for standard deviation and s.e. stands for standard error. The superscript $*$ denotes statistical significance at the 5% level.

**Table 4. Other ML Estimates**

| Parameter | Estimate | s.e. |
|---|---|---|
| | (1) | (2) |
| Autoregressive coefficients: | | |
| Sectoral productivity shocks | $-0.050$ | 0.033 |
| Sectoral demand shocks | 0.981 | 0.003 |
| Aggregate demand shock | 0.996* | 0.002 |
| | | |
| S.D. of innovations to: | | |
| Aggregate productivity shocks$\times 10^2$ | 0.087* | 0.025 |
| Aggregate demand shock $\times 10^4$ | 1.138* | 0.089 |
| | | |
| Taylor rule: | | |
| Smoothing parameter | 0.990* | 0.004 |
| Inflation coefficient | 1.503* | 0.263 |
| Output coefficient | 0.934* | 0.169 |
| Standard deviation $\times 10^4$ | 0.114* | 0.061 |

*Note*: See notes to Table 3.

**Table 5. Empirical and Theoretical Moments**

| | Consumption | | Price Changes | | | |
|---|---|---|---|---|---|---|
| | Mean | | Std. Deviation | | Autocorrelation | |
| Variable | Data | Model | Data | Model | Data | Model |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Motor vehicles and parts | 1.715 | 2.856 | 3.801 | 12.495 | 0.337 | 0.718 |
| Furnishings and household durables | 4.022 | 4.001 | 4.639 | 6.382 | −0.009 | 0.347 |
| Recreational goods | 9.520 | 8.061 | 4.439 | 6.626 | −0.008 | 0.351 |
| Other durable goods | 3.861 | 3.977 | 7.116 | 8.703 | −0.172 | 0.020 |
| Food at home | 0.900 | 1.652 | 3.162 | 4.381 | 0.265 | 0.414 |
| Clothing and footwear | 1.974 | 3.331 | 5.867 | 8.406 | 0.004 | 0.336 |
| Gasoline and other energy goods | −0.644 | 0.011 | 59.865 | 41.566 | 0.328 | −0.030 |
| Other nondurable goods | 2.256 | 1.795 | 3.617 | 5.034 | −0.133 | 0.201 |
| Housing and utilities | 0.674 | 1.067 | 1.691 | 3.131 | 0.336 | 0.598 |
| Health care | 1.981 | 1.361 | 1.776 | 2.329 | 0.113 | 0.405 |
| Transportation services | 1.490 | 1.675 | 6.099 | 6.508 | −0.047 | 0.054 |
| Recreation services | 1.691 | 1.305 | 2.507 | 3.615 | 0.101 | 0.348 |
| Food services and accommodations | 1.246 | 1.159 | 2.135 | 3.810 | −0.071 | 0.588 |
| Financial services and insurance | 1.178 | 1.036 | 8.746 | 7.929 | −0.171 | −0.029 |
| Other services | 1.699 | 1.321 | 2.122 | 3.111 | 0.318 | 0.599 |
| Correlation | 0.956 | | 0.976 | | 0.517 | |
| $R^2$ | 0.915 | | 0.952 | | 0.267 | |

*Note*: The predicted moments are the sample average of the moments computed using 1000 simulations with number of observations equal to the sample size $T = 301$.

**Table 6. Explaining the Aggregate Inflation Response to Sectoral Shocks**

| | Response to | | | |
|---|---|---|---|---|
| | Productivity Shocks | | Demand Shocks | |
| Variable | Estimate | s.e. | Estimate | s.e. |
| | (1) | (2) | (3) | (4) |
| Intercept | $-0.260^*$ | 0.086 | 0.046 | 0.053 |
| Price rigidity $\times 10^2$ | $-0.508^*$ | 0.080 | $0.543^*$ | 0.081 |
| Standard deviation | $10.382^*$ | 1.547 | $-792.198^*$ | 61.308 |
| Consumption weight | $1.504^*$ | 0.539 | $-0.953^*$ | 0.324 |
| Input-output | $0.152^*$ | 0.052 | $-0.032$ | 0.042 |
| $R^2$ | 0.772 | | 0.940 | |
| Number of obs. | 15 | | 15 | |

*Note*: s.e. denotes Huber-White heteroskedasticity consistent standard errors.

Table 7. **Unconditional Variance Decomposition of Aggregate Inflation**

| | Aggregate Shocks | Sectoral Shocks | |
|---|---|---|---|
| | | Productivity | Demand |
| | (1) | (2) | (3) |
| Aggregate productivity | 5.381 | | |
| Aggregate demand | 7.606 | | |
| Monetary policy | 9.795 | | |
| Motor vehicles and parts | | 1.891 | 5.003 |
| Furnishings and household durables | | 0.490 | 0.180 |
| Recreational goods | | 0.575 | 0.457 |
| Other durable goods | | 1.061 | 0.116 |
| Food at home | | 1.637 | 0.837 |
| Clothing and footwear | | 1.468 | 0.602 |
| Gasoline and other energy goods | | 15.196 | 20.010 |
| Other nondurable goods | | 5.442 | 1.370 |
| Housing and utilities | | 3.227 | 2.353 |
| Health care | | 1.482 | 0.702 |
| Transportation services | | 0.717 | 0.448 |
| Recreation services | | 0.474 | 0.215 |
| Food services and accommodations | | 0.547 | 0.370 |
| Financial services and insurance | | 4.118 | 4.277 |
| Other services | | 1.175 | 0.781 |

*Note*: The unconditional variance decomposition is approximated by the variance of the conditional inflation forecast 5000 periods ahead.

**Table 8. Unconditional Variance Decomposition of Rate of Sectoral Price Changes**

| | Own Shock | | Aggregate Shocks | | |
|---|---|---|---|---|---|
| Sector | Productivity | Demand | Productivity | Demand | Monetary Policy |
| | (1) | (2) | (3) | (4) | (5) |
| Motor vehicles and parts | 53.718 | 45.942 | 0.041 | 0.164 | 0.074 |
| Furnishings and household durables | 81.106 | 9.651 | 0.483 | 4.115 | 0.878 |
| Recreational goods | 75.115 | 19.377 | 0.406 | 2.557 | 0.738 |
| Other durable goods | 79.038 | 2.384 | 0.542 | 6.390 | 0.987 |
| Food at home | 71.777 | 8.743 | 0.863 | 1.102 | 1.571 |
| Clothing and footwear | 77.682 | 18.835 | 0.315 | 2.078 | 0.574 |
| Gasoline and other energy goods | 48.678 | 51.012 | 0.028 | 0.199 | 0.051 |
| Other nondurable goods | 76.240 | 10.462 | 1.205 | 3.390 | 2.193 |
| Housing and utilities | 69.046 | 25.898 | 1.021 | 0.551 | 1.858 |
| Health care | 64.686 | 19.044 | 3.373 | 0.853 | 6.139 |
| Transportation services | 71.457 | 21.378 | 0.555 | 3.000 | 1.010 |
| Recreation services | 67.296 | 13.400 | 1.515 | 7.286 | 2.757 |
| Food services and accommodations | 72.676 | 22.953 | 0.719 | 1.100 | 1.308 |
| Financial services and insurance | 52.178 | 44.136 | 0.767 | 0.423 | 1.396 |
| Other services | 77.428 | 15.105 | 1.003 | 1.412 | 1.825 |

*Note*: Rows do not add to 100 because the contribution of sectoral shocks, other than own, are not reported to save space.

## Appendix A: Inflation Decomposition

The linearized solution of the model takes the state-space form

$$X_{t+1} = HX_t + \vartheta_{t+1}, \tag{47}$$

$$Y_t = GX_t, \tag{48}$$

where (47) is the state equation, (48) is the observation equation, $X_t$ and $\vartheta_t$ are $(4S+5) \times 1$ vectors with $S$ being the number of sectors, $H$ is a $(4S+5) \times (4S+5)$ matrix with the parameters of the exogenous shock processes and the coefficient of the decision rules of the endogenous predetermined variables, $Y_t$ is a $J \times 1$ vector of observable variables, and $G$ is a $J \times (4S+5)$ matrix whose elements are the coefficients of the decision rules of the observable variables.

To develop intuition, imagine a model with no endogenous state variables in $X_t$. In that case, (48) would provide the exact decomposition of each variable in $Y_t$ in terms of all exogenous shocks at every point time. In our more general model, $X_t$ contains endogenous state variables that depend on current and past exogenous shocks in the manner we make precise now. Decompose $X_t$ in (47) as a $(2S+3) \times 1$ vector with the exogenous shocks, $Z_t$, and a $(2S+2) \times 1$ vector with the endogenous state variables, $K_t$,

$$X_{t+1} = \begin{bmatrix} Z_{t+1} \\ K_{t+1} \end{bmatrix} = \begin{bmatrix} H_{11} & 0 \\ H_{21} & H_{22} \end{bmatrix} \begin{bmatrix} Z_t \\ K_t \end{bmatrix} + \begin{bmatrix} \omega_{t+1} \\ 0 \end{bmatrix}, \tag{A3}$$

where $H_{11}$, $H_{21}$, and $H_{22}$ are conformable matrices with the parameters of the exogenous shock processes ($H_{11}$) and the coefficient of the decision rules of the endogenous predetermined variables ($H_{21}$ and $H_{22}$). Note that (A3) implies

$$Z_t = H_{11} Z_{t-1} + \omega_t, \tag{49}$$

$$K_t = H_{21} Z_{t-1} + H_{22} K_{t-1}. \tag{50}$$

Rewrite (48) as

$$Y_t = \begin{bmatrix} G_1 & G_2 \end{bmatrix} \begin{bmatrix} Z_t \\ K_t \end{bmatrix} = G_1 Z_t + G_2 K_t, \tag{A6}$$

where $G_1$ and $G_2$ are respectively conformable matrices with the coefficients of the exogenous shocks and the endogenous predetermined variables in the decision rules of the observable variables. Iterating backwards $\tau$ periods in (50) and using (49) allow us to write

$$Y_t = G_1 Z_t + G_2 \sum_{j=0}^{\tau} (H_{22})^j H_{21} Z_{t-1-j}. \tag{A7}$$

Equation (A7) decomposes exactly the observable variables in $Y_t$ in terms of current and past exogenous shocks and is the basis of the inflation decompositions reported in Sections 5 and 6 in the text.

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