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Relative Price Shocks and Inflation

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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 use a 15-sector New Keynesian model 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. Decomposing the 2012-2019 inflation shortfall, and its surge starting in 2021, we find that sectoral shocks were major contributors to the inflation deviations from target.

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

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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 two recent episodes, namely 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.[1] The analysis is based on an estimated multi-sector New Keynesian model with 15 consumption categories from the Personal Consumption Expenditures (PCE) price index and with heterogeneity in price rigidity, in the volatility of sectoral productivity and demand shocks, and in the rate 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.[2]

Such analysis immediately confronts 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 (DSGE)

[1] In order to focus on the mechanism that we want to highlight here, we abstract from the complementarities in production considered by the literature on production networks. Balke and Wynne (2000, p. 286) report that input-output effects on their own do not appear to deliver significant interactions between inflation and the characteristics of the cross-section distribution of price changes. This may be partly due to the fact that at low levels of disaggregation, the Input-Output (I-O) Table features large entries along the main diagonal. In the polar case where the I-O Table is diagonal and there are no input-output interactions, the amplification of monetary policy shocks would arise solely from the presence of intermediate goods in the production function as in Basu (1995). We leave these issues for future research.

[2] 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.

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. A key assumption of 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 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.[3]

Our paper makes three contributions to the literature. The first involves basic analysis of inflation and relative price shocks. We construct and estimate a model that addresses the empirical observations that the mean and standard deviation of sectoral price changes are different across 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. 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

[3]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%.

the structural shocks of the model, the largest contributors to the cumulative shortfall of the price level from the 2% trend implied by the Fed's target were the aggregate productivity shock (initially) and then shocks to gasoline and energy goods and to health care. About one-third 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.[4] 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 accounts for only 1/4 of the inflation surge. Most of the surge was driven by relative price shocks—both productivity and, especially, demand—to motor vehicles, gasoline, and housing.

The paper proceeds as follows. Section 2 contains a review that places our work in the literature and highlights our contribution. Section 3 describes the model and its balanced growth path. Section 4 describes the empirical approach and reports parameter estimates. Section 5 presents the basic analysis of inflation and relative price shocks. Section 6 covers the two episodes of the inflation shortfall from 2012-2019 and then the surge starting in 2021. 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.

[4] Exercises of this nature are standard in *Monetary Policy Reports* produced by central banks (e.g., the Federal Reserve, the Bank of Canada, and others). 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.

2. Literature Review

We split our discussion of the vast literature on relative prices and inflation into two parts: first, research that pre-dates the COVID pandemic, and second, research specifically concerned with the pandemic-related rise in inflation.

2.1 Pre-Pandemic

There is a large and varied body of research on relative prices and inflation that was conducted before the pandemic. One branch focuses on the role of oil shocks in driving short-run inflation fluctuations, for example, Kilian and Zhou (2021), and the references therein. Our paper embodies a generalization of that mechanism: we find that gasoline shocks are the most volatile relative price shocks, but that in any given period other categories may experience unusually large shocks that account for sizable movements in inflation. Another branch of the literature studies causality in the opposite direction, that is, from inflation to the variability of relative prices. These papers are concerned mainly with periods when inflation was not stable—in particular the 1970s and 1980s, with Parks (1978) being a key reference. 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.

While our analysis is conducted in the context of an estimated DSGE model, several papers analyze the empirical relationship between inflation and the distribution of price changes from a statistical perspective. A leading example of this research is Reis and Watson (2010), who employ a factor model and conclude that most inflation volatility is associated with relative-price movements.[5] As we will see, our structural model leads us to the same conclusion. Boivin et al. (2009) and Mackowiak et al. (2009) also use factor models to study the relationship between inflation and sector-specific shocks. In line with their statistical results, we find that most of the monthly fluctuations in price changes across consumption categories are due to sectoral shocks, but in contrast to Boivin et al. (2009), we find that sectoral productivity and demand shocks account for most of the variance of inflation.

Pastén et al. (2024) calibrate a large model with intermediate inputs, driven by produc-

[5]Note that Reis and Watson (2010) also discuss a DSGE model, but their analysis focuses on the factor model.

tivity shocks. They find that sectoral productivity shocks are important drivers of aggregate output, and that sectoral heterogeneity in price stickiness is quantitatively important. We find that both sector-specific demand and supply shocks are important drivers of inflation, and that heterogeneity in shock variance across sectors is required in order to explain the relationship between inflation and the distribution of relative price changes.

The papers closest to ours are Ball and Mankiw (1995), Balke and Wynne (2000), and Smets et al. (2019). Like us, they each bring some theory to bear on the relationship between relative prices and inflation. Ball and Mankiw (1995) note that there is an empirical relationship between the level of inflation and measures of asymmetry in the distribution of relative price changes. They propose an explanation based on a menu cost model: with fixed costs of price adjustment, inflation tends to move with the price change of sectors hit by the largest shocks to their desired price while prices do not change in sectors hit by small shocks to their desired price. In our model, Rotemberg costs mean that any firm hit by a shock will adjust its price. In equilibrium, the interaction of policy and shocks delivers a relationship between inflation and the distribution of actual relative prices consistent with the data.

Balke and Wynne (2000) argue that the pattern identified by Ball and Mankiw can be explained without relying on sticky prices and they assume instead that prices are completely flexible. These authors calibrate a multi-sector RBC model where monetary policy is characterized by a constant money-growth rule. Our paper extends Balke and Wynne's work by estimating a richer model in which there are sectoral demand as well as supply shocks, monetary policy follows a feedback rule for the nominal interest rate, and prices are sticky, with the degree of price stickiness allowed to vary across consumption categories. Like Smets et al. (2019), we estimate a DSGE model and use the Kalman filter to decompose the behavior of inflation into aggregate and sectoral shocks. They study network interactions absent from our model and estimate over a longer sample in which inflation was not stable. In comparison to these papers, our analysis concentrates on the period from 1995 to 2019 when the monetary policy regime was stable, so that the conditions for estimating a rational expectations model that is approximated around a steady state are more likely to be satisfied.

Our paper also relates to the literature that 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 et al. (2021) also emphasize that in a stable monetary policy regime, sector-specific factors can play a major role in driving inflation.

2.2 Inflation During the Pandemic and Its Aftermath

Our paper provides a model-based accounting for the behavior of U.S. inflation in which inflation is determined by the interaction of monetary policy with a variety of shocks, most notably shocks to supply and demand for different categories of consumption. Although our work was begun before the pandemic, we do apply it to study inflation after the onset of the pandemic. There has been an explosion of research that attempts something similar, and in this section we list many of those recent papers and explain what sets our work apart. The key general points are as follows. First, we are focused on how inflation is determined through the interaction between monetary policy, other aggregate shocks, and shocks that fundamentally affect relative prices, and we abstract from how sector-specific demand and supply shocks propagate through the economy. Second, we do not use the pandemic data for esimation, instead filtering the data for this period using our model estimated on pre-pandemic data. Finally, our model is fully dynamic and estimation includes the monetary policy rule and the processes driving sectoral supply and demand shocks.

Guerrieri et al. (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. Our 15-sector model is able to match the joint behavior of inflation and sectoral relative price changes. We then apply the estimated model to infer the contributions to inflation of sectoral shocks. In addition to gasoline, we find that shocks to motor vehicle productivity and demand were also important contributors to the inflation surge.

Just as we do, Shapiro (2022) analyzes COVID-era inflation within a broader framework for analyzing inflation over a longer period. Shapiro (2022) uses a structural VAR to decompose inflation into supply-driven and demand-driven components. In that framework, supply and demand are microeconomic concepts, and the underlying data covers disaggregated PCE prices and quantities. Our DSGE model provides a natural analogue to Shapiro's two components: the contributions of sectoral supply and demand shocks. However, the DSGE framework leaves room for inflation to be explained by other shocks, in particular aggregate shocks. In contrast, the supply-driven and demand-driven components together account for all the variation in inflation in the structural VAR. In section 6 we contrast our results for the inflation surge to Shapiro's decomposition.

Rubbo (2024) calibrates a rich model with a large number of sectors and a network structure. By estimating our model under full information we are able to overcome an important issue raised by Rubbo (p. 38), namely that "it is difficult to distinguish the components of aggregate inflation driven by the output gap vs relative demand and supply shocks, because we do not observe the aggregate output gap nor the relative price wedges." In addition, Rubbo models monetary policy as a money supply rule that makes nominal income exogenous, whereas we estimate an interest rate feedback rule. di Giovanni et al. (2023) analyze a multi-country version of the model in Baqaee and Farhi (2022), which also features a network structure. This model is essentially static, while ours is dynamic and allows us to study inflation as resulting from the interaction between monetary policy and sectoral shocks to supply and demand.

Similar to our paper, Gagliardone and Gertler (2023) provide decompositions of inflation into the contributions of sectoral and aggregate shocks in an estimated DSGE model. Their analysis uses two sectors, oil and non-oil, whereas in our model inflation may be driven by relative price shocks to 15 consumption categories. Ferrante et al. (2023) analyze the pandemic as a shock that reallocates demand from services to goods using a 66-sector model with an input-output structure. While the pandemic period lies outside our estimation sample, the filtering exercise in Section 6.2 uses post-2019 data, together with the estimated model, allows us to infer the shocks during that period.

With the dramatic COVID-era economic fluctuations there has been much discussion of supply constraints as a contributor to inflation. Two notable papers that incorporate supply constraints into explicit models are Comin et al. (2023), using a multi-sector model, and Bai et. al (2024), using a one-sector model. Other papers on pandemic-era inflation, while not considering explicit supply constraints, impose nonlinear aggregate Phillips curves that have a similar flavor. Harding et al. (2023) and Benigno and Eggertsson (2023) are both 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. Our model has multiple sectors and is linear: it does not have the sources of nonlinearity present in the papers with supply constraints or those with nonlinear Phillips curve, and in any case we study the linearized version of the model. While there are legitimate concerns about linearization, the sample we use for estimation is one in which the policy regime was arguably stable and the fluctuations in inflation were small by historical standards. According to our inflation decompositions a multi-sector framework is necessary for explaining the behavior of inflation both during the stable-inflation and COVID periods (note that Benigno and Eggertsson focus on core inflation rather than overall). Bernanke and Blanchard's (2023) empirical analysis also finds that sectoral shocks were important contributors to the high inflation episode that started in 2021.

Ball et al. (2022) construct an empirical decomposition of the inflation surge into (1) movements in core inflation arising from the labor market, (2) delayed pass-through into core inflation of shocks to headline inflation, and (3), shocks to headline inflation. Like us, they emphasize that shocks to headline inflation come not only from energy and food, and thus they use a weighted median as their measure of core.

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.

3. The Model

The economy consists of an infinitely-lived representative household, continua of firms producing final consumption goods in a finite number of sectors, and a monetary authority. Within each sector, firms are monopolistic competitors that produce differentiated goods using labor as the sole input of production. There are exogenous shocks to aggregate and sectoral productivity, aggregate demand, sectoral demand, and monetary policy.

3.1 Households

The household maximizes

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

where E_τ denotes the conditional expectation as of time τ, $\beta \in (0,1)$ is the discount factor, η_t is a preference shock, C_t is consumption, N_t is hours worked, and ψ and χ are positive preference parameters. The time endowment is normalized to be one. The preference shock follows the process,

$$\eta_t = \varrho \eta_{t-1} + \varsigma_t, \tag{2}$$

where $\varrho \in (-1,1)$ is a parameter and ς_t is an independent and identically distributed (i.i.d.) innovation drawn from a normal distribution with mean zero and variance σ_ς^2.

Consumption is a Cobb-Douglas aggregate of goods produced in different sectors $s = 1, 2, \ldots, S$,

$$C_t = \prod_{s=1}^{S} \left(\xi^s\right)^{-\xi^s} \left(c_{s,t} - u_{s,t}\right)^{\xi^s}, \tag{3}$$

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 $u_{s,t}$ is a sector-specific demand shock. The demand shock resembles a subsistence level of consumption for any good in sector s. Higher values of $u_{s,t}$ are positive demand shifters that raise the expenditure share devoted to sector s above ξ_s. The sector-s demand shock follows the process,

$$u_{s,t} = \varrho_s u_{s,t-1} + \zeta_{s,t}, \tag{4}$$

where $\varrho_s \in (-1,1)$ and $\zeta_{s,t}$ is an i.i.d. innovation drawn from a normal distribution with mean zero and variance $\sigma_{\zeta,s}^2$.[6] Within each sector, there is a continuum of monopolistically-competitive firms that each produce a differentiated good. The household's preferences for these goods are represented by the CES aggregator

$$c_{s,t} = \left(\int c_{i,s,t}^{(\theta-1)/\theta} \right)^{\theta/(\theta-1)}, \tag{5}$$

where $c_{i,s,t}$ 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.

[6] Because sectoral consumption has trend growth, we assume that the standard deviation of the shock in (3) grows over time; otherwise the sectoral demand shocks would become asymptotically irrelevant. To be formally correct, we would use notation that distinguishes the shock in (3) from that in (4), as the former does not have constant variance.

In every period, the household faces the budget constraint

$$P_t C_t + B_t \leq P_t w_t N_t + R_{t-1} B_{t-1} + D_t, \tag{6}$$

where P_t is the aggregate price level, B_t is nominal bonds, w_t is the real wage, R_t is the gross nominal interest rate, and D_t are profits from firms, which are transferred to the household in the form of dividends. The price index is

$$P_t = \prod_{s=1}^{S} P_{s,t}^{\xi_s}. \tag{7}$$

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

$$\frac{\psi \left(1 - N_t\right)^{-\chi}}{1/C_t} = w_t, \tag{8}$$

meaning that the marginal rate of substitution between leisure and consumption equals the real wage; the optimal consumption of good i produced in sector s is

$$c_{i,s,t} = \xi_s \left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta} \left(\frac{P_{s,t}}{P_t}\right)^{-1} C_t + u_{s,t}, \tag{9}$$

where

$$P_{s,t} = \left(\int P_{i,s,t}^{1-\theta} di\right)^{1/(1-\theta)} \tag{10}$$

is a sector-specific price index; and the optimal (total) consumption satisfies the intertemporal Euler equation

$$\frac{e^{\eta_t}}{P_t C_t} = \beta R_t E_t \left(\frac{e^{\eta_{t+1}}}{P_{t+1} C_{t+1}}\right). \tag{11}$$

3.2 Firms

Firm $i \in (0,1)$ in sector s produces output $(y_{i,s,t})$ using the technology

$$y_{i,s,t} = e^{a_t} e^{z_{s,t}} n_{i,s,t}^{\alpha}, \tag{12}$$

where e^{a_t} and $e^{z_{s,t}}$ are, respectively, the aggregate and sectoral productivity factors, $n_{i,s,t}$ is labor input, and $\alpha \in (0,1)$ is a parameter.[7] Labor is completely mobile across firms and sectors.[8] Sectoral productivity follows a random walk with drift,

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

[8]We abstract from potentially important frictions in the labor market and leave them for future research. Regarding the recent inflation surge, Bernanke and Blanchard (2023) conclude that labor market tightness made a modest contribution to inflation (at least initially) and that most of the early increase in inflation came from the goods market. Other research that examines the role of the labor market in the inflation surge includes, among others, Ball et al. (2022), Gagliardone and Gertler (2023), and Amiti et al. (2023).

$$z_{s,t} = (1-\rho_s)\mu_s + z_{s,t-1} + \rho_s(z_{s,t-1} - z_{s,t-2}) + \epsilon_{s,t}, \tag{13}$$

where μ_s is the drift, $\rho_s \in (-1,1)$, and $\epsilon_{s,t}$ is an i.i.d. 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. Aggregate productivity follows the process,

$$a_t = (1-\rho)\mu + a_{t-1} + \rho(a_{t-1} - a_{t-2}) + \varepsilon_t, \tag{14}$$

where μ is drift, $\rho \in (-1,1)$, and ε_t is an i.i.d. innovation drawn from a normal distribution with mean zero and variance σ^2_a. Without loss of generality, we normalize $\mu = 0$, but allow for nonzero μ_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.

Each firm incurs a price-adjustment cost, quadratic in the size of the nominal price adjustment, as in Rotemberg (1982). The cost is specified in units of labor and is proportional to the firm's labor input in production. The per-unit cost, $\Phi_{i,s,t}$, for firm i in sector s in period t is

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

where $\phi_s \geq 0$ and π_s is the steady-state rate of sectoral price change. There is complete indexation to the sectoral rate of price changes.[9] The firm chooses output, labor input, and the price of its good to maximize profits, where costs comprise labor costs and adjustment costs. The maximization is subject to the demand function (9) and the technology (12). The solution to this problem delivers the following optimality condition for firm i in sector

[9] 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 adjustment costs are zero in the deterministic steady state.

s:

$$(\theta-1)\left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta}\frac{y_{s,t}P_{s,t}}{P_t}=\frac{\theta w_t P_{s,t}}{\alpha P_{i,s,t}}\left(\left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta}\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha} \tag{16}$$
$$+\frac{\theta w_t P_{s,t}}{\alpha P_{i,s,t}}\frac{\phi_s}{2}\left(\frac{P_{i,s,t}}{\pi_s P_{i,s,t-1}}-1\right)^2\left(\left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta}\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha}$$
$$-w_t\phi_s\left(\frac{P_{i,s,t}}{\pi_s P_{i,s,t-1}}-1\right)\left(\left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta}\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha}\frac{P_{s,t}}{\pi_s P_{i,s,t-1}}$$
$$+E_t\left(\frac{w_{t+1}}{R_t}\frac{P_{s,t}P_{t+1}}{P_{i,s,t}P_t}\phi_s\left(\frac{P_{i,s,t+1}}{\pi_s P_{i,s,t}}-1\right)\left(\left(\frac{P_{i,s,t+1}}{P_{s,t+1}}\right)^{-\theta}\frac{y_{s,t+1}}{e^{a_{t+1}}e^{z_{s,t+1}}}\right)^{1/\alpha}\frac{P_{i,s,t+1}}{\pi_s P_{i,s,t}}\right).$$

This equation relates the optimal price selected by firm i to its marginal cost, including that associated with current and future expected price adjustments.

3.3 Monetary Policy

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

$$R_t=\delta R_{t-1}+(1-\delta)(1/\beta)\exp\left(\pi+\gamma_y+\lambda_\pi\left(\pi_t-\pi\right)+\lambda_y\left(\ln(C_t)-\ln(C)\right)\right)+v_t, \tag{17}$$

where $\delta\in(-1,1)$, λ_π, and λ_y are parameters representing responsiveness to the lagged interest rate, inflation, and output, respectively, π_t is the gross inflation rate ($=P_t/P_{t-1}$), γ_y is the growth rate of output (see below), π is a policy parameter denoting the inflation target, C_t is aggregate consumption, C is consumption in the balanced-growth steady state, and v_t is a disturbance that represents movements in the interest rate beyond the control of the central bank. This disturbance is assumed to be i.i.d. and drawn from a normal distribution with mean zero and variance σ_v^2.

3.4 Equilibrium and Balanced Growth Path

The equilibrium of the model is symmetric within sectors but asymmetric across sectors. That is, in equilibrium, 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. In a symmetric equilibrium we can simplify the optimality conditions by dropping the firm-specific i subscripts.

3.4.1 Sectoral Phillips Curve

The fact that firms in the same sector are identical in equilibrium means that the price charged by each firm is equal to the sectoral price index,

$$P_{i,s,t} = P_{s,t},\ s = 1, 2, \ldots, S.$$

The firm's optimality condition can then be written as the sectoral Phillips curve,

$$(\theta - 1)\frac{y_{s,t}P_{s,t}}{P_t} = \frac{\theta w_t}{\alpha}\left(\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha} + \frac{\theta w_t}{\alpha}\frac{\phi_s}{2}\left(\frac{\pi_{s,t}}{\pi_s} - 1\right)^2\left(\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha} \tag{18}$$
$$-w_t\phi_s\left(\frac{\pi_{s,t}}{\pi_s} - 1\right)\left(\frac{y_{s,t}}{e^{a_t}e^{z_{s,t}}}\right)^{1/\alpha}\frac{\pi_{s,t}}{\pi_s} + E_t\left(\frac{w_{t+1}\pi_{t+1}}{R_t}\phi_s\left(\frac{\pi_{s,t}}{\pi_s} - 1\right)\left(\frac{y_{s,t+1}}{e^{a_{t+1}}e^{z_{s,t+1}}}\right)^{1/\alpha}\frac{\pi_{s,t}}{\pi_s}\right),$$

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 et al., 2011, and Rubbo, 2023), the slope of the linearized Phillips curve is heterogenous across sectors, in our case as a result of heterogeneity in price rigidity.

3.4.2 Market Clearing

There is a goods market clearing condition in each sector

$$y_{s,t} = c_{s,t},$$

for $s = 1, 2, \ldots, S$, and a labor market clearing condition for the economy as a whole

$$N_t = \sum_{s=1}^{S} n_{s,t} + F_t,$$

where F_t is total adjustment costs

$$F_t = \sum_{s=1}^{S}\left(\frac{\phi_s}{2}\left(\frac{\pi_{s,t}}{\pi_s} - 1\right)^2 n_{s,t}\right).$$

3.4.3 Steady-state Growth Rates, Detrending, and Model Solution

The model has an exogenous growth rate for the overall price index on the balanced growth path. That growth rate, π, is determined by the inflation target in the policy rule. The model also has S exogenous trend growth rates for sectoral productivity, μ_s. Each sector's output growth rate is equal to its productivity growth rate. Productivity growth rates determine the growth rates of output and the real wage. Then, the inflation target, along with the relative productivity growth rates, determine the growth rates of sectoral prices as follows:

$$\gamma_y = \gamma_w = \sum_{s=1}^{S} \xi_s \mu_s, \tag{19}$$

$$\pi_s = \pi + \gamma_w - \mu_s = \pi + \sum_{j=1}^{S} \xi_j \left(\mu_j - \mu_s\right). \tag{20}$$

The trend growth (or decline) in sectoral *relative* prices is determined entirely by a real factor, namely sectoral relative productivity growth,

$$\pi_s - \pi = -\mu_s + \sum_{j=1}^{S} \xi_j \mu_j.$$

In the international trade literature, this mechanism underpins the celebrated Balassa-Samuelson effect whereby different rates of productivity growth in the tradeable good sector compared with the non-tradeable 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.

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). In order to apply this method we first need to rewrite the model in terms of stationary variables. For the real wage and aggregate consumption, we divide by economy-wide average productivity to induce stationarity. For sectoral real outputs, we divide by sectoral productivity (the product of the aggregate and sector-specific productivity shifters). For sectoral relative prices, we divide by the ratio of economywide average productivity to sectoral productivity.

4. Empirical Analysis

In this section, we describe the data and the estimation method, and we discuss the parameter estimates.

4.1 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 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 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 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 the seasonally-adjusted PCE 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. To be consistent with the model solution, which describes the dynamics of price and quantity growth rates in deviations from their steady state values, those data series are demeaned prior to the structural estimation of the model.

For estimating the model parameters, we treat the nominal interest rate as a latent, rather than an observable, variable. This econometric choice is motivated by the fact that 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 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.[10]

[10]In an earlier version of this paper (Ruge-Murcia and Wolman, 2022), we quadratically detrend the

4.2 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,

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

where X_t and ϑ_t are $(4S+5) \times 1$ vectors with S being the number of sectors, and H is a $(4S+5) \times (4S+5)$ 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

$$Q_t = GX_t,$$

where Q_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, ch. 8) shows 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 (ψ) is set to 1.8, such that households work 1/3 of the time in steady state. The preference parameter χ 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 (θ) is set to 10. This implies a mark-up of approximately 10%.

nominal interest rate and use the residual as a rough estimate of the cyclical interest rate component.

The elasticity parameter in the production function (α) is set to 0.75. The discount rate (β) is set to 0.998.

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 81 to 53 with a substantial gain in computational and statistical efficiencies.

The consumption weights are computed using the consumption expenditure shares in each sector. Recall that the optimal consumption of good i produced in sector s is

$$c_{i,s,t} = \xi_s \left(\frac{P_{i,s,t}}{P_{s,t}}\right)^{-\theta} \left(\frac{P_{s,t}}{P_t}\right)^{-1} C_t + u_{s,t}.$$

Using the fact that the equilibrium is symmetric within sectors, which implies $P_{i,s,t} = P_{s,t}$, setting $u_{s,t}$ equal to its unconditional mean (which is zero), and solving for ξ_s delivers

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

where $P_{s,t} c_{s,t}$ are expenditures in sector s and $P_t C_t$ are total consumption expenditures. Estimates of ξ_s for each sector are reported in Column 1 of Table 1.

Finally, the model suggests a natural strategy for calibrating the trends in sectoral productivity based on the result that sectoral price changes in steady state are

$$\pi_s = \pi + \gamma_c - \mu_s, \tag{21}$$

for $s = 1, 2 \ldots, S$. Solving for μ_s, so that $\mu_s = \pi + \gamma_c - \pi_s$, and using the fact that the model implies that the steady state values of aggregate inflation, aggregate consumption growth, and sectoral price changes are equal to their respective unconditional means, delivers estimates of μ_s for each sector. These estimates are reported in Column 2 of Table 1. Our calibration implies that recreational goods feature the largest rate of productivity growth in the U.S. economy, which accounts for the persistent decrease of the nominal price of goods in this consumption category at the rate of 0.5% per month, or about 6% per year. In line with Balassa (1964) and Samuelson (1964), the sectors with the highest productivity growth produce tradeable goods, while the sectors with the lowest productivity growth produce nontradeable goods (services).

4.3 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 2. Remaining ML estimates, including the parameters of the Taylor rule, are reported in Table 3.

Note in Table 2 that there is substantial heterogeneity in price rigidity across sectors and the null hypothesis that 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 2). 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 et al., 2014). In line with that literature, we find that price adjustment costs are generally higher in services than in other sectors. One exception is financial services and insurance for which the null hypothesis that the cost parameter is zero (i.e., $\phi = 0$), and thus 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). There are, however, some categories like gasoline and energy goods for which the hypothesis cannot be rejected at the 5% level. Quantitatively, the largest price rigidity parameters are those for motor vehicles and parts (another exception to the rule that goods have lower price adjustment costs), and housing and utilities. 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 statistically significant but quantitatively small: -0.244 with standard error (0.027). 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 motor vehicles and parts, both of which are one order of magnitude larger than for other sectors. The standard deviation of aggregate productivity innovations in Table 3 is lower than those for all but one of the sectoral productivity shocks.

The autoregressive coefficient of the sectoral demand shock is 0.992 (0.003). Table 2 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 gasoline, and motor vehicles and parts; they are again one order of magnitude larger than for other sectors.

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.

In Table 3, the autoregressive coefficient of the preference shock is 0.818, but the standard deviation of its innovations is quantitatively small and these parameters are not precisely estimated. Regarding the estimates of the monetary policy rule, the smoothing parameter is large (0.989), and statistically significant. The coefficients of inflation and output are positive and precisely estimated: 1.592 (0.602) and 0.658 (0.268), respectively.

4.4 Model Fit

Table 4 reports the standard deviation and autocorrelation of inflation and sectoral price changes predicted by the model and compares them with U.S. data. In contrast to method of moments estimators (e.g., GMM or SMM), our ML estimation procedure does not explicitly target these moments.[11] The table shows that our model quantitatively captures the low autocorrelation of sectoral price changes, and the heterogeneous volatility of those series,

[11] As 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 autocorrelations are "untargeted" moments. Notice that due to the condition (21) used to compute μ_s for each sector, our model matches perfectly the mean of sectoral price changes by construction.

notably the large standard deviation of price changes for gasoline and other energy goods.

These results are reported in an alternative manner in Panel A of Figure 1, 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. Overall, the panel shows that the moments predicted by the model are quantitatively in line with those of the data and the correlation between the two set of moments is high: 0.967.

Since the high correlation may be driven by the standard deviation of gasoline price changes (the outlier in Panel A), and in order to zoom in on the remaining moments, Panel B of Figure 1 performs the same comparison but excluding gasoline. The panel shows that the autocorrelation of motor vehicle price changes predicted by the model (0.81) is higher than the value computed from the data (0.31). Conversely, the autocorrelation of gasoline prices changes predicted by the model (-0.10) is lower than the value computed from the data (0.35). Counter-factual simulations indicate that these results are respectively driven by the relatively high (motor) and low (gasoline) estimates of the price adjustment cost parameter (see Table 2). However, in general, the plot in Panel B shows that the moments predicted by the model are quantitatively close to those of the data and the correlation between the two set of moments, after excluding gasoline, is still high: 0.726. In summary, we conclude that our model does a good job reproducing key features of the data on components of PCE inflation.

Figure 2 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 0.975. 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.

5. 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.

5.1 Impulse Responses

Figure 3 reports the responses of relative prices ($P_{s,t}/P_t$) to a negative productivity shock in each sector. For example, Panel A reports the response of the relative price of motor vehicles (thick blue line) and other relative prices (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 (13)). The relative prices are plotted normalized by their respective trends implied by their average growth rates. Thus, the fact that the IRFs show permanent level effects means that the shocks generate permanent deviations of relative prices from their prior trends. Depending on the degree of price stickiness in the sector, convergence to the new long-run level may be slow and monotonic or rapid with some overshooting and oscillations. Fluctuations in the relative price of the good produced in the sector that receives the shock are generally an order of magnitude larger than the fluctuations in the relative price of goods produced by the other 14 sectors.[12]

Figure 4 reports the responses of relative prices ($P_{s,t}/P_t$) to a negative demand shock in each sector with the size of the shock equal to one standard deviation of the demand innovation, $\sigma_{\zeta,s}$ (see (4)). In all panels, the demand shock leads to a large and persistent decrease in the relative price of the good produced in that sector (thick dashed line). This decrease is generally one or more orders of magnitude larger than the increase in the relative price of 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 4. The results in Figures 3 and 4 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. This property is also evident in the variance decomposition of sectoral price changes reported in Table 5. Recall that the variance decomposition is the proportion of the mean squared error of each sectoral price change at different horizons that is accounted for by each of the shocks.

Figure 5 reports the response of inflation to aggregate and sectoral shocks. The horizontal

[12]Recall that the aggregate price index, P_t, is a geometric average of sectoral prices (see eq. (7)) and hence the sum of the weighted responses of relative prices must add up to zero.

axis is months, and the vertical axis is the inflation deviation from steady state, expressed in percentage points at an annual rate. Panel B reports the inflation response to a monetary policy shock that reduces the nominal interest rate by σ_ν. Panel C reports the inflation response to a negative preference shock of size σ_ζ. The other panels report the inflation response to negative productivity (thick blue line) and demand (thin red line) shocks with size equal to one standard deviation of their respective innovation. Note that the scale of the vertical axis is different across panels. Different shock sizes across sectors and, to some extent, different price stickiness and expenditure shares across sectors, imply heterogeneity in the effects of relative price shocks on inflation. Quantitatively, the largest effects are due to shocks to aggregate productivity (Panel A), monetary policy (Panel B), motor vehicles (Panel D), gasoline (Panel J), finance and insurance (Panel P), housing and utilities (Panel L), and health (Panel M).

5.2 Accounting for the Variance of Inflation

Figure 6 plots the variance decomposition for the inflation rate at different horizons; Table 6 reports the short and long-horizon values. The horizontal axes in Figure 6 represent months and the vertical axes represent percentages. Panel A in Figure 6 shows that the aggregate productivity shock accounts for a substantial proportion of the variance of the inflation forecast error at all horizons: upwards of 17% at all horizons. Panel B shows that monetary policy accounts for around 11.8% of the inflation forecast error at the one-month horizon and 11.5% in the long run. Panel C shows that relative price shocks—both productivity (thick blue line) and demand (thin red line)—jointly account for around 71% of the inflation forecast error at all horizons, with demand shocks accounting for 50% of the forecast error and productivity shocks accounting for 21%.[13] The finding that relative price shocks account for a large proportion of the inflation forecast error at all horizons is consistent with results in Reis and Watson (2010, p. 146) who report that 76% of the movements in inflation are accounted for by a relative-price index.[14] A similar result is reported by Smets et al. (2019) who find that sectoral shocks, by way of pipeline pressures, are an important contributor to the variance and persistence of headline inflation.

[13]The shock to the discount rate accounts for less than 0.009% of the inflation forecast error at all horizons and is not plotted in Figure 6.

[14]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.

The remaining panels in Figure 6 (D through R) report the contribution of relative price shocks in each sector to the variance decomposition of inflation. Panel J shows that relative price shocks to gasoline account for approximately 46% of the variance of the inflation forecast error at all horizons, with demand shocks accounting for a higher proportion of the variance (31%) than productivity shocks (15%). The contribution of gasoline demand shocks is high. We see two reasons for our estimated model to deliver this result. First, because we assume Cobb-Douglas preferences across the 15 consumption categories, expenditure shares are constant in response to sectoral productivity shocks. To the extent that the actual gasoline expenditure share comoves positively with the relative price of gasoline, our model would interpret this comovement as coming from gasoline demand shocks. Second, our model abstracts from network effects, whereby demand for gasoline may be affected by other sectoral shocks which then feed through to the demand for gasoline.

Panels Q, D, L, M, and K show that relative price shocks to finance and insurance, motor vehicles, housing and utilities, health, and other nondurables substantially contribute to the variance of inflation (roughly 7.1%, 4.8%, 3%, 1.3%, and 2.4%, respectively). Demand shocks appear to be quantitatively more important than productivity shocks in all cases. Research based on dynamic factor models (e.g., see Boivin et al., 2009) typically finds that aggregate factors are the main driver of inflation.[15] Using a structural model with input-output interactions, Onatski and Ruge-Murcia (2013) show that macroeconomic shocks can indeed be considered factors in that 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.

Table 5 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); and the monetary policy shock (Column 4). The table shows that, except for health care, the own productivity shock accounts for most of the variance of all sectoral price changes. The contribution of the own demand shock is also substantial. The contribution of the aggregate shocks varies across sectors. In particular, the aggregate productivity and monetary policy shocks respectively account for 18% and 13% of the unconditional variance of price changes

[15] Boivin et al. (2009) emphasize in addition the differential responses of sectoral prices to aggregate and sectoral shocks. Carvalho et al. (2021) show how adding input-output linkages and labor market segmentation can help a multi-sector New Keynesian model match these patterns.

in health care, but less of other sectoral price changes. The contributions from other sectors' productivity and demand shocks are negligible.[16] The finding that the sector-specific shocks account for most of the variance of sectoral price changes is consistent with results reported in Boivin et al. (2009) and Mackowiak et al. (2009) based on estimated dynamic factor models. Boivin et al. (2009) report that 85% percent of the monthly disaggregated price-change fluctuations are attributable to sector-specific shocks, while Mackowiak et al. (2009) 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.

It is interesting to note that there is basically no relationship between price rigidity and the proportion of the variance that is accounted for by the monetary policy shock. The correlation between the price rigidity parameters in Table 2 and the proportions in Column 4 is -0.264 and not statistically significant. In contrast, the correlation between the standard deviation of sectoral productivity shocks in Table 2 and the proportions in Column 3 is -0.513 and statistically significant at the 5% level: in sectors with less volatile productivity innovations, aggregate productivity explains a larger proportion of the variance of price changes.

5.3 Inflation and the Distribution of Relative Price Changes

Panel A in Figure 7 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.[17] 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 7 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

[16]These figures are not reported to save space, but their sum can be computed by substracting the contributions in Table 4 from 100% for each sector.

[17]This empirical relationship is discussed in Wolman (2023) and examined in more detail by Hornstein et al. (2024).

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,

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

which implies

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

where Γ is the share of relative price increases, and Δr^{+} and Δr^{-} 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 economywide 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 (Figure 5). It is theoretically 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.[18]

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 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.

[18] 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 et al. (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.

In order to better understand the model features that drive these results, we perform a comparative static exercise to examine the roles of price rigidity, heterogeneity in the volatility of demand shocks, and heterogeneity in the volatility of supply shocks. Panel C in Figure 7 again 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 where all prices are flexible. That is, all parameters ϕ_s are set to zero while the remaining parameters are those reported in Tables 1 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.

These results relate to work by Balke and Wynne (2000). Compared with Ball and Mankiw (1995), whose explanation for the relationship between relative price changes and inflation relies on price stickiness, Balke and Wynne consider a flexible-price model. There are 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.

Panels D and E plots the relationship between the monthly PCE inflation rate and the share of relative price increases based on data simulated from versions of the model where the standard deviation of all demand shocks (Panel D) or supply shocks (Panel E) are the same. That is, in Panel D all $\sigma^2_{\zeta,s}$ are set to the same value, namely the median of the estimates in Table 2. Similarly, in Panel E all $\sigma^2_{z,s}$ are set to the median of the estimates in Table 2. Panels D and E show that the close relationship between the two variables remains when we independently assume no heterogeneity in the volatility of demand or supply shocks. In contrast, Panel F shows that the relation is considerable weaked when we jointly assume no heterogeneity in the volatility of demand and supply shocks. Thus, we show that accounting for the empirical relationship between relative price changes and inflation requires heterogeneity in the variance of sectoral shock innovations.

6. 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 two episodes, one within the estimation sample and one outside it.

6.1 Inflation Shortfall 2012-2019

From 2012 to 2019, PCE inflation averaged only 1.39%. While this shortfall from target may seem minor in the context of the high inflation starting in 2021, it received significant attention at the time. For example, in one of the key documents from the FOMC's 2019-2020 review of its monetary policy framework, the authors wrote "Inflation has persistently fallen short of the Committee's 2 percent inflation goal" (Altig et al., 2020). We focus here on the post-2012 period and use the model to decompose the inflation shortfall into contributions from the various estimated shocks.[19] The shocks are the smoothed estimates obtained using the Kalman filter. Appendix A shows how this decomposition is carried out starting from the state-space representation of the model solution so that the indirect effect of the shocks via the endogenous state variables is taken into account.

If the model state variables were at their steady states and there were no shocks, then inflation would be constant at target. The model explains an episode of deviations from target inflation by a combination of initial state variables being away from steady state and subsequent shocks. Figure 8 presents four 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 deviation in percentage points from 2%.[20] The initial state for aggregate productivity by itself would have led to inflation being somewhat above target. Other state variables did not play an important role and we will henceforth discuss only the contributions from shocks.

[19]A leading theoretical explanation for the inflation shortfall is that it resulted from the interaction between the lower bound on nominal interest rates and the Fed's implicit policy rule (see, for example, Bianchi et al., 2021). Our current results cannot speak directly to that view because we do not explicitly impose a lower bound on the interest rate. Instead, we treat the interest rate as a latent variable during the estimation procedure in the spirit of the econometric model of the shadow federal funds rate in Wu and Xia (2016).

[20]We report deviations from 2% because that is the FOMC's inflation target. Mean inflation over our sample is 1.8%, so we subtract 0.2 percentage points from the model's deviations from target inflation in order to get the deviations from 2%.

Panel A reports the contribution of the aggregate productivity shock, the monetary policy shock, and the sum of all relative price shocks (both productivity and demand) to the inflation shortfall. The contribution of the aggregate preference shock is negligible and omitted for clarity. An important observation from Panel A is that monetary policy played a limited, but consistent, role in the shortfall. On average, the shortfall due to monetary policy is 0.21 percentage points (pp). Since the average inflation shortfall was $2\% - 1.39\% = 0.61$ pp, we conclude that about one-third of the shortfall is attributable to monetary policy. This result also means that most of the inflation shortfall was due to aggregate productivity and relative price shocks, although their contribution varies substantially over time. In particular, the contribution of aggregate productivity shocks was only quantitatively important in the period from 2014 to 2016, and its average contribution is only 0.08 pp. The contribution of relative price shocks to the inflation shortfall is quantitatively important for most of the sample, and particularly large in 2014-2016, when the shortfall was the largest.

Panel B differs from Panel A in that it separately reports the sum of all productivity shocks and the sum of all demand shocks, in addition to the aggregate productivity shock and the monetary policy shock. This panel shows that sectoral productivity shocks made a consistent but limited contribution to the inflation shortfall, reaching 0.4 pp in early 2015, but that sectoral demand shocks contributed even more to the shortfall, reaching 0.85 pp in October 2015.

Panel C attempts to shed some light on the contribution of different sectors by reporting the contribution of the joint productivity and demand shocks for gasoline and health care, in addition to the aggregate productivity and monetary policy shocks we reported earlier. Health care shocks played a substantial role initially, specially in 2013 and 2014 when their contribution reached 0.2 pp (August 2013). On average, the contribution of health care shocks is about 0.08 pp. Gasoline shocks are the most important relative price shocks in accounting for the shortfall, and in the period 2015-2016 account (along with aggregate productivity) for most of the shortfall.

Finally, Panel D splits up health care and gasoline into their respective productivity and demand shocks. Both shocks to gasoline were by far the most important relative price shocks. The contribution of gasoline productivity shocks to the inflation shortfall is comparable to that of monetary policy. The contribution of gasoline demand shocks to the shortfall is comparable to the aggregate productivity shock. Once we decompose relative price shocks in health care into productivity and demand we can see that both played a role in the shortfall but separately not a large one.

In summary, most of the inflation shortfall in 2012-2019, and in particular in the period 2015-2016 when the shortfall was the largest, is attributable to aggregate productivity shocks and to relative price shocks (both productivity and demand) to gasoline and other energy goods. On average, about 1/3 of the shortfall is attributable to monetary policy. The monetary policy contribution was stable over time, including during the period when the Fed was raising rates. While that rate increase was gradual by historical standards, according to our estimated model it represented contractionary policy.

6.2 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 Fed's 2% target. Recent work that studies inflation during this period is discussed in Section 2.2 above.

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 sceptically 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 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.

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 9 presents selected elements of the decomposition of the inflation surge. The figure plots the period from January 2020 through June 2023 and, thus, captures the onset of the pandemic and the high inflation months that followed. As before, the figure presents four 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 monetary policy shock, and the sum of all sectoral productivity and demand shocks to inflation. (The contribution of the aggregate preference shock is negligible and omitted for clarity). First note that monetary policy is estimated to have deviated little from its estimated rule, even as inflation rose well above target. The monetary policy shock can account for at most 1 pp of annual excess inflation in mid-2022. Since inflation in this period was roughly 6%, the monetary policy shock accounts for approximately 1/4 of the inflation surge. Aggregate productivity played a limited role in the decrease in inflation and accounted for slightly less than 1 pp of the inflation surge. Thus, a clear message from Panel A is that relative price shocks (both demand and productivity) accounted for most of the initial fall in inflation and for more than 1/2 of the subsequent inflation surge.

Panel B reports separately the sum of all supply and demand shocks, in addition to the aggregate productivity shock and the monetary policy shock. This plot shows that relative productivity shocks played a role comparable to the aggregate productivity shocks, with the contribution peaking in early 2022, around the time that Russia invaded Ukraine, but decreasing thereafter. The plot also shows that the largest contributors to the inflation surge were sectoral demand shocks. At its peak in mid-2022, demand shocks contributed close to 1/2 of the surge. 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. Whereas we find that productivity shocks—both aggregate and sectoral—accounted for only two-thirds as much of the peak inflation as did sectoral demand shocks, the decomposition into supply- and demand-driven components finds that supply-driven components contributed forty percent more to peak inflation than demand driven components (see Federal Reserve Bank of San Francisco, 2024).

Panel C reports the contribution of the joint supply and demand shocks in each sector. (We excluded those sectoral shocks that played a limited role so as not to crowd the picture.) In addition to aggregate productivity and monetary policy that we reported earlier, this panel reports the sum of supply and demand shocks for motor vehicles, housing, and gasoline and energy goods. Comparing Panels C and A shows that while the initial inflation decrease was strongly driven by gasoline shocks, the surge in 2021 and 2022 was driven by many sectors with these three being the most prominent. Panel D decomposes relative price shocks to motor vehicles, housing, and gasoline and energy goods into their respective productivity and demand components and makes the point that both types contributed to the surge, with demand and productivity shocks to gasoline being important in 2022, and housing demand shocks becoming increasingly important in 2023.

In summary, according to our estimated model, gasoline shocks drove the sharp drop in inflation early in the pandemic with monetary policy consistent with the 2% inflation target. The contribution from monetary policy shocks and aggregate productivity shocks to the subsequent high inflation was limited and most of the high inflation is instead attributable to relative price shocks, with shocks to motor vehicles, housing, and gasoline being the most prominent.

7. 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 heterogeneity across sectors in the variance of shocks and the degree of price stickiness. In addition to summarizing the contributions of the various shocks to inflation, we also decompose the behavior of inflation during two recent episodes. First, the inflation shortfall from 2012 to 2019, and second, the episode starting with the onset of the COVID pandemic, when inflation eventually rose far above target. The latter episode is 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 two 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. Sectoral Consumption Weights and Productivity Trends

Sector	Consumption Weight	Productivity Trend $\times 10^2$
	(1)	(2)
Motor vehicles and parts	0.0450	0.2831
Furnishings and household durables	0.0280	0.4036
Recreational goods	0.0321	0.8060
Other durable goods	0.0165	0.3672
Food at home	0.0802	0.1444
Clothing and footwear	0.0361	0.3440
Gasoline and other energy goods	0.0298	0.0052
Other nondurable goods	0.0822	0.1621
Housing and utilities	0.1876	0.0683
Health care	0.1595	0.1049
Transportation services	0.0346	0.1315
Recreation services	0.0397	0.0865
Food services and accommodations	0.0651	0.0753
Financial services and insurance	0.0775	0.0616
Other services	0.0862	0.0938

Table 2. ML Estimates of Sectoral Parameters

Sector	Price Rigidity		S.D. Innovations to Productivity $\times 10^2$		S.D. Innovations to Demand $\times 10^3$	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
	(1)	(2)	(3)	(4)	(5)	(6)
Motor vehicles and parts	502.761*	104.309	2.534*	0.241	1.629*	0.061
Furnishings and household durables	6.353*	2.209	0.486*	0.041	0.252*	0.012
Recreational goods	16.083*	4.087	0.629*	0.059	0.340*	0.017
Other durable goods	0.103	0.833	0.504*	0.039	0.231*	0.012
Food at home	11.346*	3.210	0.352*	0.035	0.366*	0.010
Clothing and footwear	4.140*	1.298	0.561*	0.043	0.418*	0.020
Gasoline and other energy goods	0.994	0.568	3.102*	0.318	2.611*	0.287
Other nondurable goods	1.979*	0.833	0.274*	0.018	0.470*	0.019
Housing and utilities	53.268*	10.422	0.366*	0.039	0.658*	0.032
Health care	5.900*	1.750	0.143*	0.014	0.323*	0.016
Transportation services	1.118	0.674	0.381*	0.021	0.382*	0.013
Recreation services	15.422*	3.540	0.329*	0.033	0.252*	0.013
Food services and accommodations	17.629*	3.774	0.290*	0.029	0.362*	0.016
Financial services and insurance	0.273	0.628	0.422*	0.026	0.795*	0.058
Other services	54.532*	15.618	0.418*	0.058	0.386*	0.016
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 3. Other ML Estimates

Parameter	Estimate	s.e.
	(1)	(2)
Autoregressive coefficients:		
Sectoral productivity	-0.244^*	0.027
Sectoral demand shock	0.992^*	0.003
Discount factor shock	0.818	3.803
S.D. of innovations to:		
Aggregate productivity	0.206^*	0.014
Discount factor shock $\times 10^2$	0.002	1.338
Taylor rule:		
Smoothing parameter	0.989^*	0.010
Inflation coefficient	1.592^*	0.602
Output coefficient	0.658^*	0.268
Standard deviation $\times 10^4$	0.123	0.092

Note: See notes to Table 2.

Table 4. Empirical and Theoretical Second Moments

Variable	Standard Deviation		Autocorrelation	
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
Aggregate inflation	0.187	0.155	0.387	0.060
Sectoral price changes:				
Motor vehicles and parts	0.315	0.683	0.307	0.805
Furnishings and household durables	0.377	0.424	−0.019	0.074
Recreational goods	0.355	0.433	0.026	0.250
Other durable goods	0.597	0.627	−0.170	−0.157
Food at home	0.263	0.273	0.266	0.184
Clothing and footwear	0.517	0.542	0.016	0.018
Gasoline and other energy goods	4.986	3.740	0.349	−0.094
Other nondurable goods	0.303	0.333	−0.140	−0.035
Housing and utilities	0.140	0.184	0.338	0.495
Health care	0.148	0.173	0.116	0.109
Transportation services	0.511	0.487	−0.045	−0.075
Recreation services	0.208	0.256	0.097	0.260
Food services and accommodations	0.169	0.230	−0.056	0.297
Financial services and insurance	0.722	0.568	−0.236	−0.122
Other services	0.171	0.209	0.356	0.502

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 5. Unconditional Variance Decomposition

	Own Shock		Aggregate Shock	
Variable	Productivity	Demand	Productivity	Monetary Policy
	(1)	(2)	(3)	(4)
Sectoral price changes:				
Motor vehicles and parts	77.524	22.130	0.143	0.097
Furnishings and household durables	70.686	21.628	3.004	2.038
Recreational goods	72.753	22.057	2.000	1.356
Other durable goods	66.260	28.190	2.217	1.504
Food at home	65.392	19.543	5.870	3.982
Clothing and footwear	66.763	27.974	2.076	1.408
Gasoline and other energy goods	61.190	38.686	0.057	0.039
Other nondurable goods	50.538	33.071	6.530	4.430
Housing and utilities	62.235	21.643	6.341	4.302
Health care	34.066	18.080	18.821	12.768
Transportation services	53.005	38.692	3.305	2.242
Recreation services	58.472	26.142	5.918	4.015
Food services and accommodations	51.338	30.731	6.896	4.678
Financial services and insurance	52.103	41.315	2.672	1.812
Other services	70.027	17.037	4.897	3.322

Table 6. Variance Decomposition of Inflation

	Aggregate Shocks		Sectoral Productivity		Sectoral Demand	
	1-month	Uncond.	1-month	Uncond.	1-month	Uncond.
	(1)	(2)	(3)	(4)	(5)	(6)
Monetary policy	17.34	17.00				
Aggregate productivity	11.76	11.53				
Aggregate demand	0.01	0.01				
Motor vehicles and parts			0.11	0.69	3.67	4.09
Furnishings and household durables			0.16	0.15	0.23	0.23
Recreational goods			0.17	0.16	0.36	0.36
Other durable goods			0.13	0.15	0.21	0.19
Food at home			0.45	0.42	0.73	0.72
Clothing and footwear			0.44	0.44	0.80	0.77
Gasoline and other energy goods			13.76	15.13	33.39	31.43
Other nondurable goods			0.71	0.75	1.69	1.60
Housing and utilities			0.42	0.56	2.23	2.40
Health care			0.48	0.47	0.95	0.91
Transportation services			0.27	0.30	0.76	0.72
Recreation services			0.07	0.07	0.22	0.22
Food services and accommodations			0.14	0.13	0.57	0.57
Financial services and insurance			1.93	2.19	5.23	4.91
Other services			0.11	0.15	0.52	0.56

Note: The unconditional decomposition is approximated by its value 2400 periods ahead..

Appendix A: Inflation Decomposition

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

$$X_{t+1} = HX_t + \vartheta_{t+1}, \tag{22}$$

$$Q_t = GX_t, \tag{23}$$

where (22) is the state equation, (23) is the observation equation, X_t and ϑ_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, Q_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, (23) would provide the exact decomposition of each variable in Q_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 (22) 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

$$Z_t = H_{11}Z_{t-1} + \omega_t, \tag{24}$$

$$K_t = H_{21}Z_{t-1} + H_{22}K_{t-1}. \tag{25}$$

Rewrite (23) as

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

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 τ periods in (25) and using (24) allow us to write

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

Equation (A7) decomposes exactly the observable variables in Q_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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Figure 1: Moment Fit

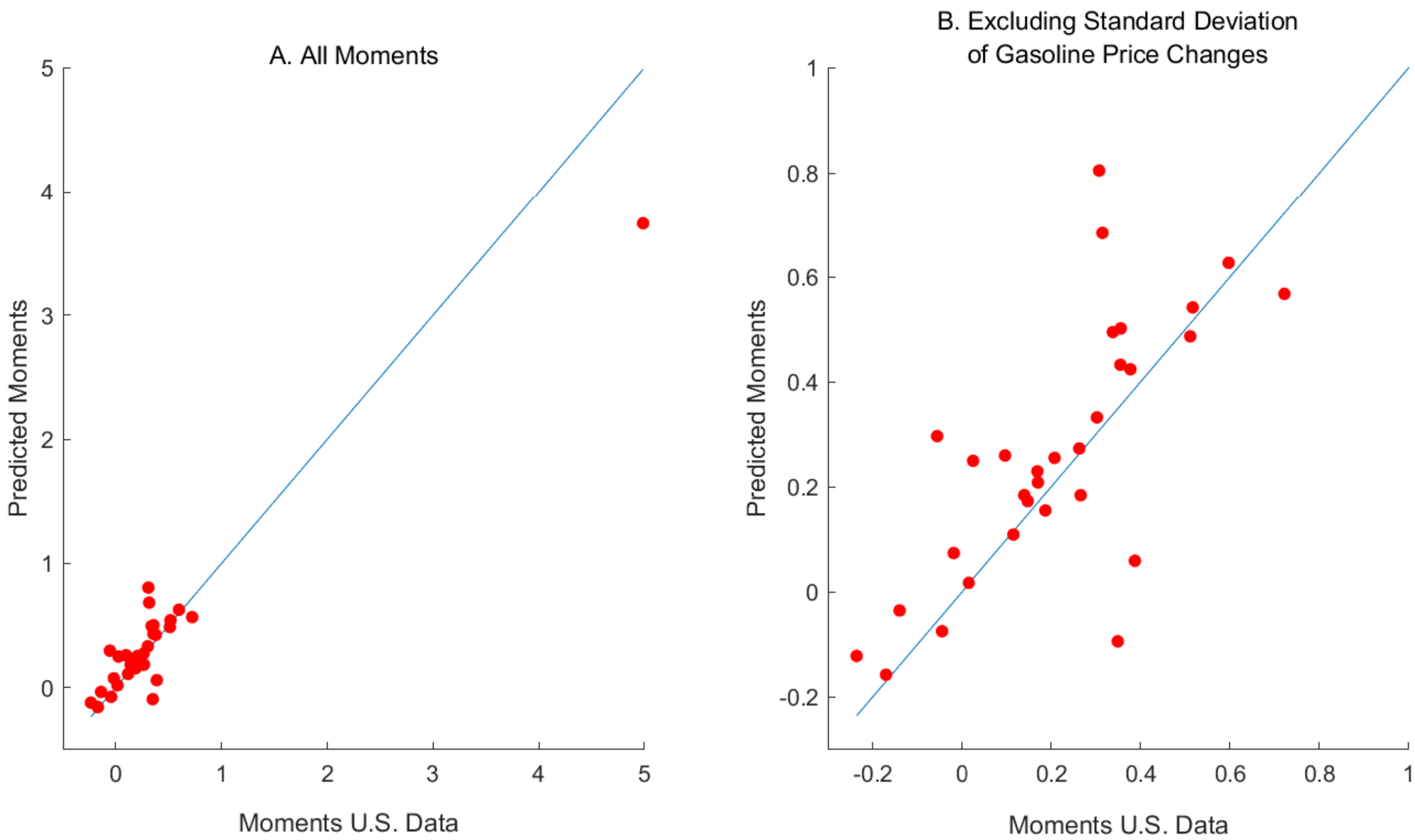

Figure 2: Inflation Fit

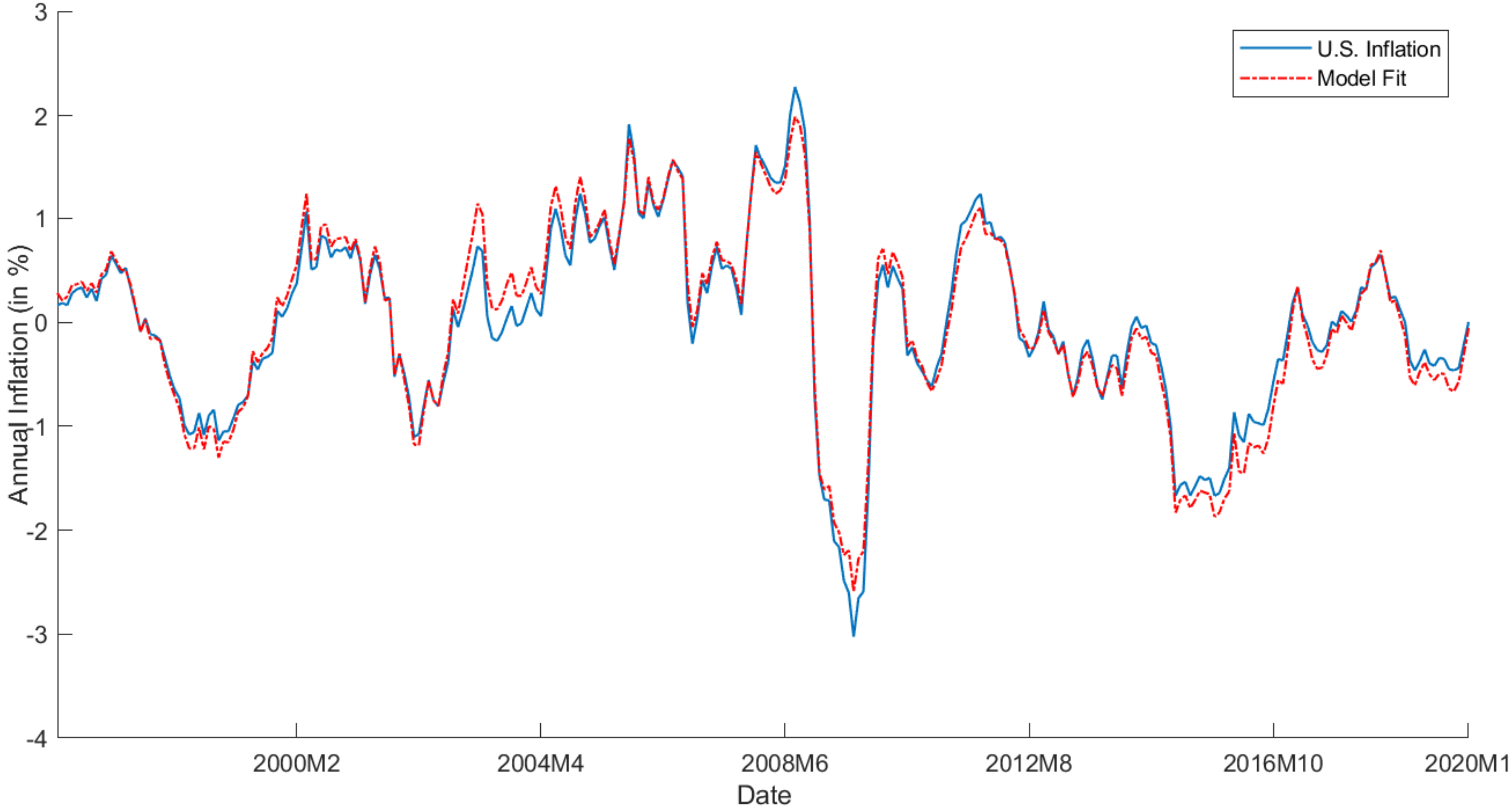

Figure 3: Responses of Relative Prices to a Negative Productivity Shock to Own Sector

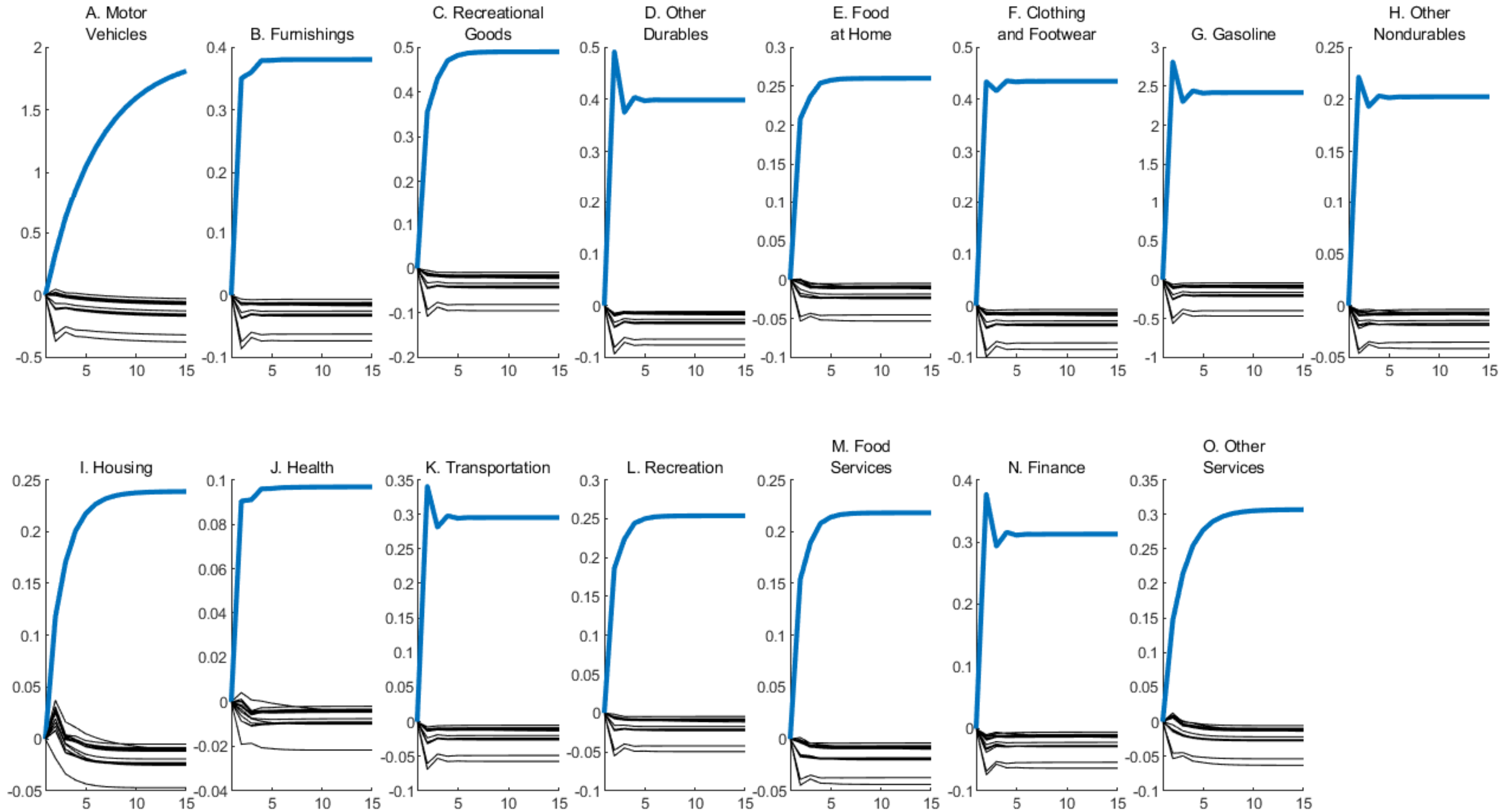

Figure 4: Responses of Relative Prices to Demand Shocks to Own Sector

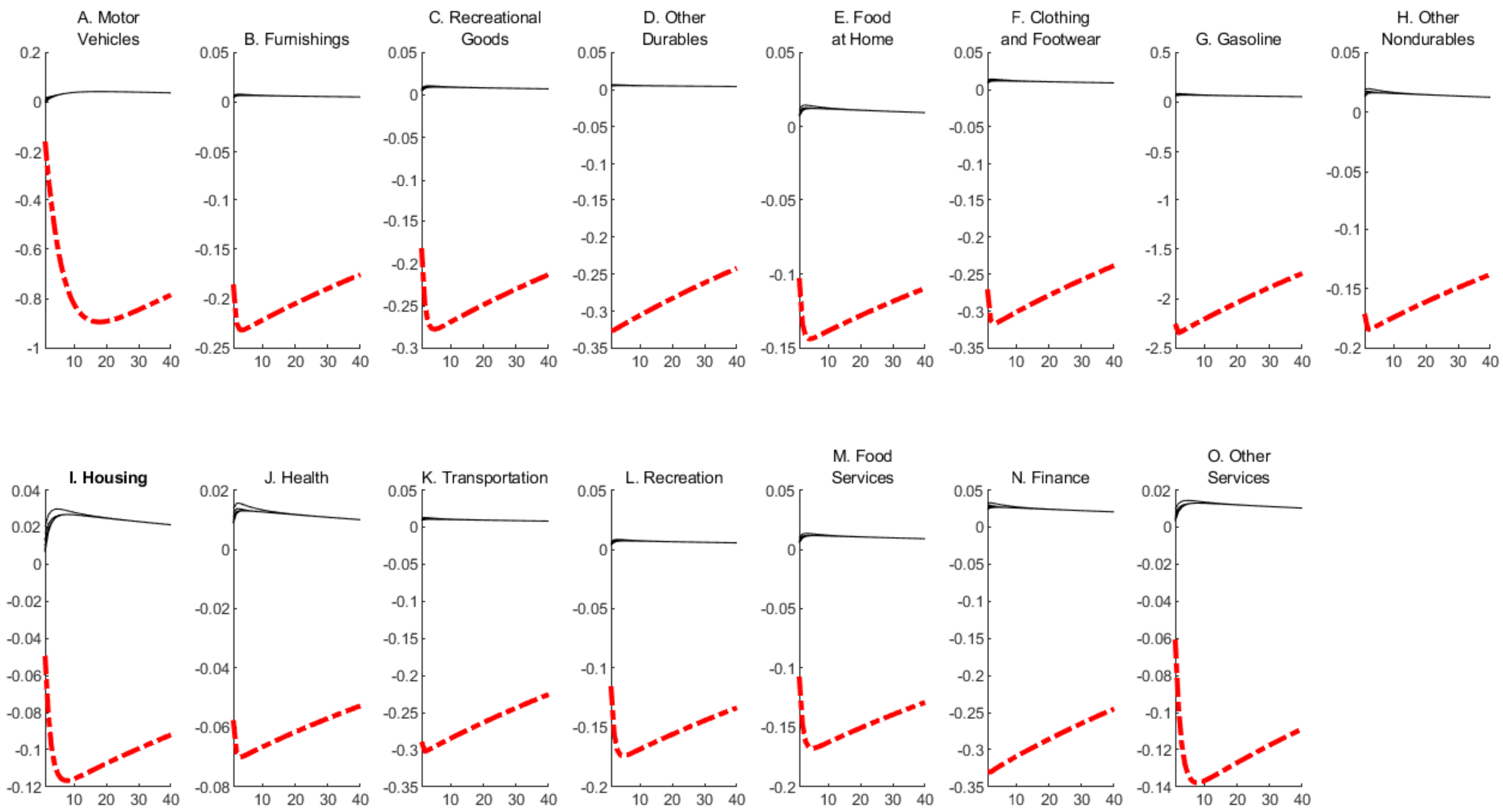

Figure 5: Inflation Responses

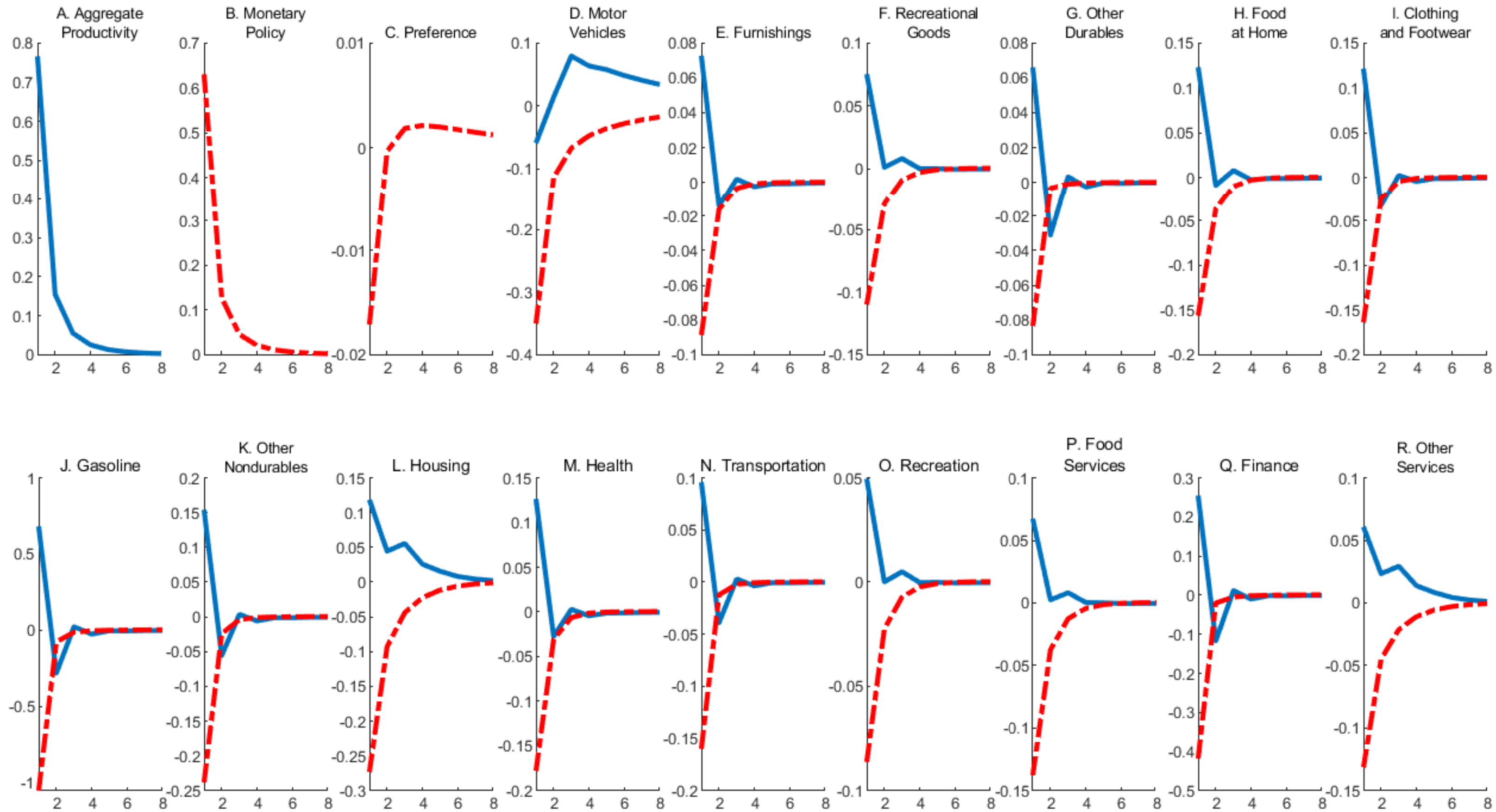

Figure 6: Variance Decomposition Inflation Rate

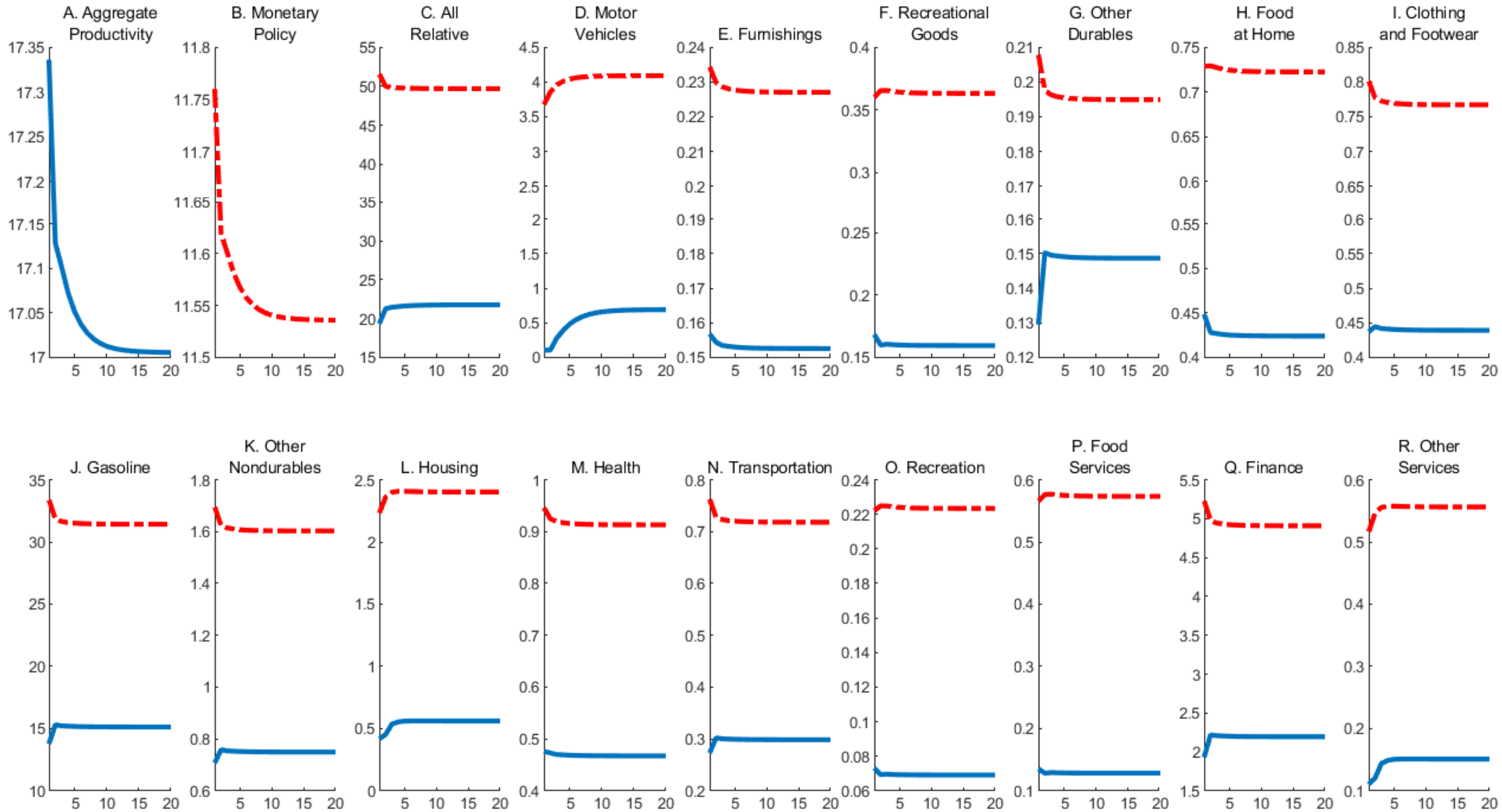

Figure 7: Inflation and the Share of Price Changes Larger than Inflation

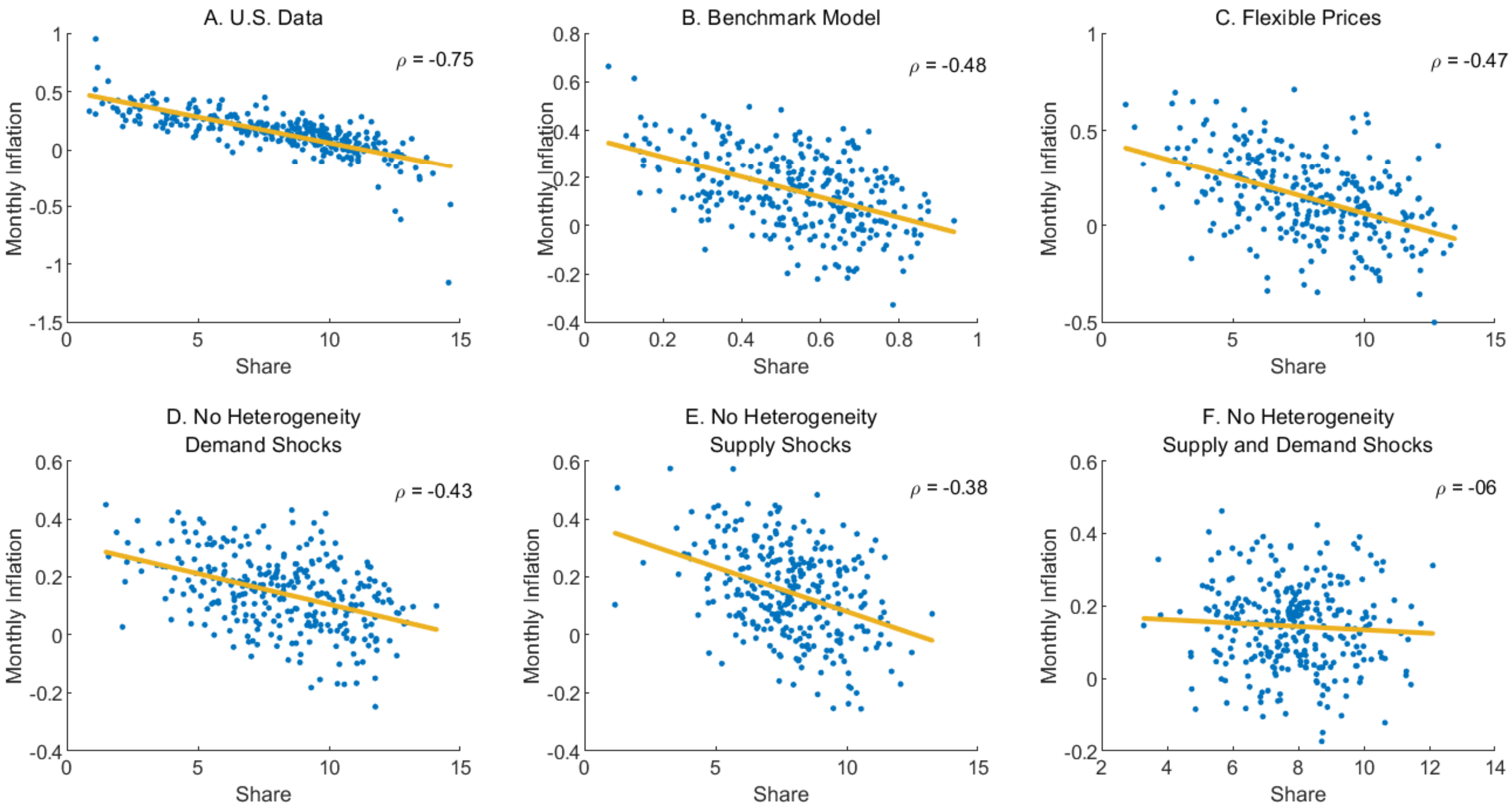

Figure 8: Inflation Shortfall and Contribution from Selected Shocks

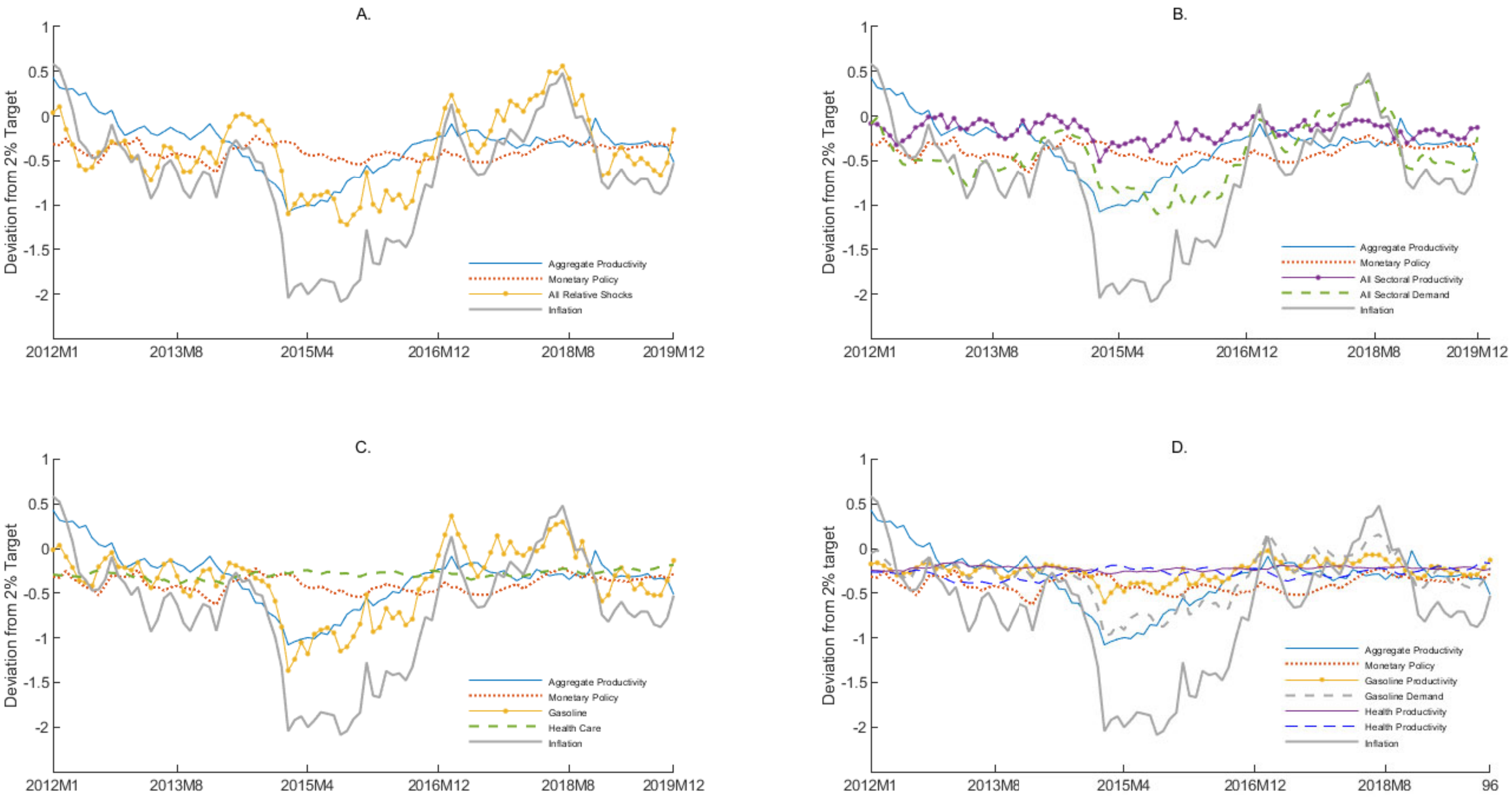

Figure 9: Inflation Surge and Contribution from Selected Shocks