The Inflationary Effects of Sectoral Reallocation*

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PRELIMINARY AND INCOMPLETE

Abstract

The COVID-19 pandemic has led to an unprecedented shift in household consumption expenditures from services to goods. This paper studies the effect of such demand reallocation in a multi-sector New Keynesian model featuring input-output linkages and frictions to increasing factor inputs in the form of hiring costs. These costs hamper the adjustment of the supply of goods in response to the shift in demand, causing inflationary pressures which propagate through the production network. The inflationary effects of the demand reallocation shock are amplified by the fact that goods prices are more flexible than those of services. We take the model to the data and estimate a version that allows for reallocation shocks, idiosyncratic productivity shocks at the sectoral level, and an aggregate labor supply shock. The demand reallocation shock can account for a large portion of the rise in U.S. inflation in the aftermath of the pandemic.

KEYWORDS: Sectoral Reallocation, Inflation, Input-Output Models, Moment-matching exercise.

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1 Introduction

Figure 1 plots the share of household consumption expenditures on goods in the United States. The COVID-19 pandemic has led to an unprecedented increase in the demand for goods relative to services, interrupting the steady decline in the share of spending on goods over the past 50 years. A popular narrative is that this reallocation in demand has put pressure on supply chains, which have struggled to adjust and have exhibited bottlenecks in a number of key sectors. At the same time, US CPI inflation has risen to levels not seen since the 1980s, reaching 7 percent by the end of 2021. Figure 2 shows that this has largely been driven by a surge in goods inflation, while the rise in inflation in services has been much more muted. In addition, the rise in inflation has been accompanied by a large rise in the dispersion of inflation across sectors (as shown in Figure 3).

In this paper, we develop a multi-sector New-Keynesian model of the U.S. economy to quantify the aggregate and cross-sectional implications of this reallocation of demand. The model features input-output linkages between sectors, heterogeneity in sectoral price rigidity, and costs of reallocating inputs across sectors.[1] In particular, we assume that firms face convex hiring costs when increasing labor inputs, while downward labor adjustments are frictionless.[2] This modeling strategy captures the observation that, while employment collapsed abruptly in many sectors at the onset of the pandemic, it recovered more slowly thereafter. We use the model to study the effect of a simple preference shock that alters the relative demand for goods and services, calibrated to match the rise in the expenditure share on goods that has occurred since the onset of COVID-19. A key feature of the model is that such a shock differentially affects sectors of the economy based on their location in supply chains for the production of goods and services.

We assess the transmission mechanisms of the model for aggregate variables via traditional impulse responses and describe the main forces behind our results. Additionally, we assess the empirical implications of the model for prices and quantities at the industry level by comparing the evolution of the model objects with their data counterparts between 2019 and 2021. After presenting our model and the approach we use to take the model to the data (Sections 2 and 3), we proceed in two steps.

In the first step (Section 4), we consider the model dynamics in the aftermath of a reallocation shock. At the aggregate level, our demand reallocation shock would not have any implication for

[1] We calibrate the industry structure of the model following the U.S. input-output tables provided by the BEA as in Baqaee and Farhi (2020). We calibrate heterogeneity in price rigidity to match the evidence presented in Pasten, Schoenle and Weber (2020). We estimate the cost of reallocating inputs as explained in Section 3.

[2] As our model does not include capital, these hiring costs can be thought of as a reduced-form way to capture a variety of frictions affecting a firm's ability to increase its labor input or its productive capacity more broadly.

quantities or prices absent input adjustment costs: goods production would immediately jump on impact, while services production would decline, leaving relative prices unchanged (see Figure 4). However, in our baseline model with costly labor adjustment the demand reallocation shock causes a peak increase in inflation of about 4 percentage points (see Figure 4). In the model, inflation occurs in response to a reallocation shock for two main reasons. First, because of the hiring costs, goods-producing sectors can increase their labor input only gradually. While these firms can potentially adjust production by using more intermediate inputs, these are only imperfect substitutes for primary inputs, causing a slow adjustment in quantities and a large rise in prices. Furthermore, since goods are also used as intermediate inputs, these inflationary pressures propagate across sectors through the production network. In contrast, service sectors reduce production swiftly, with limited reductions in prices. Second, the inflationary effects of the shift in demand are amplified by the heterogeneity in price rigidity that exists across sectors. A key feature of the data on price adjustment is that industries that produce goods have significantly more flexible prices than those that produce services. We find that, all else equal, allowing for heterogeneity in price rigidity across sectors increases the inflationary effects of the preference shock by around 25 percent (see Figure 5).

At the industry level, we show that our simple demand reallocation shock is able to explain a good proportion of the cross-sectional evolution of prices and quantities since the onset of COVID-19. As shown in Figure 6, not only does the shock explain why goods prices have risen more than services prices, but it also accounts for the observed heterogeneity within goods-producing and within services-producing industries, despite the fact that it affects final demand for goods and services uniformly. Both input-output linkages and sectoral heterogeneity in price stickiness contribute to this result (see Figure 12). In the model as in the data, sectors producing goods which are directly consumed by households or selling inputs which are heavily used in the production of these goods experience a larger increase in inflation. In contrast, industries providing services to consumers or inputs to the service sectors experience weaker inflationary pressures. Furthermore, sectors with more flexible prices exhibit larger price changes, all else equal.

While this simple demand reallocation shock can explain a significant proportion of the cross-sectional developments across industries between 2019 and 2021, there are a number of sectors for which price and quantity dynamics are hard to reconcile with the dynamics following an aggregate reallocation shock. One striking example is the "Motor Vehicle Parts and Dealer" sector, which has experienced a 25% decline in quantities and a 60% rise in prices between 2019 and 2021. Such evidence is suggestive of the importance of pandemic-related supply disruptions in some sectors, which may have contributed to the aggregate effects of supply chain bottlenecks more broadly.

Additionally, an important feature of the macroeconomic landscape during the pandemic was an aggregate decline in labor supply, which may have further exacerbated the economy's productive capacity in the short run.

To understand the relative importance of demand and supply disruptions, we enrich our model by considering two additional shocks in Section 5. First, by linking industry data from different sources, we measure the evolution of total factor productivity at the industry level between 2019 and 2021 and feed the estimated idiosyncratic component of these productivity series into our multi-sector model. Second, we consider an additional, aggregate labor supply shock that occurs early in 2020 and reduces agents' willingness to work. We then use a moment-matching exercise to estimate the magnitude of the reallocation costs, production function elasticities, and the size of the aggregate labor supply shock. This way, we provide a coherent accounting of whether these demand and supply factors can explain the dynamics of inflation since the onset of COVID-19. Importantly, our moment matching exercise only targets two aggregate variables—the decline in aggregate employment, and the difference in PCE inflation between goods and services. The remaining moments being targeted are the cross-sectional implications of model for prices, output and employment across detailed U.S. industries.

The estimated model can explain a large bulk of the rise in U.S. inflation during the COVID recovery, even though aggregate inflation was not a target of the estimation exercise. In the model as in the data, inflation rises by about 5 percentage points as the combined result of demand reallocation, idiosyncratic TFP and aggregate labor supply shocks, with the reallocation shock accounting for the large bulk of the rise. However, while playing a limited role in explaining aggregate inflation, the idiosyncratic supply shocks improve the model's ability to explain the cross-sectional evolution of both prices and quantities, thus bolstering our confidence in using our model for making prediction at the aggregate economy level. In addition, our estimation delivers values of production function elasticities that are at the lower end of the range typically used in the literature, suggesting that supply constraints caused by labor adjustment costs play an important role to match the cross-sectional evidence for prices and quantities during the pandemic.

Our key contribution is to show that a simple input-output model can explain the heterogeneous nature of industry dynamics in the post-COVID recovery, can account for a large portion of the movement in aggregate inflation that was observed between 2019 and 2021, and can provide a coherent accounting of the various shocks and frictions that have shaped inflation in the post-pandemic recovery. COVID-19 has motivated a small number of recent papers to study the effects of household preference shocks that reallocate demand between sectors. Fornaro and Romei (2022) and Guerrieri et al. (2021) study such shocks in stylized models with two sectors and two periods. In contrast, we focus on the implications of how such shocks play out through the production network in a quantitative, estimated infinite-horizon model. We show that the inclusion of input-output linkages is crucial both for understanding and decomposing the cross-sectional and aggregate effects of such a shock.

Section 2 describes the multi-sector model, which we calibrate and estimate in Section 3. Section 4 studies the cross-sectional and aggregate effects of the demand reallocation shock. In Section 5 we study the effects of two sources of supply shocks: i) idiosyncratic productivity shocks at the sectoral level and ii) an aggregate labor supply shock. In Section 6 we further explore the mechanisms in the model and study various extensions of our experiments.

2 Model

This section describes a multi-sector New Keynesian model featuring input-output linkages. The economy consists of N sectors. The model contains two frictions: costs to adjusting prices and costs to reallocating labor across sectors. In order to incorporate price-adjustment costs, we assume that in each sector $i = \{1, ..., N\}$ there are three types of firms: final good producers, intermediate good producers, and labor agencies.

A representative final good producer aggregates the output of a continuum of monopolistically competitive intermediate good producers. Intermediate goods are produced using labor and a bundle of material inputs by firms that set prices subject to quadratic price adjustment costs. Sector-specific labor is supplied to intermediate good producers by labor agencies that hire labor from the representative household and face convex hiring costs.

Below we describe the problem faced by each type of firm before turning to the problem of the representative household. We then set out the central bank's monetary policy rule and the model's market clearing conditions.

2.1 Final Good Producers

In each sector, i, a representative final good producer aggregates the output of a continuum of monopolistically competitive intermediate good producers:

$$Y_t^i = \left[\int_0^1 y_t^i(s)^{\frac{\epsilon-1}{\epsilon}} ds \right]^{\frac{\epsilon}{\epsilon-1}} \tag{1}$$

The solution to the final good producer's problem implies the following demand curve for intermediate goods in each sector:

$$Y_t^i(s) = \left(\frac{P_t^i(s)}{P_t^i}\right)^{-\epsilon} Y_t^i \tag{2}$$

2.2 Intermediate Good Producers

In each sector, i, a continuum of intermediate good producers supply differentiated goods to the final good producer subject to price adjustment costs. Intermediate goods are produced according to the following production function:

$$Y_t^i(s) = \left(\alpha^{\frac{1}{\epsilon_Y}} \left(M_t^i(s)\right)^{\frac{\epsilon_Y - 1}{\epsilon_Y}} + (1-\alpha)^{\frac{1}{\epsilon_Y}} \left(L_t^i(s)\right)^{\frac{\epsilon_Y - 1}{\epsilon_Y}}\right)^{\frac{\epsilon_Y}{\epsilon_Y - 1}} \tag{3}$$

Material inputs $M_t^i(s)$ are a CES bundle of the outputs of the N sectors of the economy:

$$M_t^i(s) = \left(\sum_{j=1}^{N} \Gamma_{i,j}^{\frac{1}{\epsilon_M}} \left(M_{j,t}^i(s)\right)^{\frac{\epsilon_M - 1}{\epsilon_M}}\right)^{\frac{\epsilon_M}{\epsilon_M - 1}} \tag{4}$$

The parameters $\Gamma_{i,j}$ determine the importance of the output of sector j as an input of production in sector i. The intermediate good producers problem can be split into two stages: a cost minimization problem and a price-setting problem.

2.2.1 Cost Minimization

Given the CES aggregator in equation 4, the cost minimization problem implies the following price index for materials:

$$P_t^{M,i} = \left(\sum_{j=1}^{N} \Gamma_{i,j} (P_t^j)^{1-\epsilon_M}\right)^{\frac{1}{1-\epsilon_M}} \tag{5}$$

Given this price index for materials, $P_t^{M,i}$, and a price of labor in sector i, $P_t^{L,i}$, a second cost-minimization problem determines the marginal cost of production in sector i:

$$MC_t^i = \left(\alpha (P_t^{M,i})^{1-\epsilon_Y} + (1-\alpha)(P_t^{L,i})^{1-\epsilon_Y}\right)^{\frac{1}{1-\epsilon_Y}} \tag{6}$$

2.2.2 Price Setting

Given the marginal cost derived in the previous section, intermediate good producers set prices subject to quadratic adjustment costs. The recursive form of their problem is:

$$
\begin{aligned}
V_t^i(P_{t-1}^i(s)) = \max_{P_t^i(s)} & \left(\frac{P_t^i(s)}{P_t^i}\right)^{-\epsilon} Y_t^i(P_t^i(s) - MC_t^i) \\
& - \frac{\kappa_i}{2}\left(\frac{P_t^i(s)}{P_{t-1}^i(s)}\right)^2 P_t^i Y_t^i + E_t\left[M_{t+1}V_{t+1}^i(P_{t-1}^i(s))\right]
\end{aligned}
\tag{7}
$$

The solution to the price setting problem is the following sector-level New Keynesian Phillips curve:

$$
1 - \epsilon + \epsilon\frac{MC_t^i}{P_t^i} - \kappa_i(\Pi_t^i - 1)\Pi_t^i + \kappa_i E_t\left(M_{t+1}\frac{(\Pi_{t+1}^i)^2}{\Pi_{t+1}}(\Pi_{t+1}^i - 1)\frac{Y_{t+1}^i}{Y_t^i}\right) = 0 \tag{8}
$$

where M_{t+1} is the stochastic discount factor of the representative household and $\Pi_t = \frac{P_t}{P_{t-1}}$.

2.2.3 Labor Agencies

In each sector, labor is supplied to the intermediate good producers by labor agencies that hire labor from the representative household. We assume that these agencies face convex hiring costs.[3][4] Importantly, these costs are asymmetric, since labor agencies have to pay them only when increasing labor. The recursive form of the labor agencies problem is:

$$
V_t^i(L_{t-1}^i) = \max_{L_t^i} P_t^{L,i}L_t^i - W_tL_t^i - \mathbb{1}_{L_t^i > L_{t-1}^i} W_t L_t^i \frac{c}{2}\left(\frac{L_t^i}{L_{t-1}^i} - 1\right)^2 + E_t\left[M_{t+1}V_{t+1}^i(L_t^i)\right] \tag{9}
$$

The solution to this problem is the following dynamic equation for sectoral labor demand:

$$
\begin{aligned}
P_t^{L,i} = W_t + \mathbb{1}_{L_t^i > L_{t-1}^i} W_t & \left(\frac{c}{2}\left(\frac{L_t^i}{L_{t-1}^i} - 1\right)^2 + c\left(\frac{L_t^i}{L_{t-1}^i} - 1\right)\frac{L_t^i}{L_{t-1}^i}\right) \\
& - \mathbb{1}_{L_{t+1}^i > L_t^i} E_t\left(M_{t+1} c W_{t+1}\left(\frac{L_{t+1}^i}{L_t^i} - 1\right)\left(\frac{L_{t+1}^i}{L_t^i}\right)^2\right)
\end{aligned}
\tag{10}
$$

[3] Given that we use a non-linear solution of the model, We assume that these costs are non-pecuniary, in the sense that do not enter the labor market clearing condition in order to avoid possible large resource costs arising from labor reallocation. We follow the same approach for the Rotemberg adjustment costs.

[4] There is a large literature studying convex hiring costs, for example, Merz and Yashiv (2007) and Gertler and Trigari (2009).

Equation 10 is key to understand the inflationary dynamics in our model, as it introduces a wedge between the aggregate wage and the price of labor in each industry.

2.3 Households

There is a representative household whose total consumption is a bundle of consumption of goods and of services:

$$C_t = \left(\frac{C_t^g}{\omega_t}\right)^{\omega_t} \left(\frac{C_t^s}{1-\omega_t}\right)^{1-\omega_t} \tag{11}$$

We allow the relative demand for goods, ω_t, to vary over time. The solution to the household's cost minimization problem implies:

$$P_t^g C_t^g = \omega_t P_t C_t \tag{12}$$

$$P_t = (P_t^g)^{\omega_t} (P_t^s)^{1-\omega_t} \tag{13}$$

Equation 12 implies that with this preference structure ω_t is equal to the expenditure share on goods. Figure 1 suggests that ω_t rose from 0.31 before the pandemic to a high of 0.36 in early 2021. Thus this is the size of the shift in ω_t that we will study in Section 4.

Goods consumption and services consumption are both bundles of the consumption of each of the N sectors:

$$C_t^g = \Pi_{i=1}^N \left(\frac{C_{i,t}}{\gamma_i^g}\right)^{\gamma_i^g} \tag{14}$$

$$C_t^s = \Pi_{i=1}^N \left(\frac{C_{i,t}}{\gamma_i^s}\right)^{\gamma_i^s} \tag{15}$$

where $\sum_{i=1}^N \gamma_I^g = 1$ and $\sum_{i=1}^N \gamma_I^s = 1$. We use the BEA's bridge between PCE consumption categories and NAICS industries to derive the weights in each of these aggregators. Again, the solution to the cost-minimization problem implies:

$$P_t^g = \Pi_{i=1}^N (P_t^i)^{\gamma_t^g} \tag{16}$$

$$P_t^s = \Pi_{i=1}^N (P_t^i)^{\gamma_t^s} \tag{17}$$

2.3.1 Consumption, Leisure and Saving Decisions

The representative household has the following preferences over total consumption, C_t, and hours worked, N_t:

$$U = \frac{C_t^{1-\gamma}}{1-\gamma} - \chi_t \frac{N_t^{1+\psi}}{1+\psi} \tag{18}$$

The representative household maximizes utility subject to the nominal budget constraint:

$$P_t C_t + B_{t+1} = W_t N_t + (1 + i_t) B_t + \Pi_t \tag{19}$$

The solution of the household's problem gives the following first-order conditions:

$$C_t^{-\gamma} = \beta E_t \left[C_{t+1}^{-\gamma} \frac{1 + i_{t+1}}{\Pi_{t+1}} \right] \tag{20}$$

$$C_t^{-\gamma} \frac{W_t}{P_t} = \chi_t L_t^{\psi} \tag{21}$$

2.4 Monetary Policy

Monetary policy follows a standard Taylor rule.

$$i_{t+1} = \frac{1}{\beta} - 1 + \phi \log \Pi_t \tag{22}$$

2.5 Market Clearing

The model's market clearing conditions are as follows. First, the output market must clear in each sector:[5]

$$Y_t^i = C_{i,t} + \sum_{j=1}^{N} M_{i,t}^j \quad \forall i \tag{23}$$

Second, total labor hired in each sector is equal to that supplied by the household:

$$\sum_{i=1}^{N} L_t^i = N_t^i \tag{24}$$

Finally, the bond market clears:

$$B_{t+1} = 0 \tag{25}$$

[5] We assume that the price adjustment costs in each sector do not enter that sector's market clearing condition.

3 Taking the Model to the Data

3.1 Calibration

We study a 66 sector version of the model. Consumption share parameters and input-output parameters are calibrated using the BEA's input-output tables. We use the BEA's bridge between PCE categories and NAICS industries to determine whether a sector should be classified as producing goods or services.

We calibrate price adjustment costs at the sectoral level using data from Pasten, Schoenle and Weber (2020). We convert the frequency of price adjustment at the industry level from their paper to the value of κ_i that implies the same slope of the New Keynesian Phillips curve. A key feature of their price adjustment data is that the prices of industries that produce goods are more flexible than those of industries that produce services.

The top portion of Table 1 details the other externally calibrated parameters. The Frisch inverse labor supply elasticity parameter ψ is set at 1, and the risk aversion parameter γ is set at 2. We assume a discount factor β of 0.99 and a response coefficient of interest rates to inflation $\phi = 1.5$, consistent with the Taylor principle. The goods expenditure share $\bar{\omega}$ is set at 0.31, the elasticity of substitution ϵ across final varieties is 10, the shares of intermediate goods in production α is 0.5.

3.2 Estimation

We estimate the remaining objects by minimizing the distance between the model objects and their data counterparts.

The parameters we estimate are c, the hiring cost parameter; ϵ_M, the elasticity of substitution between intermediate inputs; ϵ_Y, the elasticity of substitution between labor and intermediate inputs; and $\Delta\chi$, the size of the labor supply shock (a shock to the parameter χ). We group these parameters in the vector $\boldsymbol{\theta}$.

A crucial parameter in driving the model dynamics is the size of the labor adjustment costs, c. This parameter determines how quickly production is able to reallocate between sectors following the preference shock. The evolution of relative prices shown in Figure 2 provides a way of indirectly inferring the size of such adjustment costs and paves the way for our estimation strategy. If labor is fully flexible and c equals 0, the preference shock has no effect on relative prices: only quantities adjust at the sectoral level, and there are no effect on aggregate inflation, consumption or employment. On the other hand, if hiring is costly, then the quantity of goods produced will only adjust slowly, and the relative price of goods will rise sharply. In addition, since production employs both labor and intermediate inputs, the parameters ϵ_Y and ϵ_M are important for determining how the effect of shocks feeds through the production network to sectoral output and prices.

We want our model to match the heterogeneous behavior of inflation, output and employment growth that was observed in 2020-2021 relative to the pre-COVID period. For each of our 66 industries, we calculate the percent change in prices relative to a sector-specific trend[6] between 2019Q4 and 2021Q4. We repeat the same procedure for output and employment.[7]. We stack these cross-sectional changes in three vectors $\mathbf{y}_d$, $\mathbf{p}_d$, $\mathbf{l}_d$. Additionally, we want our model to capture the differential rise in inflation between goods and services throughout the same period, as well as the aggregate decline in employment between 2019 and 2021. Inflation in the goods and services sector rose by 6 and 1 percentage points between 2019 and 2021, respectively ($\Delta\pi_d^G - \Delta\pi_d^S = 5\%$). Employment declined about 4 percent relative to trend, on average, in 2020 and 2021 compared to 2019 ($\Delta L_m = 4\%$). Our estimated parameters solve the following problem.

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} \left[\psi\left(\boldsymbol{\theta}\right)\right]' W \left[\psi\left(\boldsymbol{\theta}\right)\right] \tag{26}$$

$$\psi\left(\boldsymbol{\theta}\right) = \begin{bmatrix} \sigma\left(\mathbf{y}_d\right) - \sigma\left(\mathbf{y}_m\left(\boldsymbol{\theta}\right)\right) \\ \sigma\left(\mathbf{p}_d\right) - \sigma\left(\mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \sigma\left(\mathbf{l}_d\right) - \sigma\left(\mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{y}_d, \mathbf{y}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{p}_d, \mathbf{p}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{l}_d, \mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \Delta L_d - \Delta L_m\left(\boldsymbol{\theta}\right) \\ \left(\Delta\pi_d^G - \Delta\pi_d^S\right) - \left(\Delta\pi_m^G\left(\boldsymbol{\theta}\right) - \Delta\pi_m^S\left(\boldsymbol{\theta}\right)\right) \end{bmatrix}' \tag{27}$$

where $\sigma\left(\mathbf{y}_d\right)$, for instance, denotes the cross-sectional standard deviation of the percent change in industry output between 2019 and 2021; and where $\rho\left(\mathbf{y}_d, \mathbf{y}_m\left(\boldsymbol{\theta}\right)\right)$ denotes the correlation between industry changes in output and the corresponding model objects throughout the same period.

The estimated parameters are reported in the bottom portion of Table 1. Of note, we find

[6] Calculated over the 2005-2019 period.

[7] Some industries—e.g., data processing—boomed during the pandemic. Some had large increases in output—e.g.wood products—, some had large declines—e.g. air transportation. Some others had outsized declines in employment—e.g., hotels

Table 1: Parameter Values

Calibrated Parameters	**Value**	**Target/Source**
γ	2	Standard
χ	1	Normalization
ψ	1	Standard
ϕ	1.5	Standard
β	0.99	Standard
ϵ	10	Standard
$\bar{\omega}$	0.31	Goods Expenditure Share
α	0.5	Pasten, Schoenle and Weber (2020)
κ	0.05 to 98	Pasten, Schoenle and Weber (2020)
Estimated Parameters	**Value**	**Target/Source**
c	25.96 (15.75)	Estimated (s.e.)
ϵ_M	0.01 (0.28)	Estimated (s.e.)
ϵ_Y	0.48 (0.04)	Estimated (s.e.)
$\Delta\chi$	0.0614 (0.0190)	Estimated (s.e)

low elasticities of substitution across goods and even lower across materials, and an important role for the aggregate labor supply shock in accounting for the aggregate decline in employment. The elasticities that we estimate are in line with those estimated using different approaches (e.g. Atalay (2017)). As already mentioned, without hiring costs, the model would predict no dispersion in cross-sectional prices in response to the demand reallocation shock. We have also found that constraining production function elasticities to unity leads to a significant decline in the models ability to fit cross-sectional moments.

4 The COVID-19 Demand Reallocation Shock

With the estimated parameters in hand, we turn off the aggregate labor supply shock ($\Delta\chi = 0$), we turn off the idiosyncratic TFP shocks, and we now turn to our main experiment, which is to study the effect of an increase in demand for goods relative to services.

As explained in Section 2.3, the size of this shift can be calibrated using data on consumption expenditure shares: with Cobb-Douglas preferences, ω_t is the share of consumption expenditure on goods. Thus, we study the response of the economy to a rise in ω_t from 0.31 to 0.36, and assume that ω_t returns to its original value with a quarterly persistence of 0.95. We solve for the full non-linear response of the model's endogenous variables to this unexpected shock using a perfect foresight solution method.

Figure 4 plots the response of key aggregate variables to the preference shock. The reallocation of demand leads to a large increase in goods consumption and a large decline in services consumption. As shown by the dashed lines in Figure 4, absent hiring costs, these changes offset each other leaving aggregate prices, consumption and employment unchanged.[8] Once we introduce adjustment costs, the increase in employment aggregated across goods-producing industries is much slower, constraining goods supply and resulting in a smaller increase in goods consumption compared with the frictionless model. As a consequence, goods prices jump, resulting in year-over-year goods inflation to peak at around 7 percent after one year.

Despite the absence of adjustment costs to cut employment, labor in the service sectors declines less than in the frictionless model, as firms internalize the fact that, after the initial drop, they will have to increase labor again and face hiring costs. While services inflation initially declines, it starts picking up once the goods consumption starts reverting, peaking at about 3.5 percent after 5 quarters.[9]. All told, the dynamics of sectoral inflation result in aggregate inflation peaking at about 4 percent after one year, which represents a sizeable portion of the increase in CPI shown in Figure 2. In our baseline model, the reallocation shock also causes a decline in aggregate employment and consumption, due to the fact that the decline in production and labor in the services sectors is steeper than the increase in the goods sectors. In Figure 5 we repeat the experiment but assuming that all sectors have the same price stickiness (equal to the average stickiness in our baseline calibration). Compared to our baseline calibration, lower price stickiness in the goods sector would result in a lower path for goods inflation, causing a peak aggregate inflation about 1 percentage point lower than in our baseline. Hence, heterogeneous price stickiness is an important element to explain the inflationary effects of a demand reallocation shock.

The model also contains rich predictions on the dynamics of sectoral prices and quantities. In particular, as shown in Figure 6, the simple relative demand shock is able to explain a good fraction of the dispersion in industry-level inflation rates and output growth over 2019 to 2021. It is noticeable that in the model prices and quantities actually rise in a number of services sectors despite the negative shock to services demand.[10] This result is due to the fact that a sector's final demand does not only depend on its final consumption, but also on its position in the supply chain of other sectors. While most services sectors reduce employment and production in response to the demand shocks, some services sectors which are heavily used as intermediates for goods production

[8] In order to guarantee this result it is important to normalize the consumption of goods and services by their expenditure shares in equation 11

[9] Furthermore, as shown in Figure A.2, inflation is stronger in services sectors used for goods production

[10] Figure A.1 reports the sector-specific impulse responses to the demand reallocation shock.

face increased demand. As shown in Figure A.2 prices increase more in sectors that are more upstream in the production of goods, whereas the opposite is true for the supply chain position with respect to services. Furthermore, as shown in the top left panel of Figure A.2 inflation is higher (lower) in the goods (services) sectors with lower price stickiness. Interestingly, as shown in Figure A.3, similar relationships between price changes and sectoral characteristics are present in the data.

5 The COVID-19 Supply Shocks

While the simple demand reallocation shock can explain a significant proportion of the cross-sectional developments across industries between 2019 and 2021, there are a number of sectors for which price and quantity dynamics are harder to reconcile only with the dynamics following an aggregate reallocation shock. One striking example is the "Motor Vehicle Parts and Dealer" sector, which has experienced a 25% decline in quantities and a 60% rise in prices between 2019 and 2021. Such evidence is suggestive of the importance of pandemic-related supply distributions in some sectors, which may have contributed to the aggregate effects of supply chain bottlenecks more broadly.

To understand the importance of idiosyncratic supply disruptions, we conduct a second experiment. By linking industry data on employment from the BLS with data on output and material inputs from the BEA, we measure the evolution of total factor productivity at the industry level between 2019 and 2021 and feed the estimated idiosyncratic component of the productivity series into our multi-sector model.

Figure 7 shows that these idiosyncratic supply shocks can explain a significant fraction of the cross-sectional evolution of both prices and quantities, even absent other shocks. Figure 8 plots the response of aggregate variables to these idiosyncratic shocks. The high dispersion in these shocks interacts with the asymmetric labor adjustment cost, causing firms which increase employment to face a steep increase in their labor costs. All told, aggregate inflation increase by about 1.5 percentage points after four quarters.

Another supply shock which our estimation exercise suggests is important was a decline in labor supply, often explained by concerns about exposure to COVID-19 in the workplace. Figure 9 shows the effect of our estimate of this shock in isolation:[11] it lowers aggregate employment and consumption, while putting upward pressure on wages and prices.

Finally, in Figure 10 we plot the impulse response functions assuming that all the three types of

[11] As mentioned in the estimation section, we calibrate this shock to obtain, together with all the other shocks, a decline in aggregate employment of about four percent, in line with the data.

shocks, i) the demand reallocation shock, ii) the idiosyncratic TFP shocks and iii) the labor supply shock, occur simultaneously. [12] Overall our model suggests that these shocks are responsible for an increase in inflation of about 5 percentage points, a good fraction of what observed in the data. In addition, as suggested by Figure 4, the demand reallocation shock accounts for most of the increase in inflation. Furthermore, Figure 11 shows that our model does a very good job in accounting for the cross-sectional dispersion of prices and quantities in the data, providing additional support for the channels described in this paper.

6 Model Extensions

6.1 Cross-Sectional Implications

As shown in Figure 6, a simple demand reallocation shock is able to explain a large fraction of the dispersion in industry-level inflation rates, even when restricting our attention to goods-producing industries. In this section we compare different versions of the model in order to understand which features are key for generating this result. We consider five different versions of the model:

1. Without I-O linkages or labor adjustment costs
2. Without I-O linkages, with homogeneous price rigidity
3. Without I-O linkages, with heterogeneous price rigidity
4. With I-O linkages, with homogeneous price rigidity
5. Baseline calibration

Figure 12 plots industry-level inflation rates in the model and the data for each of these calibrations. In the first calibration, without I-O linkages or labor adjustment costs, the model is unable to generate any dispersion in sectoral inflation rates. When we add hiring costs and homogeneous price rigidity, the model simply predicts two possible inflation rates, based on whether the industry is a provider of goods or services. If we add either heterogeneous price rigidity or I-O linkages the model predicts some dispersion in inflation rates within goods or services industries. However, the correlation in inflation rates between the model and the data is improved further when including both of these features jointly, as in our baseline calibration.

[12] The effects of the individual shocks do not sum up to the total effect of all shocks due to the nonlinearities present in our model

6.2 A Reversal of the COVID-19 Shift in Preferences

What will happen to inflation if demand suddenly shifts from away from goods back to services? We can use our model to study exactly such a shock. In this section we consider the same demand reallocation shock studied in Section 4. We then look at the effects of a sudden unexpected reversal in demand occurring two years after the original shock.[13]

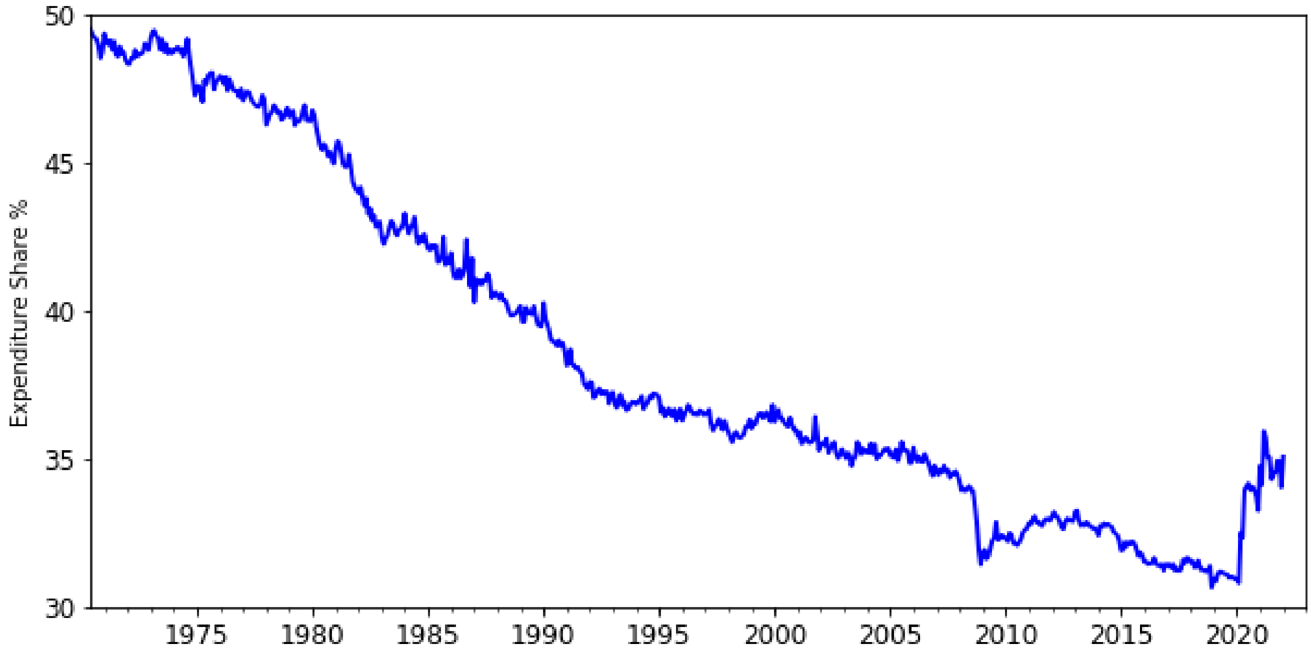
We find that such a reversal would raise inflation. Figure 13 compares outcomes in this reversal experiment with those that occur in the baseline calibration when the demand reallocation shock is persistent. In our model, the reversal would lead to renewed inflationary pressures, as service sectors struggle to increase capacity, while goods-producing sectors cut capacity. More broadly, this experiment highlights the key role that expectations of the future path of sectoral demand play in determining labor adjustment and inflationary pressure. In future work we intend to study the response of our model under various alternative assumptions on the expected persistence of the demand reallocation shock.

7 Conclusions

We study demand reallocation in a multi-sector New Keynesian model featuring input-output linkages and frictions to increasing factor inputs in the form of hiring costs. These costs hamper the adjustment of the supply of goods in response to the shift in demand, causing inflationary pressures which propagate through the production network. The inflationary effects of the demand reallocation shock are amplified by the fact that goods prices are more flexible than those of services. We take the model to the data and estimate a version that allows for demand reallocation shocks, idiosyncratic productivity shocks at the sectoral level, and an aggregate labor supply shock. The demand reallocation shock can account for a large portion of the rise in U.S. inflation in the aftermath of the pandemic.

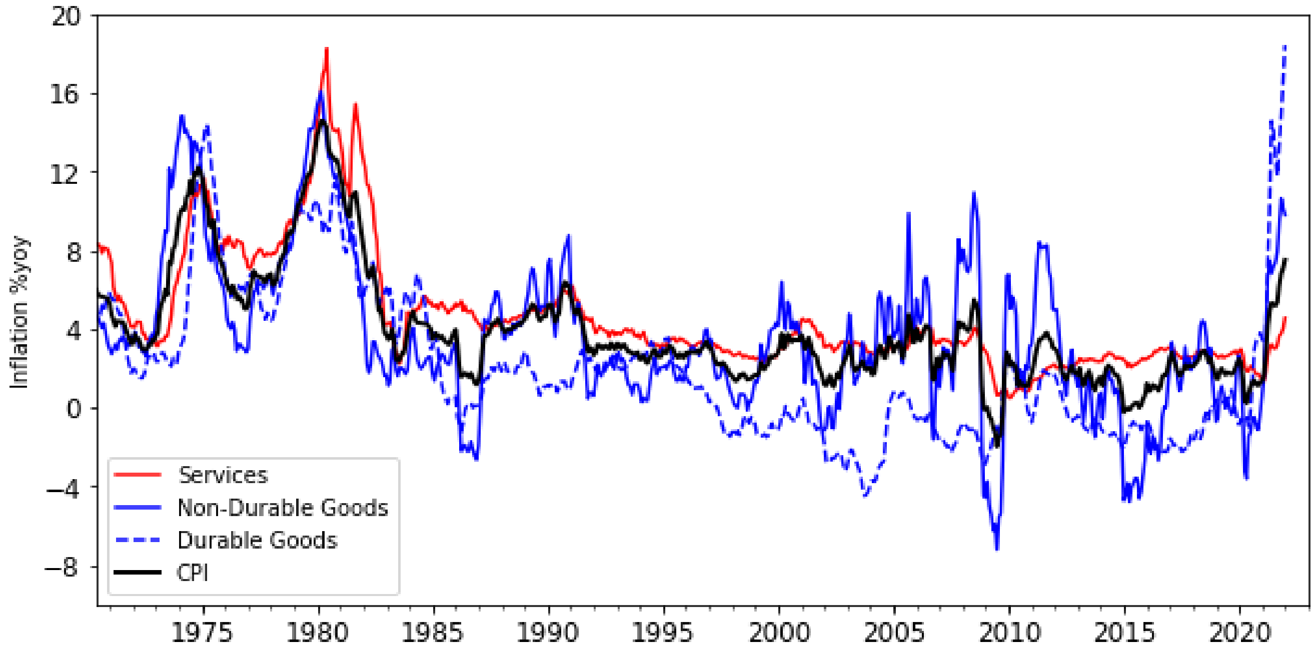
[13] We model this reversal by assuming that the persistence of the shock falls unexpectedly from 0.95 to 0.5 after two year.

Figure 1: Personal Consumption Expenditure Share: Goods



This Figure plots the share of household consumption expenditures on goods in the United States. The COVID-19 pandemic has led to an unprecedented increase in the demand for goods relative to services, interrupting the steady decline in the share of spending on goods over the past 50 years.
Data Source: US Bureau of Economic Analysis, NIPA Tables.

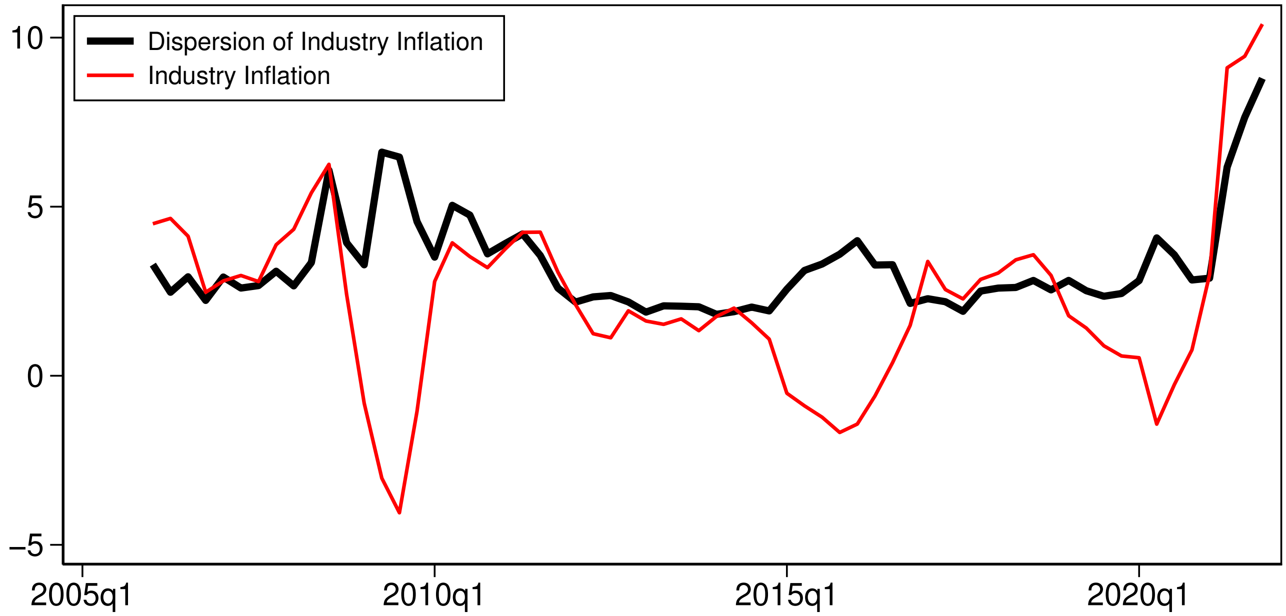
Figure 2: CPI Inflation by Major Category



US CPI inflation has risen to levels not seen since the 1980s, reaching 7 percent by the end of 2021. This Figure shows that this has largely been driven by a surge in inflation in the goods sector, while the rise in inflation in service sectors has been much more muted.

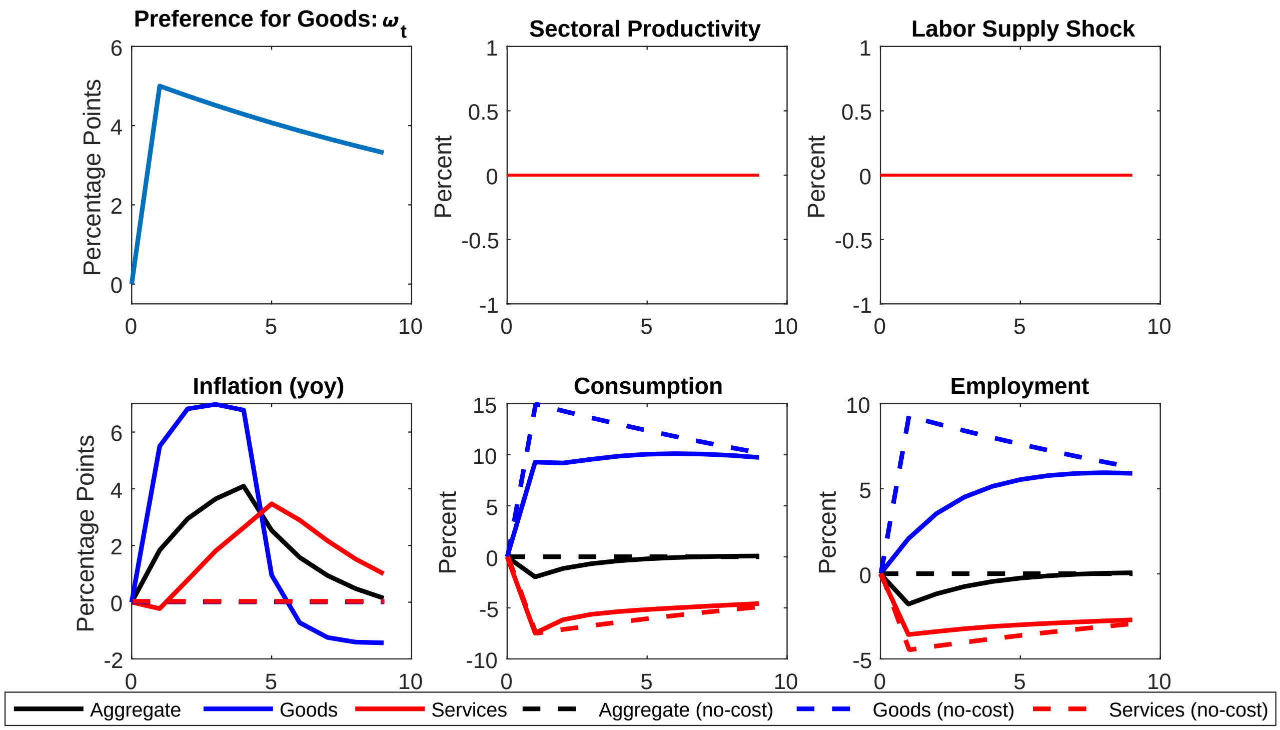
Source: US Bureau of Labor Statistics

Figure 3: Dispersion of Inflation and Industry Inflation across 66 Industries



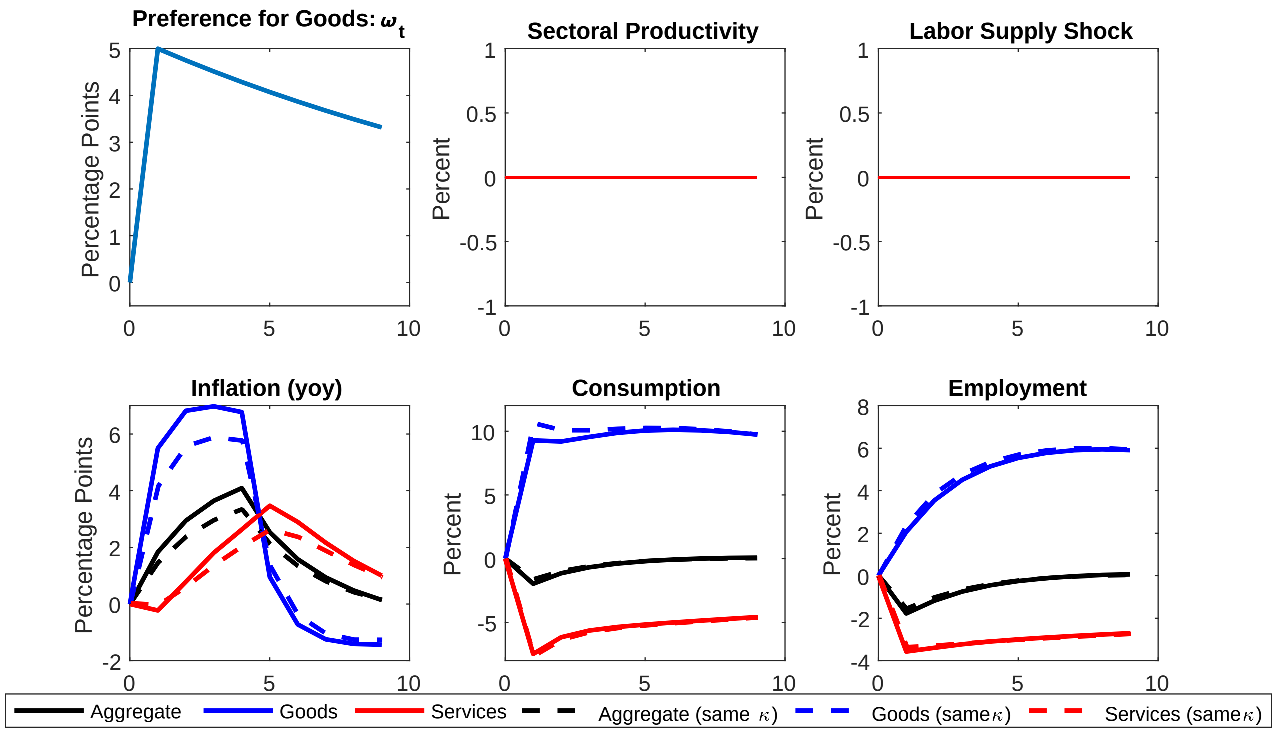
This Figure shows that the rise in inflation in 2021 has been accompanied by a large rise in the dispersion of inflation across industries. The dispersion of inflation rates across 66 private industries has risen dramatically in 2021. Source: US Bureau of Labor Statistics and authors' calculations. Industry inflation (measured in percentage points) is the average of the 4-quarter change in the chain-type price index across the 66 private industries for which BEA publishes quarterly GDP-by-industry data. Inflation dispersion in the interquartile range of inflation rates across the same industries.

Figure 4: Aggregate Effects of the Demand Reallocation Shock



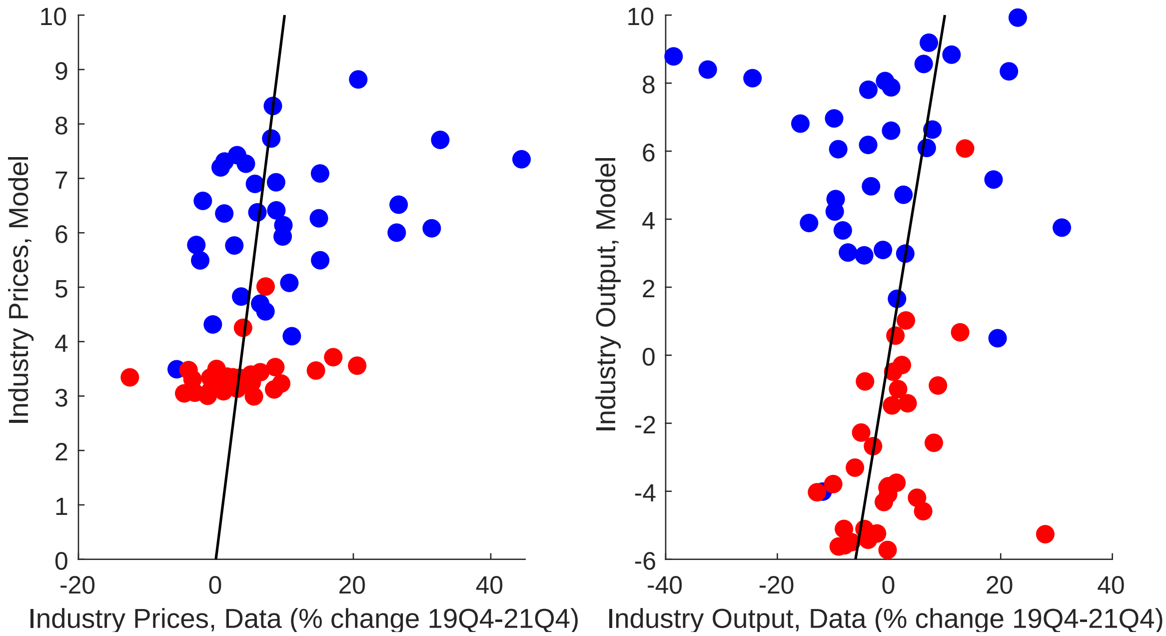
This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter.

Figure 5: Demand Reallocation Shock: Heterogeneous vs Homogeneous Price Stickiness



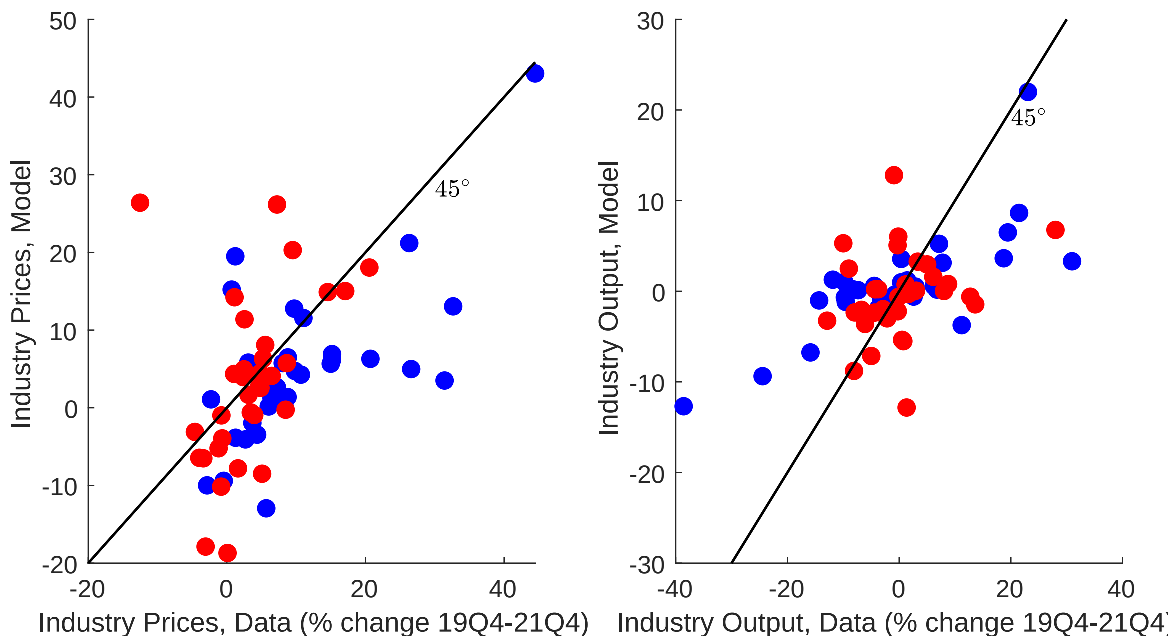
This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter.

Figure 6: Model and Data: Sectoral Responses to Demand Reallocation Shock



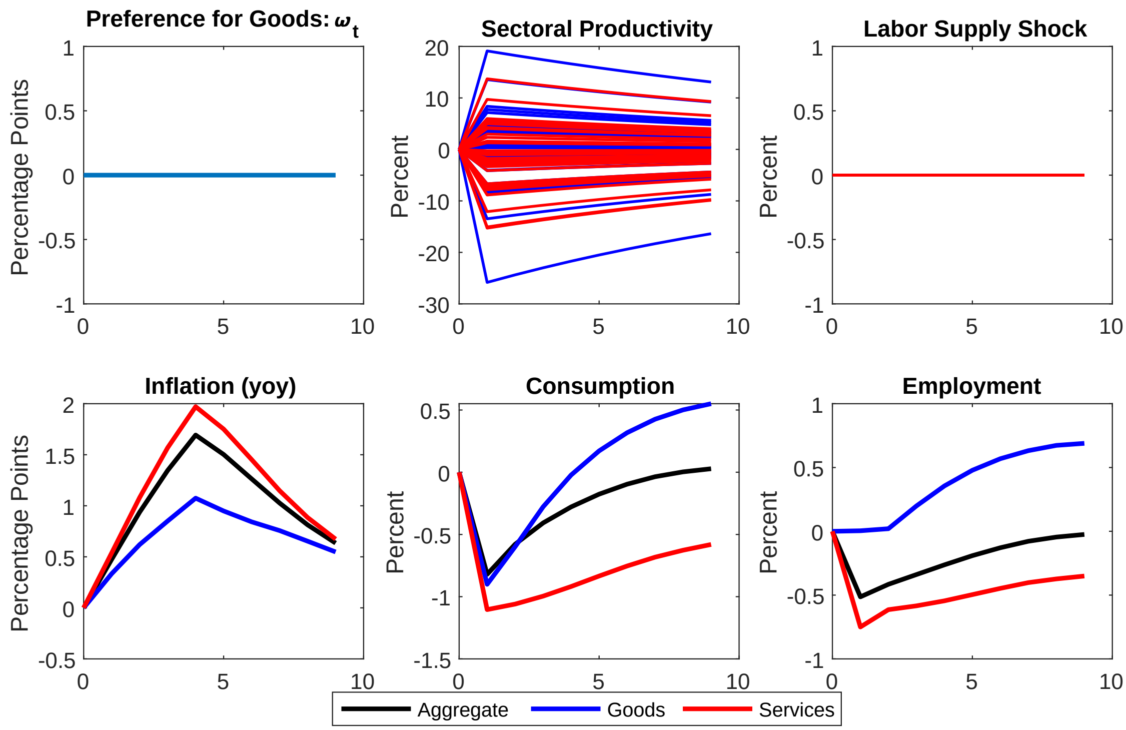
This Figure compares the cross-sectional implication of the model with the data in response to a demand reallocation shock that increases preferences for goods. Each dot is one industry. The x-axis plot inflation rates (percent change in the industry chain-type price price index) and real gross output growth for the 66 private industries for which BEA publishes GDP-by-industry data. The y-axis plot the model counterparts after the model reallocation shock, computed as the average change over the first 2 years. Services-producing industries are shown in red and goods-producing industries are shown in blue.

Figure 7: Model and Data: Sectoral Responses to Idiosyncratic TFP Shocks



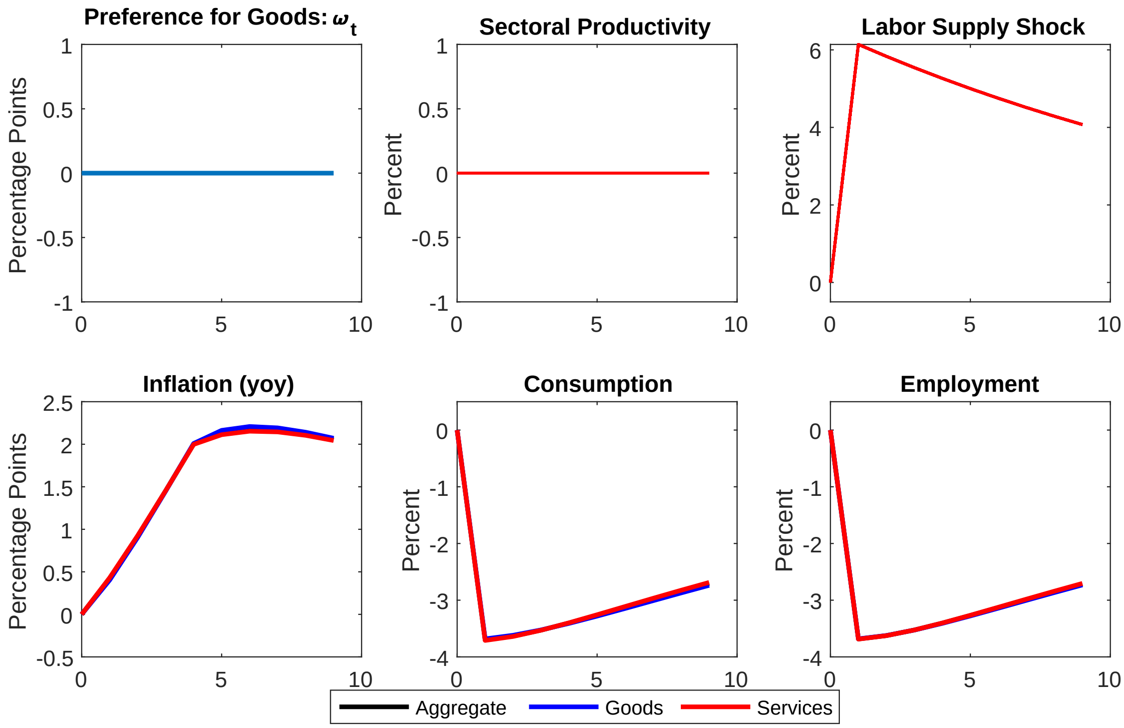
This Figure compares the cross-sectional implication of the model with the data in response to an estimated idiosyncratic TFP shocks at the industry level. Each dot is one industry. The x-axis plot inflation rates (percent change in the industry chain-type price price index) and real gross output growth for the 66 private industries for which BEA publishes GDP-by-industry data. The y-axis plot the model counterparts after the model reallocation shock, computed as the average change over the first 2 years. Services-producing industries are shown in red and goods-producing industries are shown in blue.

Figure 8: Aggregate Effects of Idiosyncratic TFP Shocks



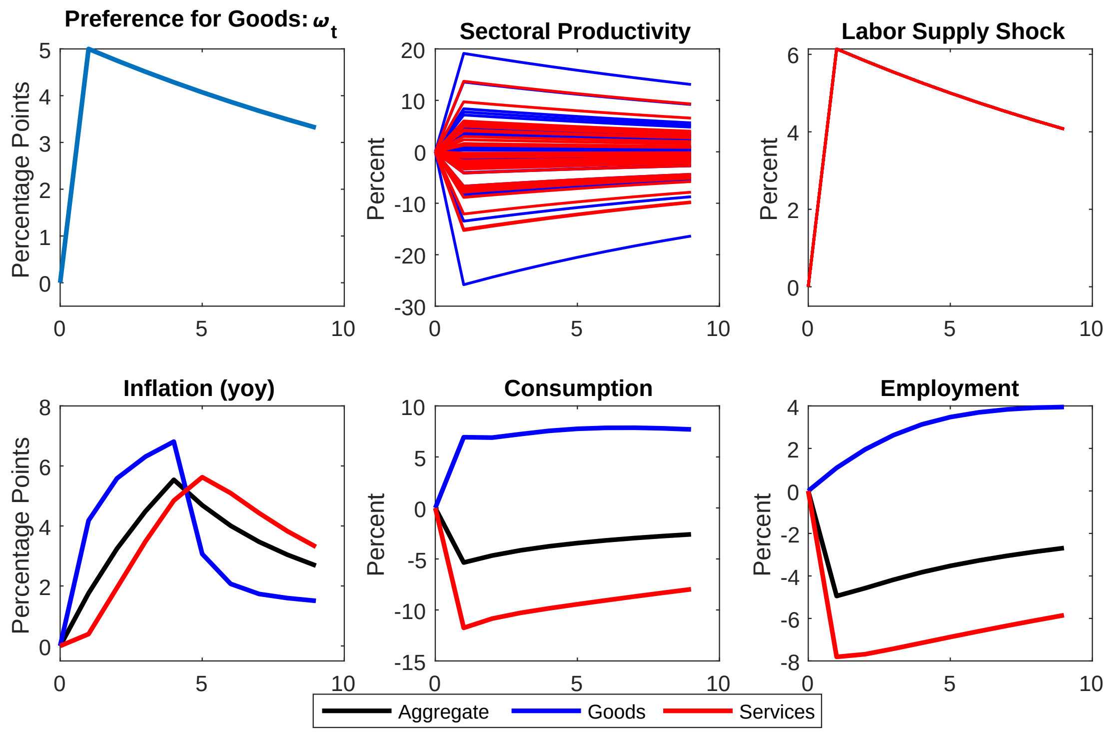
This Figure plots the impulse response of key variables to estimated idiosyncratic productivity shocks (using industry level data on output, added value and employment) in period 1. Each period is one quarter.

Figure 9: Aggregate Effects of Labor Supply Shocks



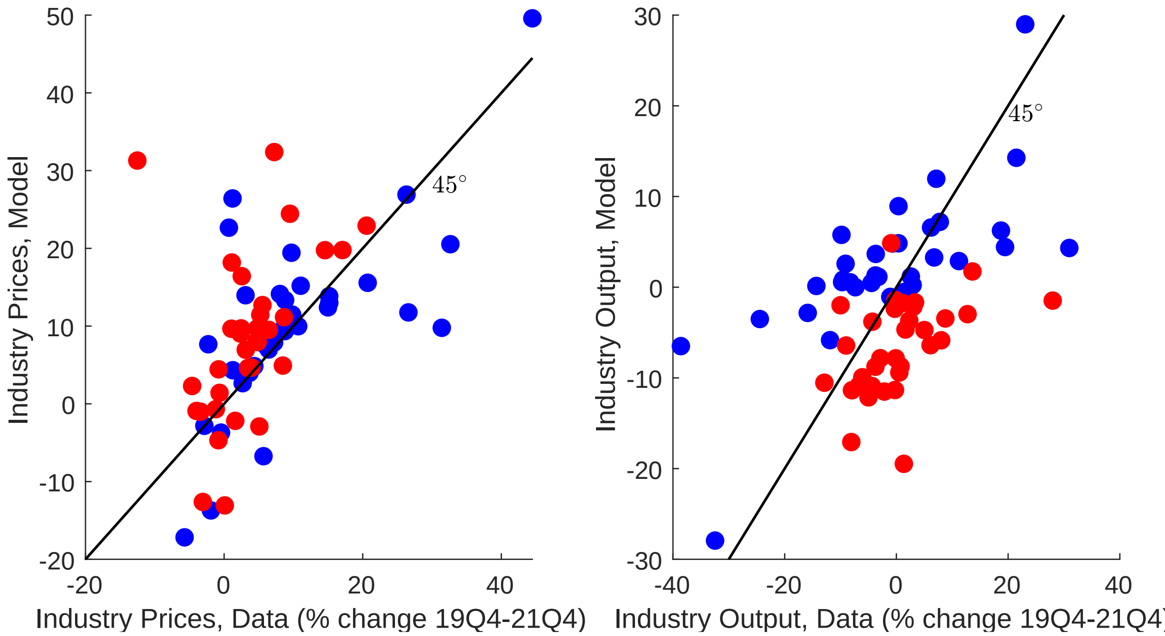
This Figure plots the impulse response of key variables to a labor supply shock that increases the disutility of labor in period 1. Each period is one quarter.

Figure 10: Aggregate Effects of All Shocks



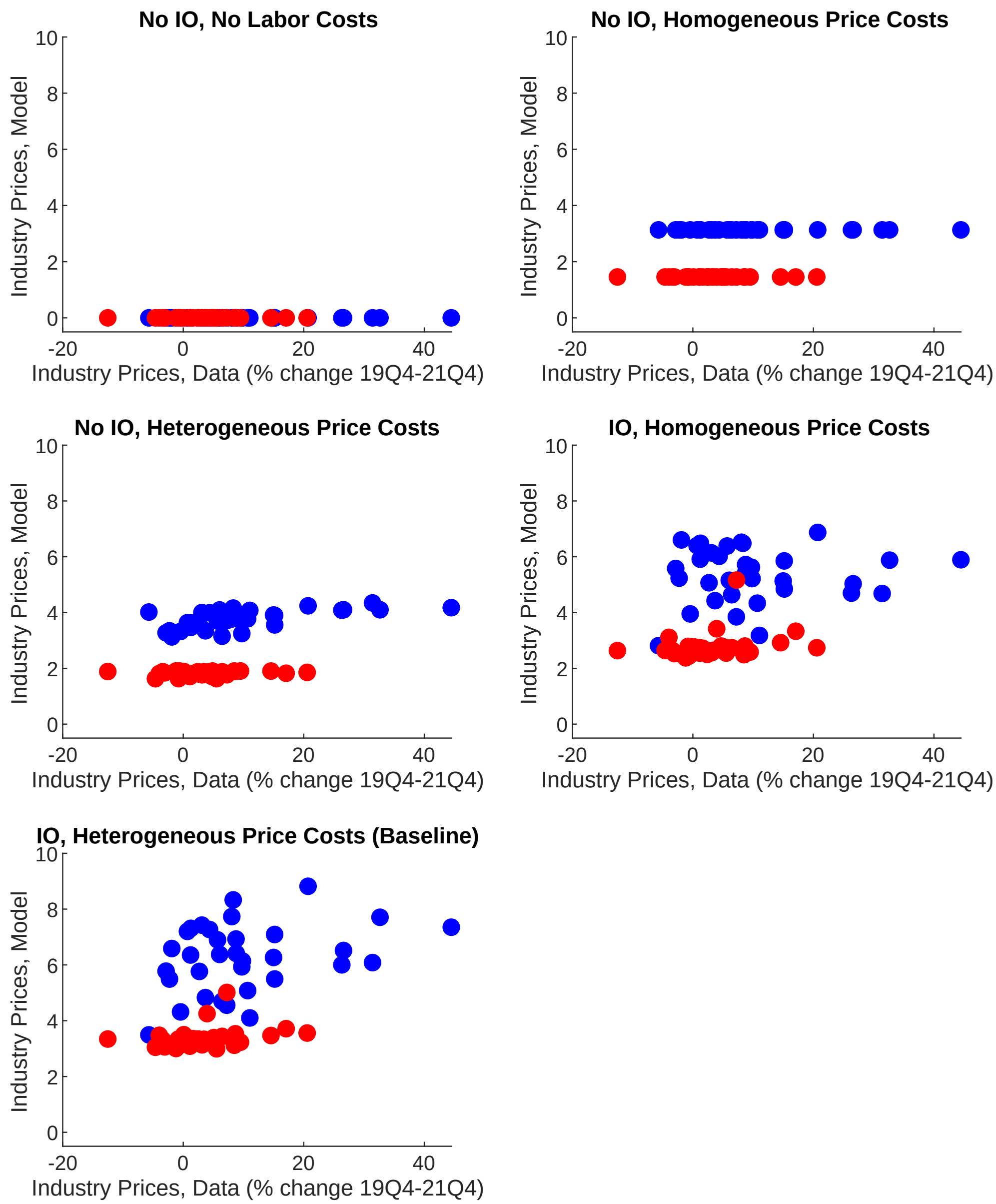
This Figure plots the impulse response of key variables to three combined shocks: (1) a demand reallocation shock that increases preferences for goods, (2) estimated idiosyncratic TFP shocks at the industry level, and (3) a negative labor supply shock. Each period is one quarter.

Figure 11: Model and Data: Sectoral Responses to All Shocks



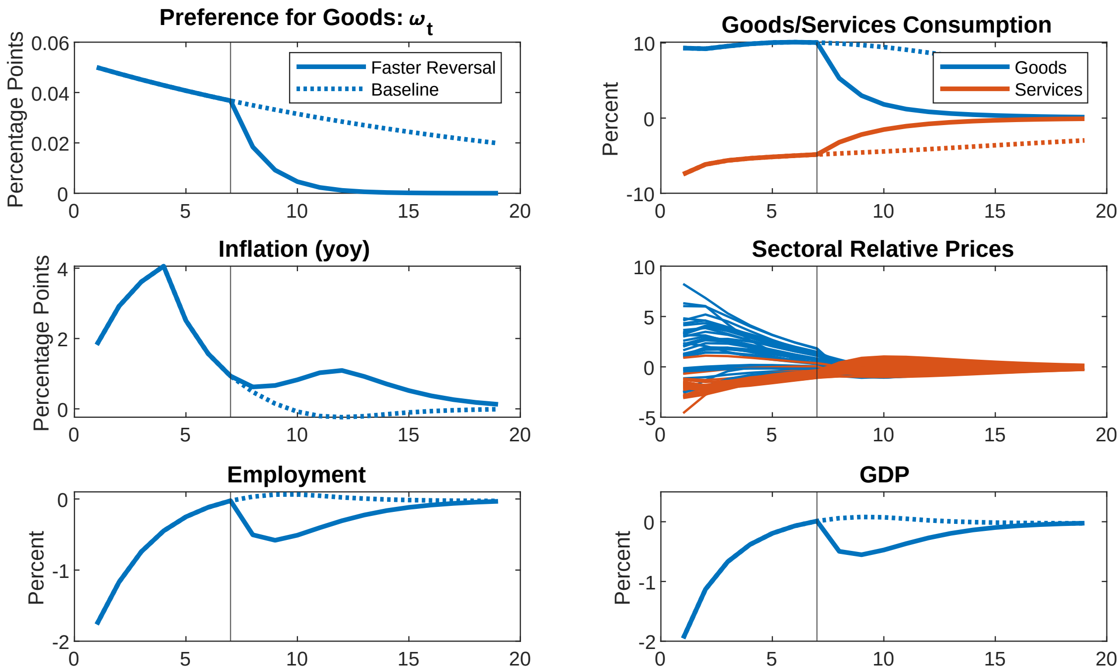
This Figure compares the cross-sectional implication of the model with the data in response to three combined shocks: (1) a demand reallocation shock that increases preferences for goods, (2) estimated idiosyncratic TFP shocks at the industry level, and (3) a negative labor supply shock. Each dot is one industry. The x-axis plot inflation rates (percent change in the industry chain-type price price index) and real gross output growth for the 66 private industries for which BEA publishes GDP-by-industry data. The y-axis plot the model counterparts after the model reallocation shock, computed as the average change over the first 2 years. Services-producing industries are shown in red and goods-producing industries are shown in blue.

Figure 12: Sectoral Inflation Response to Demand Reallocation Shock in Alternative Models



This figure compares the cross-sectional implications of different types of models, which are nested in our baseline calibration, for sectoral inflation against actual inflation between 2019Q4 and 2021Q4. The first panel reports the response of a model without input-output linkages or costly labor re-allocation. The second panel reports the response of a model with labor adjustment costs but no input-output linkages and with homogeneous price stickiness across the two sectors. The third panel reports the responses of a model with heterogeneous price rigidities across sectors but without input-output linkages. The fourth panel introduces input-output linkages but assumes that price stickiness is homogeneous across sectors. The last panel reports the responses in our baseline model.

Figure 13: Aggregate Effects of a Reversal of Demand



This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. The dotted line shows the baseline persistence. The solid lines show outcomes if the persistence unexpectedly declines from 0.95 to 0.5 after two years. Each period is one quarter. The middle-right panel displays the evolution of relative prices for each of the 66 sectors in our model. Goods-producing sectors are displayed in blue and services-producing industries are displayed in red. GDP is defined as $\sum_{i=1}^{N} C_{i,t}$.

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A Additional Figures

Figure A.1: Model Implied Sectoral Dynamics (Demand Reallocation Shock)

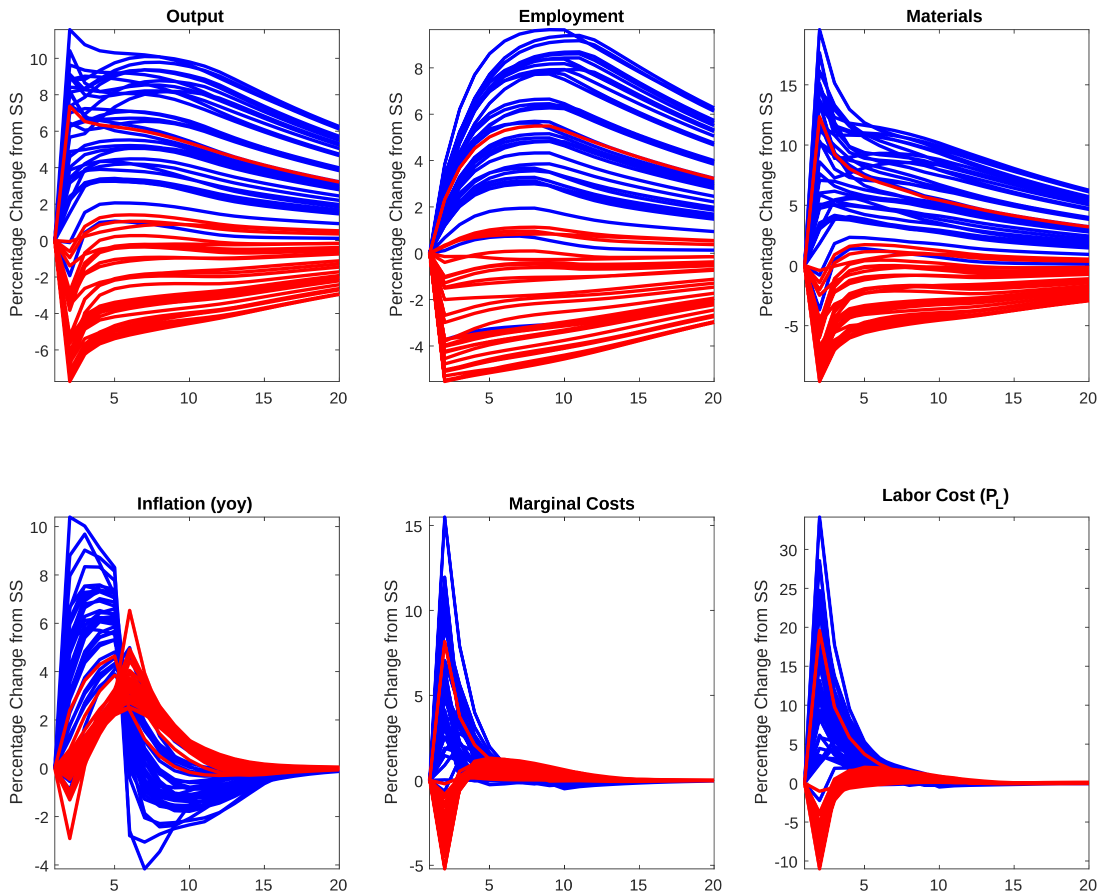
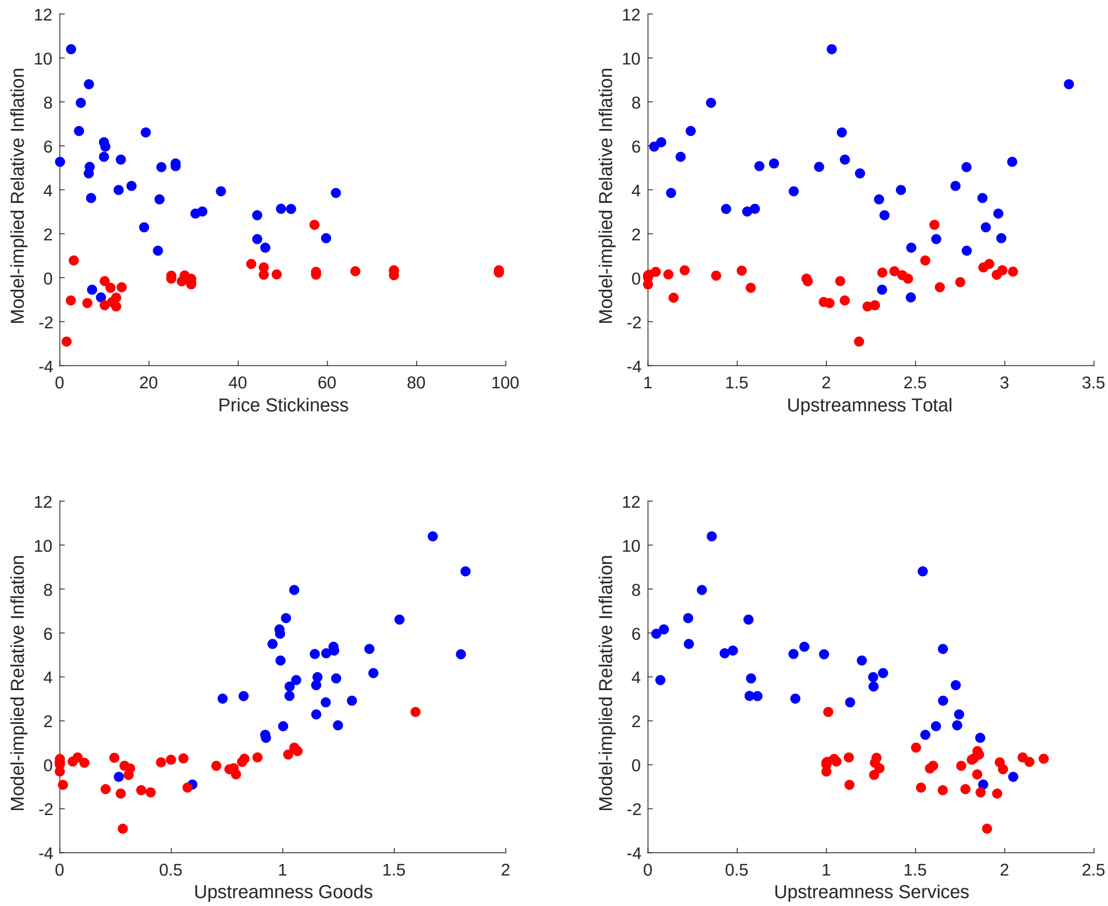
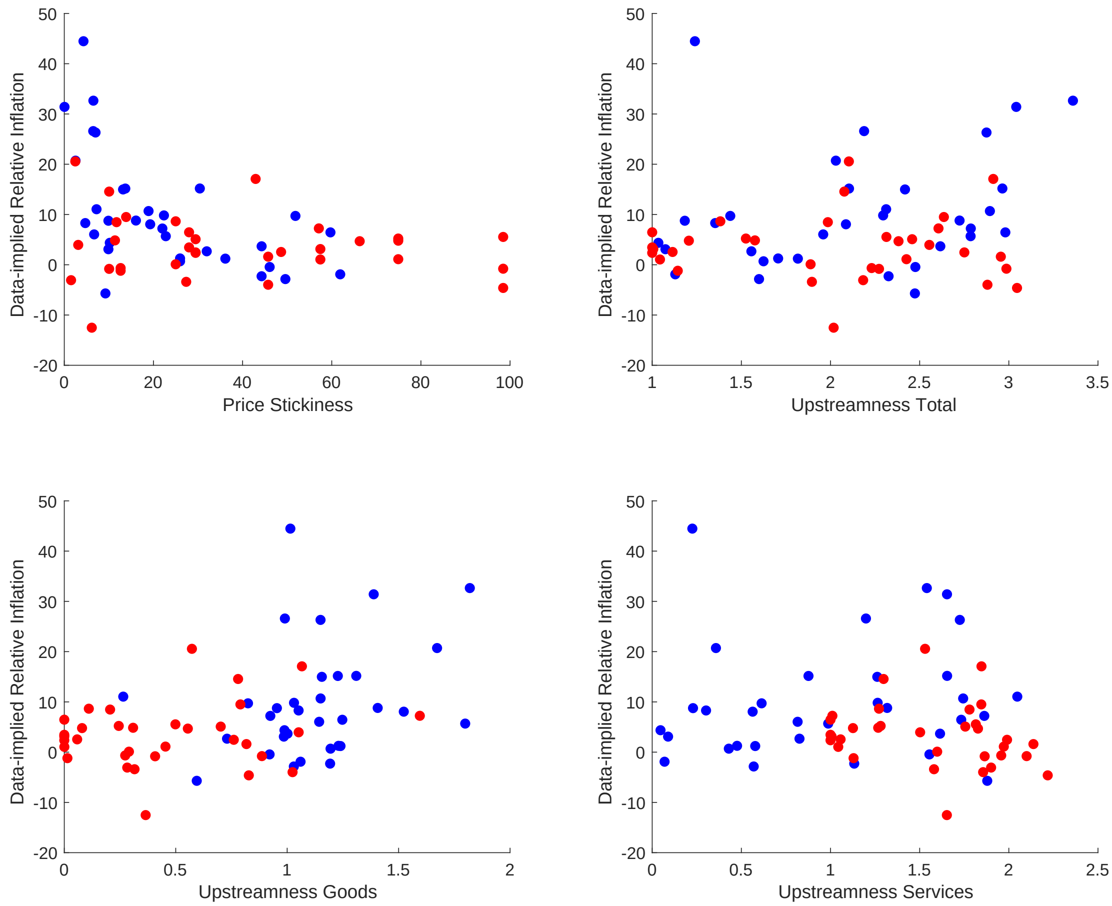


Figure A.2: Model Implied Sectoral Inflation vs Sector Characteristics (Demand Reallocation Shock)



This Figure compares the sectoral change in inflation implied by the model on impact with sector-specific characteristics. The first panel plots inflation against sectoral price stickiness, measured by the size of the Rotemberg cost. The second panel compares inflation with sectoral upstreamness computed as in Antràs et al. (2012). The third and fourth panel decompose total upstremness in goods-specific upstreamness and services-specific upstreamness, where a good is more upstream in the production of goods (services) if it is used by many goods (services) producing sectors.

Figure A.3: Data Implied Sectoral Inflation vs Sector Characteristics (Demand Reallocation Shock)



This Figure compares the sectoral change in inflation implied by the data with sector-specific characteristics. The first panel plots inflation against sectoral price stickiness, measured by the size of the Rotemberg cost. The second panel compares inflation with sectoral upstreamness computed as in Antràs et al. (2012). The third and fourth panel decompose total upstremness in goods-specific upstreamness and services-specific upstreamness, where a good is more upstream in the production of goods (services) if it is used by many goods (services) producing sectors.