The Inflationary Effects of Sectoral Reallocation*

Francesco Ferrante† Sebastian Graves‡ Matteo Iacoviello§

September 9, 2022

Abstract

The COVID-19 pandemic has led to an unprecedented shift in consumption expenditures from services to goods. This paper studies the effect of this demand reallocation in a multi-sector New Keynesian model featuring input-output linkages and costs to reallocating labor across sectors. These costs inhibit the increase in the supply of goods, causing inflationary pressures that propagate through the production network. The inflationary effects of this shock are amplified by the fact that goods prices are more flexible than those of services. We estimate the model allowing for a demand reallocation shock, sectoral productivity shocks, 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.

*We thank Andrea Prestipino for numerous conversations and seminar participants at UBC, the Spring 2022 Midwest Macroeconomics Conference and the Federal Reserve Board for helpful comments. We are also grateful to Michael Weber and Raphael Schoenle for sharing data on the frequency of price adjustment across industries. All errors and omissions are our own. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

†Federal Reserve Board. Email: francesco.ferrante@frb.gov

‡Federal Reserve Board. Email: sebastian.h.graves@frb.gov

§Federal Reserve Board. Email: matteo.iacoviello@frb.gov

1 Introduction

The COVID-19 pandemic has led to a large, abrupt, and unprecedented increase in the demand for goods relative to services.[1] A popular narrative is that this reallocation in demand has strained supply chains, leading to bottlenecks and labor shortages in a number of key sectors, thus contributing to a buildup of inflationary forces. Figure 1 illustrates consumption, inflation and employment dynamics in the U.S. economy between 2010 and 2021. The share of consumption expenditures on goods rose from 31% in 2019Q4 to 35.5% in 2021Q2 and has remained high in subsequent quarters. PCE Inflation has risen to its highest level in almost 40 years, reaching almost 6 percent by the end of 2021, driven largely by a surge in goods inflation, while the rise in inflation in services has been more muted. Finally, employment remains significantly below the pre-pandemic trend. This is explained almost entirely by a sharp fall in labor market participation as evidenced by the fact that the unemployment rate had almost declined to pre-pandemic levels by the end of 2021. Figure 2 shows that these aggregate movements have been accompanied by a large increase in the dispersion of output, prices and employment across industries.

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.[2] In particular, we assume that firms face convex hiring costs when increasing labor inputs.[3] Based on the aggregate and cross-sectional developments outlined in Figures 1 and 2, we allow for three shocks in the model: a preference shock that alters the relative demand for goods and services, sectoral productivity shocks, and an aggregate labor supply shock. Using aggregate and cross-sectional data, we then estimate the parameters governing hiring costs and production function elasticities as well as the size of the aggregate labor supply shock.[4] With this estimated model in hand, we are able to quantify the role that each of the three shocks has played in driving aggregate and cross-sectional developments in the aftermath of the COVID-19 pandemic.

We proceed by studying the aggregate and cross-sectional implications of each of the three

[1] This has interrupted a steady decline in the share of spending on goods dating back at least 60 years.

[2] We calibrate the industry structure of the model following the U.S. input-output tables provided by the BEA as in Baqaee and Farhi (2022). 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.

[3] 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.

[4] We estimate these parameters using a moment-matching exercise which 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.

shocks in isolation, before considering the fit between the model and the data when all the shocks occur simultaneously. We find that the demand reallocation shock, calibrated to match the rise in the share of consumption expenditures on goods, is able to explain a sizeable proportion (around 4 percentage points) of the increase in inflation seen in the U.S. over the course of 2021. 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 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.

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. 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. 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 services-producing sectors experience weaker inflationary pressures. Furthermore, sectors with more flexible prices exhibit larger price changes, all else equal.

We then turn to the two supply shocks in the model. First, we consider the role of idiosyncratic productivity shocks. The inclusion of such shocks is motivated by the large increase in the dispersion of sector-level variables shown in Figure 2. It is also motivated by the fact that, while the demand reallocation shock can explain price and quantity dynamics in many sectors, there are a number of sectors whose data are hard to reconcile with such a shock. One striking example is the "Motor Vehicle Parts and Dealer" sector, which has experienced a 40% decline in quantities and a 50% rise in prices between 2019 and 2021.[5] Such evidence is suggestive of the importance of pandemic-related

[5] These numbers are relative to the sector's pre-pandemic trend. See the Appendix for further details.

supply disruptions in some sectors, which may have contributed to the aggregate effects of supply chain bottlenecks more broadly. Consequently, 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. We find that these idiosyncratic shocks significantly improve the model's cross-sectional fit, but play a minor role in driving aggregate inflation and employment. The final shock that we consider is a shock to aggregate labor supply, motivated by the persistent decline in employment shown in Figure 1. We estimate the size of this labor supply shock and find that it explains roughly three-quarters of the decline in employment in the post-pandemic period. However, its role in driving inflation is smaller: in isolation this shock would raise inflation by around 1.5 percentage points, less than half of that seen in response to the demand reallocation shock.

When we consider the effect of all three shocks simultaneously, we find that the estimated model can explain almost all 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 inflation rises by about 4.5 percentage points, largely driven by the demand reallocation shock.[6] The model also explains a large proportion of the cross-sectional dynamics of prices and quantities: both the demand reallocation shock and the sectoral productivity shocks are important for this finding. The labor supply shock is important for explaining the persistent decline in aggregate employment, but plays a small role in explaining aggregate inflation and no role in the model's cross-sectional fit.

Using our model we are also able to conduct various experiments pertaining to the persistence and possible reversal of the demand reallocation shock. We find that an unexpected reversal of the demand reallocation shock would be inflationary, driven by services prices, as such sectors would struggle to increase capacity. In a second experiment, we consider a version of the model in which households and firms are repeatedly surprised about the persistence of the demand reallocation shock. In such a version the inflationary pressures of the shock are muted somewhat, as services-producing sectors do not cut capacity as much as under our baseline assumption in which the persistence of the shock is known immediately.

Section 2 describes the 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: idiosyncratic productivity shocks at the sectoral level and an aggregate labor supply shock. In Section 6 we further explore the mechanisms in the model and study various extensions of our experiments.

[6] Due to the non-linearities inherent in the model, the total effect of the three shocks is not equal to the sum of the individual effects.

1.1 Related Literature

One of the contributions of our paper is our use of the COVID-19 pandemic period to estimate production function elasticities in a multi-sector model featuring input-output linkages. We find values broadly similar to those in Atalay (2017) despite markedly different estimation strategies.[7]

The model in our paper builds on those used in the rapidly growing literature studying the role of production networks in propagating the effects of monetary policy, such as La'O and Tahbaz-Salehi (2022) and Pasten, Schoenle and Weber (2020).[8] The latter paper shows that heterogeneity in price stickiness across sectors amplifies the real effects of monetary policy significantly. We use their estimates of price stickiness at the industry level to show that heterogeneity in price rigidity also amplifies the inflationary effects of a reallocation of demand from services to goods due to the fact that services-producing sectors have stickier prices than goods-producing sectors on average.

In using a model of production networks to understand developments since the onset of the COVID-19 pandemic, our paper also builds on the work of Baqaee and Farhi (2022). While their quantitative application studies the initial lockdown phase of the pandemic, our focus is on post-lockdown dynamics, particularly the surge in inflation that occurred in 2021. Another key difference is that they study a two-period model with no factor adjustment across sectors. In comparison, we estimate the size of factor adjustment costs in an infinite-horizon economy. In this framework we are able to study how expectations about the persistence of shocks affect labor reallocation and inflation.

A number of other recent papers have considered the implications of the demand reallocation shock that is central to our analysis. Guerrieri et al. (2021) and Fornaro and Romei (2022) study the optimal response of monetary policy to such a shock in models with two periods and two sectors.[9] In contrast to these normative analyses, our focus is on quantifying the contribution that the demand reallocation shock has made to the rise in US inflation and contrasting it with other shocks that have occurred over the same period.

In this vein, the papers most closely related to our work are two contemporaneous studies by Anzoategui, Comin and Johnson (2022) and di Giovanni et al. (2022). The former shows how the effects of a demand reallocation shock depend on potentially binding capacity constraints, both

[7] Our estimated parameters are also close to those calibrated by Baqaee and Farhi (2022) and related papers.

[8] In related work, Ozdagli and Weber (2017) and Ghassibe (2021) provide empirical evidence on the importance of production networks in monetary policy transmission.

[9] In both models the demand reallocation shock is inflationary due to downward nominal wage rigidity. The former considers how monetary policy can affect labor reallocation in such an environment, while the latter focuses on monetary policy spillovers in an open-economy setting.

domestic and foreign. The latter uses the model of Baqaee and Farhi (2022) in order to quantify the contributions of different shocks to the run-up in inflation in the post-lockdown period. In such a two-period model with no labor adjustment across sectors, demand reallocation shocks only cause inflation in the presence of downward nominal wage rigidity. In contrast, we study an infinite-horizon model without wage rigidity where demand reallocation shocks cause inflation due to costs of reallocating labor across sectors, which we estimate using aggregate and cross-sectional data.[10] The main similarity between our papers is that they also find that idiosyncratic supply shocks explain a relatively small portion of the increase in US inflation. The main difference is that in their model the key driver of inflation is an aggregate demand shock, identified as the part of inflation that is not explained by observed employment changes. In contrast, in our model the reallocation of demand from services to goods is the key driver of inflation dynamics.[11]

2 Model

This section describes a multi-sector New Keynesian model featuring input-output linkages. Time is discrete and infinite. 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 these frictions, we assume that in each sector $i = \{1, ..., N\}$ there are three types of firms: a representative competitive producer, monopolistically competitive firms, and labor agencies.

In each sector, the representative competitive producer aggregates the output of a continuum of monopolistically competitive firms. These firms use labor and intermediate inputs to produce their differentiated products, and set prices subject to quadratic price adjustment costs. Sector-specific labor is supplied to these firms 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.

[10] See Figure 3, which shows that the demand reallocation shock would have no effect on inflation in our model if we set labor adjustment costs to zero.

[11] While we have no direct aggregate demand shock in our model, it is possible that fiscal stimulus has affected the demand for goods relative to services. de Soyres, Santacreu and Young (2022) provide empirical evidence for this channel.

2.1 Representative Competitive Producer

In each sector, i, a representative competitive producer aggregates the output of a continuum of monopolistically competitive firms:

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

The solution to the competitive producer's problem implies the following demand curve for differentiated products 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 Monopolistically Competitive Firms

In each sector, a continuum of firms supply differentiated products to the representative competitive producer subject to price adjustment costs. These differentiated products are produced according to the following production function:[12]

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

To study sectoral productivity shocks, we allow productivity in each sector, A_t^i, to vary over time. $L_t^i(s)$ denotes labor haired by firm s in sector i at time t. Intermediate 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 economy's input-output matrix is encoded in the parameters $\Gamma_{i,j}$ which determine the importance of the output of sector j as an input of production in sector i. The problem of a monopolistically competitive firm can be split into two stages: a cost minimization problem and a price-setting problem.

[12] As such, our model abstracts from capital. Vom Lehn and Winberry (2022) is a recent paper that focuses on the investment network.

2.2.1 Cost Minimization

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

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

Given this price index for intermediate inputs, $P_t^{M,i}$, 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:

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

2.2.2 Price Setting

Given the marginal cost just derived, firms set prices subject to quadratic adjustment costs.[13] 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 monopolistically competitive firms by a representative labor agency that hires labor from the representative household. We assume that these agencies face convex hiring costs denoted in units of labor, the size of which is key to our results and which

[13] We assume that these price adjustment costs are non-pecuniary and thus do not show up in market clearing conditions.

we estimate in Section 3.[14] In contrast, agencies are able to freely decrease employment in each sector.[15] The recursive form of the labor agency's problem is:

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

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

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

This equation 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:

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

To study the demand reallocation shock, we allow the relative demand for goods, ω_t, to vary over time. The solution to the household's cost minimization problem implies:

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

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

With this preference structure, equation 12 implies that 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 0.355 in early 2021. Thus this is the size of the shift in ω_t that we will study in Section 4.

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

[15] In extensions of the model we have estimated separately convex costs for increasing and decreasing employment. Estimates of firing costs in such exercises are very close to zero. The lack of firing costs is consistent with the observation that, while employment collapsed abruptly in many sectors at the onset of the pandemic, it recovered more slowly thereafter.

Goods consumption and services consumption are both bundles of the consumption of output from 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:

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

To incorporate a labor supply shock, we also allow the disutility of labor supply, χ_t, to vary over time. 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:[16]

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

Second, the aggregate labor market must clear:

$$\sum_{i=1}^{N} L_t^i \left(1 + \mathbb{1}_{L_t^i > L_{t-1}^i} \frac{c}{2} \left(\frac{L_t^i}{L_{t-1}^i} - 1\right)^2\right) = N_t \tag{24}$$

Finally, the bond market clears:

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

3 Taking the Model to the Data

In order to bring this model to the data, we assume that the US economy has been hit by three distinct shocks in the post-lockdown period. First, a demand reallocation shock (an increase in ω_t). Second, an aggregate labor supply shock (an increase in χ_t). And finally, sectoral productivity shocks (changes in A_t^i). We will show that allowing for these three shocks we are able to explain a large proportion of movements in both aggregate and cross-sectional variables in the 2019Q4-2021Q4 period. We will assume that these shocks occur simultaneously and that following the shocks the exogenous variables all revert back to their steady-state values following AR(1) processes:

$$\omega_{t+1} = (1 - \rho_\omega)\bar{\omega} + \rho_\omega \omega_t \tag{26}$$

$$\chi_{t+1} = (1 - \rho_\chi) + \rho_\chi \chi_t \tag{27}$$

$$A_{t+1}^i = (1 - \rho_A) + \rho_A A_t^i \tag{28}$$

We proceed by externally calibrating a number of the model's parameters, along with the size of the demand reallocation shock and the idiosyncratic productivity shocks. We then estimate the remaining parameters (the production function elasticities and the hiring costs) as well as the size of the aggregate labor supply shock. Given the non-linearities inherent in the model, we estimate these parameters and show impulse response functions following perfect foresight transitions.

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

3.1 Calibrated Parameters and Shocks

We study a 66 sector version of the model. The model's input-output matrix, $\Gamma_{i,j}$ is calibrated using the BEA's input-output tables. We use the BEA's bridge between PCE categories and NAICS industries to calibrate the sectoral consumption shares γ_i^g and γ_i^s. In subsequent sections we will denote sectors as services-producing if more of their output is directly consumed as services than as goods. This classification leaves us with 32 services-producing sectors, 28 goods-producing sectors, and 6 sectors that produce neither goods nor services, as none of their output is directly consumed.[17]

We calibrate price adjustment costs at the sectoral level using data from Pasten, Schoenle and Weber (2020).[18] 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 the 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 0.995 and a response coefficient of interest rates to inflation $\phi = 1.5$, consistent with the Taylor principle. The steady-state goods expenditure share $\bar{\omega}$ is set at 0.31, the elasticity of substitution ϵ across final varieties is 10, the shares of intermediates in production α is 0.5.

Given our assumption on household preferences, the expenditure share on goods in the model is simply equal to ω_t. We calibrate the size of the demand reallocation shock to match the increase in the goods expenditure share between 2019Q4 and 2021Q2. We calibrate the size of the idiosyncratic sectoral productivity shocks to changes in sectoral TFP, the measurement of which we describe in Appendix A. We calibrate the persistence of the demand reallocation shock to match the evolution of the path of ω_t in the data. We set the persistence of the other shocks to 0.95, a standard value for quarterly business cycle models.

3.2 Estimated Parameters and Shocks

The parameters we estimate are c, the hiring cost parameter, ϵ_M, the elasticity of substitution between intermediate inputs, and ϵ_Y, the elasticity of substitution between labor and intermediate

[17] Most sectors produce only goods or services: only 12 of the 66 sectors have both $\gamma_i^g > 0$ and $\gamma_i^s > 0$.

[18] The use of the PPI data to construct their estimates of the frequency of price adjustment at the sector level is discussed in more detail in Gorodnichenko and Weber (2016).

inputs. We also estimate the size of the labor supply shock, denoted $\Delta\chi$. We group these parameters in the vector $\boldsymbol{\theta}$ and estimate them by minimizing the distance between various cross-sectional and aggregate moments from data and their model counterparts.

Our cross-sectional moments are based on industry employment, output and inflation developments. For each of the 66 sectors, we calculate the percent change in prices between 2019Q4 and 2021Q4 relative to a sector-specific trend.[19] We repeat the same procedure for output and employment and stack these cross-sectional changes in three vectors: $\mathbf{y}_d$, $\mathbf{p}_d$, $\mathbf{l}_d$.

We also target two aggregate moments, both shown in Figure 1. First, the differential rise in goods inflation relative to services inflation from 2019Q4 to 2021Q4. Goods inflation rose by 6 percentage points, whereas services inflation rose by only 1 percentage point. Thus, we target $(\Delta\pi_d^G - \Delta\pi_d^S = 5\%)$. Second, we target the decline in aggregate employment relative to trend over the same period. This decline was 4 percent at the end of 2021. Our estimated parameters solve the following problem.

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} \left[\psi\left(\boldsymbol{\theta}\right)\right]' W \left[\psi\left(\boldsymbol{\theta}\right)\right] \tag{29}$$

$$\psi\left(\boldsymbol{\theta}\right) = \begin{bmatrix} \sigma\left(\mathbf{y}_d\right) - \sigma\left(\mathbf{y}_m\left(\boldsymbol{\theta}\right)\right) \\ \sigma\left(\mathbf{p}_d\right) - \sigma\left(\mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \sigma\left(\mathbf{l}_d\right) - \sigma\left(\mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{y}_d, \mathbf{y}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{p}_d, \mathbf{p}_m\left(\boldsymbol{\theta}\right)\right) \\ \rho\left(\mathbf{l}_d, \mathbf{l}_m\left(\boldsymbol{\theta}\right)\right) \\ \Delta L_d - \Delta L_m\left(\boldsymbol{\theta}\right) \\ \left(\Delta\pi_d^G - \Delta\pi_d^S\right) - \left(\Delta\pi_m^G\left(\boldsymbol{\theta}\right) - \Delta\pi_m^S\left(\boldsymbol{\theta}\right)\right) \end{bmatrix}' \tag{30}$$

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.

Before turning to the parameter estimates, we discuss briefly the relationship between these moments and the parameters we are estimating. There is clearly a direct link between the size of the labor supply shock and the decline in aggregate employment. The size of the hiring cost is

[19] We calculate the trend over the 2005-2019 period.

closely related to difference in goods and services price inflation.[20] As we will show in the next section, with no hiring costs there would be no change in relative prices in response to a demand reallocation shock. On the other hand, if hiring is costly, goods production will increase more slowly, and the relative price of goods will rise. Finally, the production function elasticities are important in determining how each of the shocks that hit the model propagate through the production network. We have found that constraining these elasticities to unity would lead to a significant decline in the model's ability to fit cross-sectional moments.

The estimated parameters are reported in the bottom portion of Table 1. Of note, we find a relatively low elasticity of substitution between labor and intermediates and an elasticity close to zero between different intermediates. Despite very different methodologies, these are in line with those estimated using different approaches (e.g. Atalay (2017)). As will be discussed in Section 5.2, we also find an important role for the aggregate labor supply shock in accounting for the aggregate decline in employment. The hiring costs that we estimate are relatively modest: for example, these imply that the labor agency would need to pay hiring costs of around 0.3% of its payroll in order to increase employment by 1% in a given quarter. In practice these costs are small in aggregate: when we subject the model to all shocks, the total hiring costs paid are equal to 0.15% of output in the period when the shocks occur, 0.08% of output in the next quarter, and quickly converge to zero thereafter. We discuss the robustness of our estimation strategy in Appendix B.

4 The COVID-19 Demand Reallocation Shock

With the estimated parameters in hand, we now consider the role of each shock in turn. To start, we turn off the aggregate labor supply shock ($\Delta\chi = 0$), we turn off the idiosyncratic TFP shocks ($\Delta A_t^i = 0\,\forall i$), and we consider our main experiment, which is to study the effect of an increase in demand for goods relative to services. In order to highlight important features of the model, we contrast the effect of this shock in our baseline model with that which would occur (i) if there were no labor adjustment costs and (ii) if price stickiness were homogeneous across sectors.

Figure 3 undertakes the first comparison and plots the response of key variables to the demand reallocation shock. The reallocation of demand leads to a large increase in goods consumption and a large decline in services consumption. The dotted lines show that, absent hiring costs, these changes

[20] The size of the hiring cost also plays an important role in determining the evolution of sectoral quantities and prices.

would offset each other leaving aggregate prices, consumption and employment unchanged.[21] Once we introduce hiring costs, the increase in employment in 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 of the costs of increasing production, goods prices jump, resulting in year-over-year goods inflation peaking above 6 percent after one year.

In contrast, employment in services-producing sectors falls immediately, as such firms face no costs in reducing their workforce.[22] The asymmetry caused by hiring costs is key in understanding the inflationary effects of this shock: in services-producing sectors the decline in demand translates largely into a fall in quantities rather than prices. In contrast, in goods-producing sectors the increase in demand pushes up prices due to the costs firms face in increasing their capacity. While services inflation initially declines, it then also rises, peaking at about 3 percent after 5 quarters.[23]. All told, the dynamics of sectoral inflation result in aggregate inflation peaking just under 4 percent after one year, which represents a sizeable portion of the increase in CPI shown in Figure 1. The demand reallocation shock can also explain a roughly 1.5 percent decline in both aggregate consumption and employment in the baseline model.

In Figure 4 we repeat the experiment but assuming that all sectors have the same price stickiness (equal to the average stickiness in our baseline calibration). As goods prices tend to be more flexible than services prices, this raises price stickiness in goods-producing sectors and lowers it in services-producing sectors, on average.[24] Compared to our baseline calibration, higher price stickiness in the goods sector would result in a lower path for goods inflation, causing a peak aggregate inflation almost one percentage point lower than in our baseline. Hence, heterogeneous price stickiness is an important element to explain the inflationary effects of the demand reallocation shock.

Despite the simplicity of the demand reallocation shock, the model contains rich predictions on the dynamics of sectoral prices and quantities. Figure 5 shows that this relative demand shock is able to explain a good fraction of the dispersion in industry-level inflation rates and output growth. The positive correlation between inflation in the model and the data holds not only across all sectors but also within the sets of goods-producing or services-producing sectors. It is noticeable

[21] This result requires that we normalize the consumption of goods and services by their expenditure shares in equation 11.

[22] Despite the absence of adjustment costs to cutting employment, labor in the service sectors declines less than in the frictionless model. This primarily occurs as firms internalize the fact that they will face hiring costs in the future when they cut employment.

[23] Furthermore, as shown in Figure A.3, inflation is stronger in services sectors used for goods production

[24] In our baseline calibration, the mean value of κ_i in goods producing sectors is 24, while in services producing sectors it is 36.

that in the model prices and quantities actually rise in a number of services sectors despite the negative shock to services demand.[25] This occurs as a sector's final demand depends not only 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 face increased demand. As shown in Figure A.3 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.3 inflation is higher (lower) in the goods (services) sectors with lower price stickiness. Figure A.4 shows that similar relationships between price changes and sectoral characteristics are present in the data.

5 The COVID-19 Supply Shocks

5.1 Idiosyncratic Productivity Shocks

While the simple demand reallocation shock can explain a significant proportion of the cross-sectional developments across industries, 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 40% decline in quantities and a 50% rise in prices between 2019Q4 and 2021Q4, as shown in Figure 6. 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 sectoral supply disruptions, we now consider in isolation the role of idiosyncratic productivity shocks. 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 the model. Details of our measurement of sectoral TFP are provided in Appendix A. Figure 7 plots the measured change in productivity between 2019Q4 and 2021Q4 for each of the sectors in our model.[26]

Starting with the cross-sectional implications, Figure 8 shows that these idiosyncratic supply

[25] Figure A.1 provides further sector-specific impulse responses for the demand reallocation shock.

[26] As with the other sectoral variables, we calculate these relative to a sector-specific trend between 2005 and 2019. Our estimates of industry productivity appear to be close to those of Fernald and Li (2022).

shocks can explain a significant fraction of the cross-sectional evolution of both prices and quantities, even absent other shocks. Figure 9 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 that increase their employment to experience a steep increase in their labor costs. All told, aggregate inflation increase by about 1.5 percentage points after four quarters.

5.2 Labor Supply Shock

While the demand reallocation shock and idiosyncratic productivity shocks explain a significant fraction of recent sectoral and aggregate price and quantity dynamics, together they explain only a little over a quarter of the decline in employment experienced in the US. This is the motivation for the third shock considered in our estimation exercise, to aggregate labor supply. In popular discussion this shock has been labelled the "Great Resignation", and is often explained by concerns about exposure to COVID-19 in the workplace.

Figure 10 shows the effect of our estimate of this shock in isolation. This shock operates as a negative labor supply shock would in a much simpler New Keynesian model: it lowers aggregate employment and consumption while putting upward pressure on wages and prices. On its own this shock leads to a rise in inflation that is a little less than half of the size of that which occurs in response to the demand reallocation shock.

6 All 3 COVID-19 Shocks

Having considered the three types of shock in isolation, we now show their effects when they occur simultaneously (as used in our estimation procedure). Figure 11 plots the impulse response functions in this case. Overall our model suggests that these shocks are responsible for an increase in inflation of around 4.5 percentage points, the majority of that which was observed in the data. Interestingly, the model exhibits significant non-linearities: summing the inflationary effects of the individual shocks would lead to an increase in inflation around 50 percent larger than seen in Figure 11. This occurs as the negative labor supply shock reduces the expansion in hiring that occurs in goods-producing sectors in response to the demand reallocation shock, and consequently the run-up in hiring costs that such firms face.

Turning to the cross-sectional implications, Figure 12 shows that the combination of these three shocks provides an excellent description of cross-sectional developments in prices and quantities.

For example, the correlation between sectoral inflation rates in the model and the data is 0.68. Even if one is only interested in aggregate developments, we consider this to be strong additional evidence in favor of the channels described in this paper.

7 Model Extensions

In this section we undertake a number of extensions. First we show the cross-sectional response of prices to the demand reallocation shock in a number of simpler models that are nested in our baseline calibration. This shows the importance of both the input-output structure and heterogeneity in price stickiness across sectors. We then consider the implications of the demand reallocation shock under different assumptions about the shocks persistence, and how persistent it was expected to be.

7.1 A Decomposition of Cross-Sectional Implications

As shown in Figure 5, a simple demand reallocation shock is able to explain a large fraction of the dispersion in industry-level inflation rates. 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 13 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 predicts little dispersion in inflation, based on only on whether the industry is a direct provider of goods or services (or both).[27] If we add either heterogeneous price rigidity or I-O

[27] In the version of the model with no I-O linkages we recalibrate the labor adjustment cost parameter, c, in order to generate the same average difference between goods and services prices as in the baseline model.

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.

We find it particularly encouraging that there is a sizeable correlation between inflation in the model and the data not only when considering all sectors but also considering the subsets of sectors that produce goods or services. This shows the important role that the input-output linkages and heterogeneous price rigidity play in our results.

7.2 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. We model this reversal by assuming that the persistence of the shock falls unexpectedly from 0.975 to 0.5 after two years.

We find that such a reversal would raise inflation by around a percentage point. Figure 14 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, primarily driven by services-producing sectors which struggle to increase capacity in response to their unexpected increase in demand.

7.3 Unexpected Persistence of the COVID-19 Shift in Preferences

In Section 4 we assumed that the persistence of the shock to the preference for goods, ω_t, is known to agents in the model immediately. It is perhaps more likely that the persistence of the shift in demand from services to goods has been surprisingly high, particularly since lockdown restrictions have been lifted.

To investigate the importance of our assumption, we now study the impact of a demand reallocation shock that is unexpectedly persistent. In particular, we assume that agents initially believe that the shock has a quarterly persistence of 0.5, even though the relative demand for goods, ω_t, follows the same path as in Section 4 and Figure 3. Consequently, for the first two years, agents are repeatedly surprised by the persistence of ω_t. At this point we assume that agents finally realize the true persistence of the shock.[28]

Figure 15 plots the response of key variables in our model to such a sequence of shocks. This shows that in such a scenario less labor is shed in services-producing sectors, while fewer employees are hired by goods-producing sectors. An implication of this reduction in reallocation is that price dispersion is higher than in the baseline. In particular, prices in services-producing sectors fall much more than in the baseline, as their decline in demand feeds less into quantities than it does in the baseline.

The bottom-left panel of Figure 15 shows that the lower services price inflation in this scenario is largely responsible for lower headline inflation. Aggregate inflation peaks at around 2.5 percent in this scenario, as opposed to almost 4 percent under our baseline assumption on expectations. On the other hand, when agents finally realize the persistence of the shock, there is a second bout of inflation, as services-producing sectors lay off workers and raise prices.

Overall, the experiments in Section 7.2 and 7.3 highlight the key role that expectations of the future path of sectoral demand play in determining the amount of reallocation that occurs following a shift in demand across sectors and the inflation that such a shock will cause.

8 Conclusion

In this paper, we have estimated a multi-sector New Keynesian model with input-output linkages in order to quantify the role that demand reallocation, sector-specific disturbances, and a decline in aggregate labor supply have played in driving price and quantity dynamics as the U.S. economy has recovered from the COVID-19 pandemic.

Our main finding is that the shift in consumption demand from services towards goods can explain a large proportion of the rise in U.S. inflation in the post-lockdown period. This demand reallocation shock is inflationary due to the costs of increasing production in goods-producing sectors and because such sectors tend to have more flexible prices than those producing services. We find smaller positive contributions to inflation from sectoral productivity shocks and an aggregate labor supply shock, despite the fact that the latter explains around three-quarters of the decline in employment. Our confidence in the model and its predictions is boosted by the fact that it provides an excellent description of cross-sectional developments in prices and quantities.

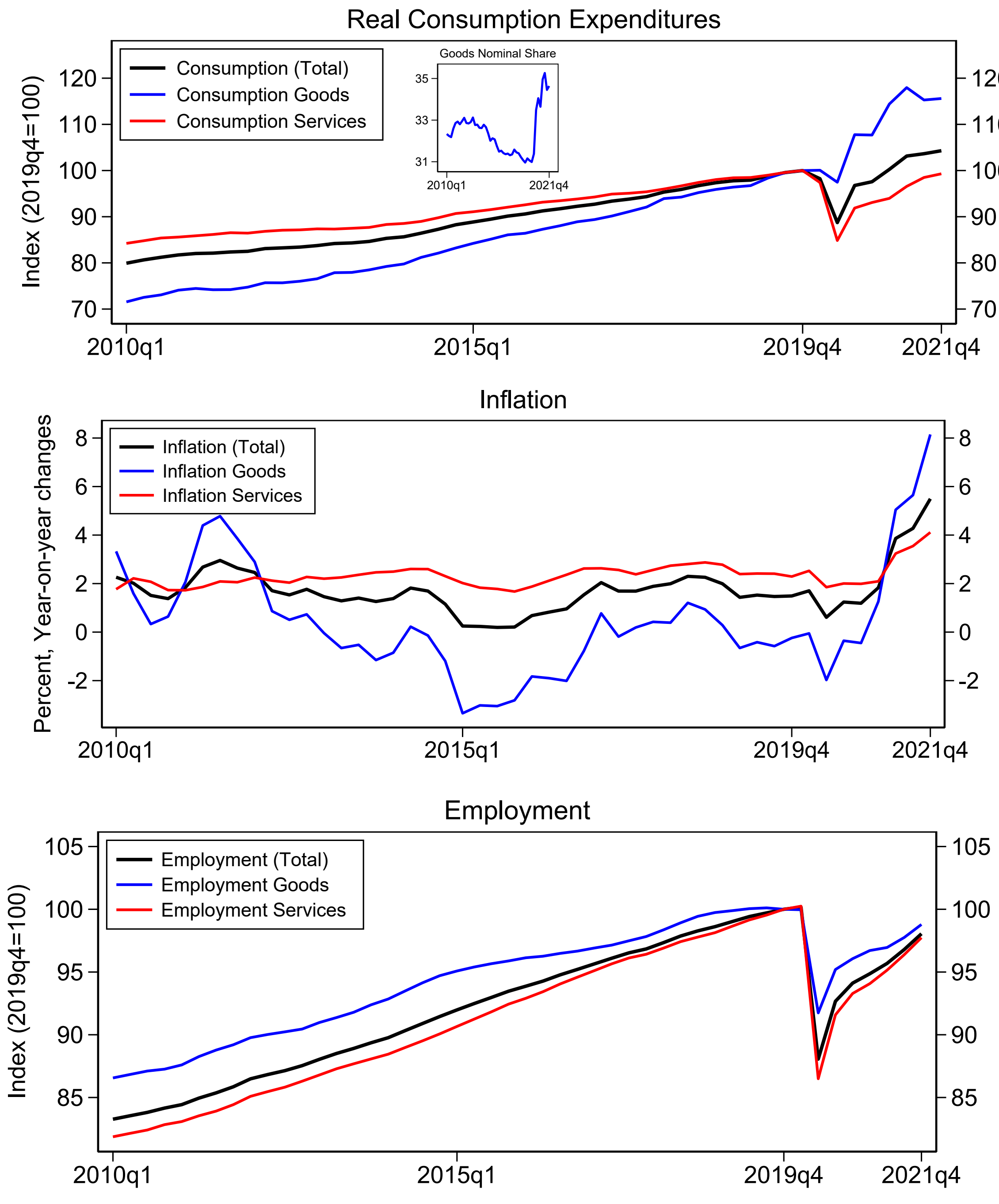
[28] While the expectation process in this scenario may seem more realistic than in our baseline, solving for the equilibrium is significantly more computationally intensive, as we must solve for a new perfect foresight solution for each period in which agents are surprised by the persistence of the demand shock. It is also difficult to know in reality how fast people updated their expectations about the demand shock's persistence.

We have used the model to undertake a number of experiments relating to the persistence of the demand reallocation shock and how persistent it was expected to be. Looking forward, we have studied what may occur if there is an unexpected reversal in the reallocation of demand from goods back to services. Our model predicts that this would be no panacea for the high inflation that the U.S. is currently experiencing: inflation would rise in such a scenario as services-producing sectors struggle to expand their production.

Table 1: Parameter Values

Calibrated Parameters/Shocks	**Value**	**Target/Source**
γ	2	Standard
χ	1	Normalization
ψ	1	Standard
ϕ	1.5	Standard
β	0.995	Standard
ϵ	10	Standard
$\bar{\omega}$	0.31	Goods Expenditure Share
α	0.5	Pasten, Schoenle and Weber (2020)
κ_i	0.05 to 98	Pasten, Schoenle and Weber (2020)
ρ_ω	0.975	Path of Goods Expenditure Share
ρ_χ	0.95	Standard
ρ_A	0.95	Standard
Δ_ω	0.045	Δ Goods Expenditure Share
ΔA_t^i	-0.29 to 0.25	Measured Sectoral TFP
Estimated Parameters/Shocks	**Value**	**Target/Source**
c	31.3 (17.4)	Estimated (s.e.)
ϵ_M	0.01 (0.27)	Estimated (s.e.)
ϵ_Y	0.58 (0.05)	Estimated (s.e.)
$\Delta\chi$	0.11 (0.04)	Estimated (s.e)

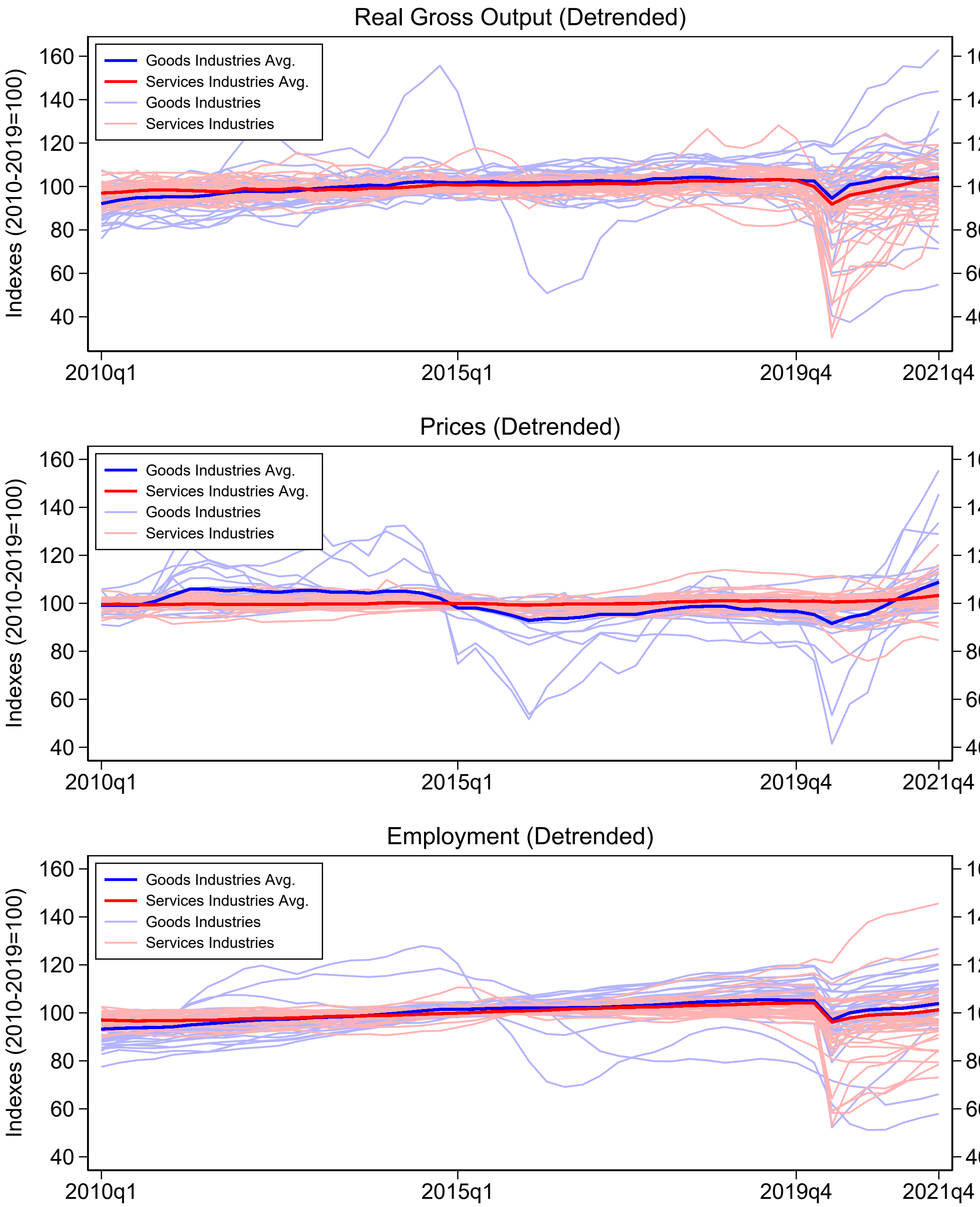
Figure 1: Aggregate COVID Dynamics



This Figure plots aggregate dynamics for the U.S. economy around the COVID-19 pandemic. The COVID-19 pandemic has led to an unprecedented increase in the demand for goods relative to services (top panel). Personal Consumption Expenditures inflation has risen, more for goods than for services (middle panel). Employment has initially declined before recovering, more in the goods than in the service sector (bottom panel). In the inset box in the top panel, the Goods Share is expressed as the share in total PCE of nominal goods consumption.

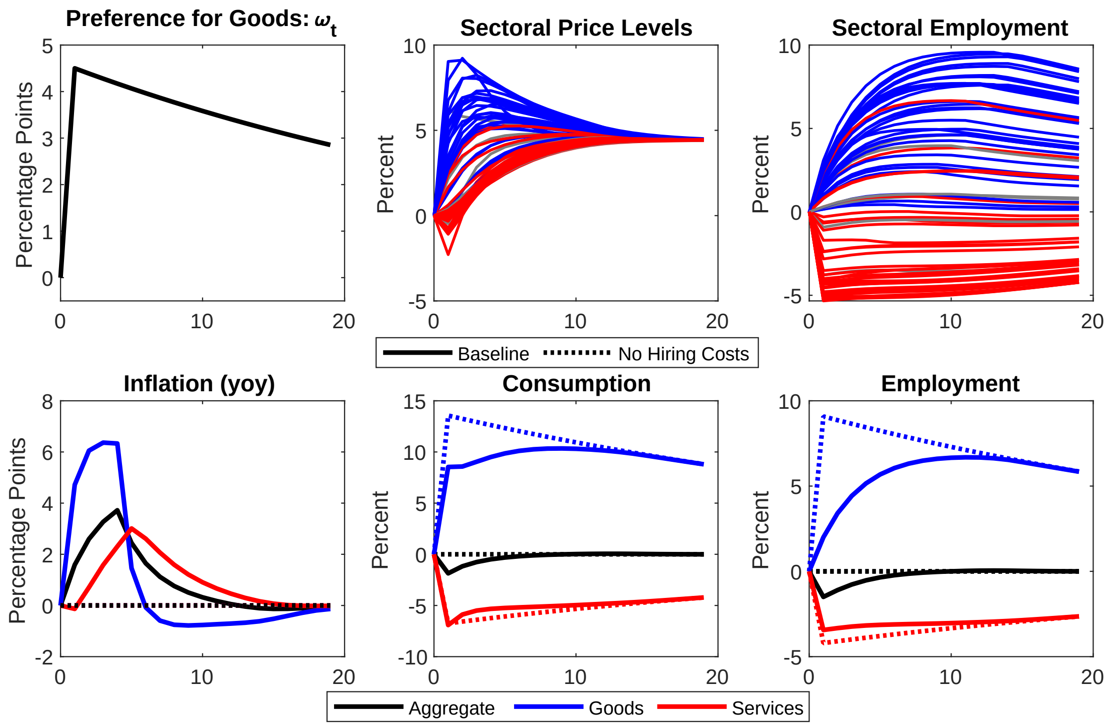
Data Sources: US Bureau of Economic Analysis, BLS, NIPA Tables, and authors' calculations.

Figure 2: Cross-sectional COVID Dynamics



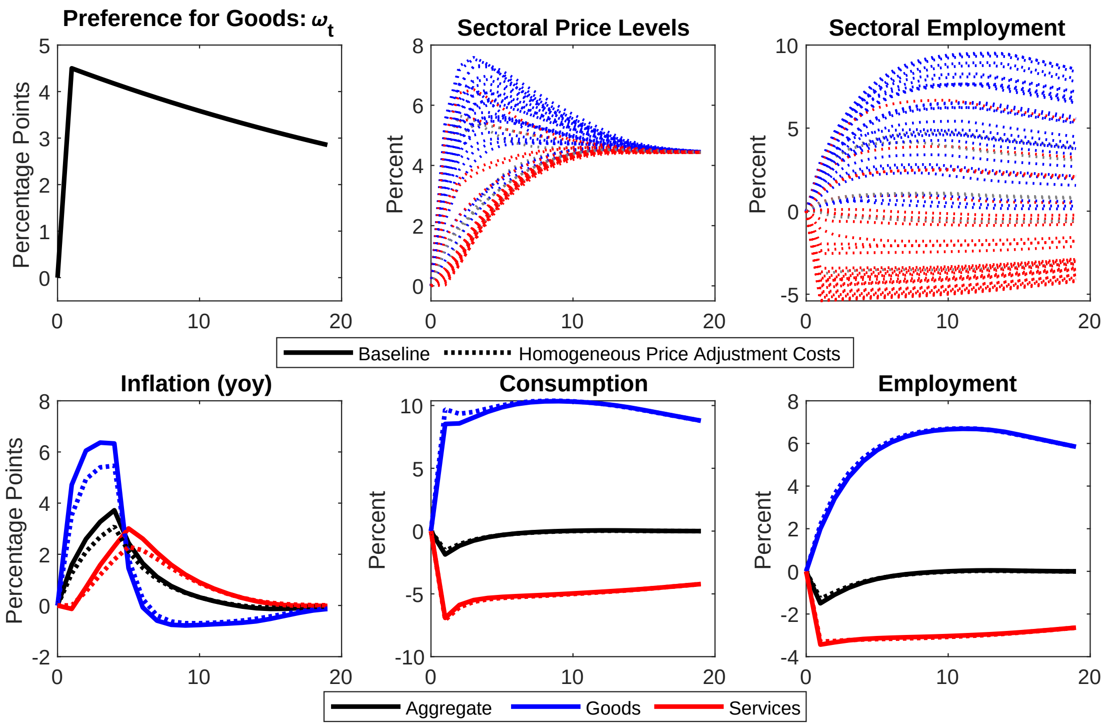
This Figure plots industry dynamics around the COVID-19 pandemic. Each line denotes one of the 66 private industries for which BEA publishes quarterly data on gross output, prices, and intermediate inputs. Employment data are published at the 3-digit NAICS code level and aggregated at the BEA industry level using the concordance described in https://www.uspto.gov/sites/default/files/documents/oce-ip-economy-supplement.pdf. Individual industries and averages (weighted by industry gross output) are indexed to 100 in the 2010-2019 period. Variables at the industry level are detrended by calculating for each industry a log-linear time trend from 2005:Q1 through 2019:Q4. Data Source: US Bureau of Economic Analysis, NIPA Tables.

Figure 3: Aggregate Effects of the Demand Reallocation Shock



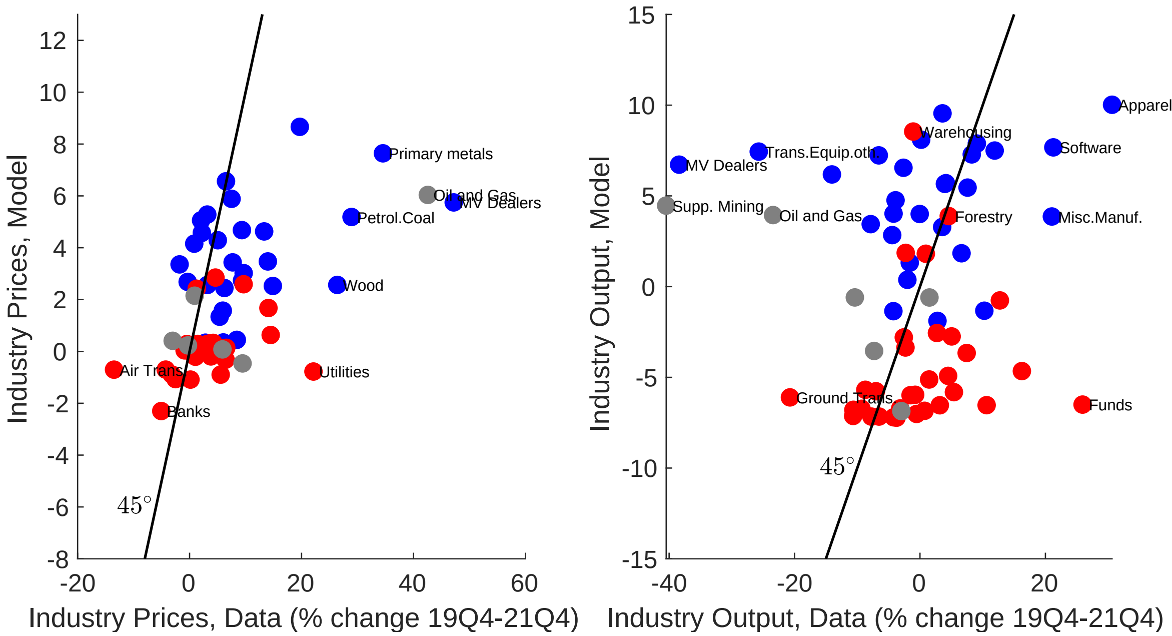
This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter. Solid lines denote the baseline model. Dotted lines denote the response of aggregates if there were no hiring costs. For clarity, we only plot sectoral variables in the baseline model. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 4: Demand Reallocation Shock: Heterogeneous vs Homogeneous Price Stickiness



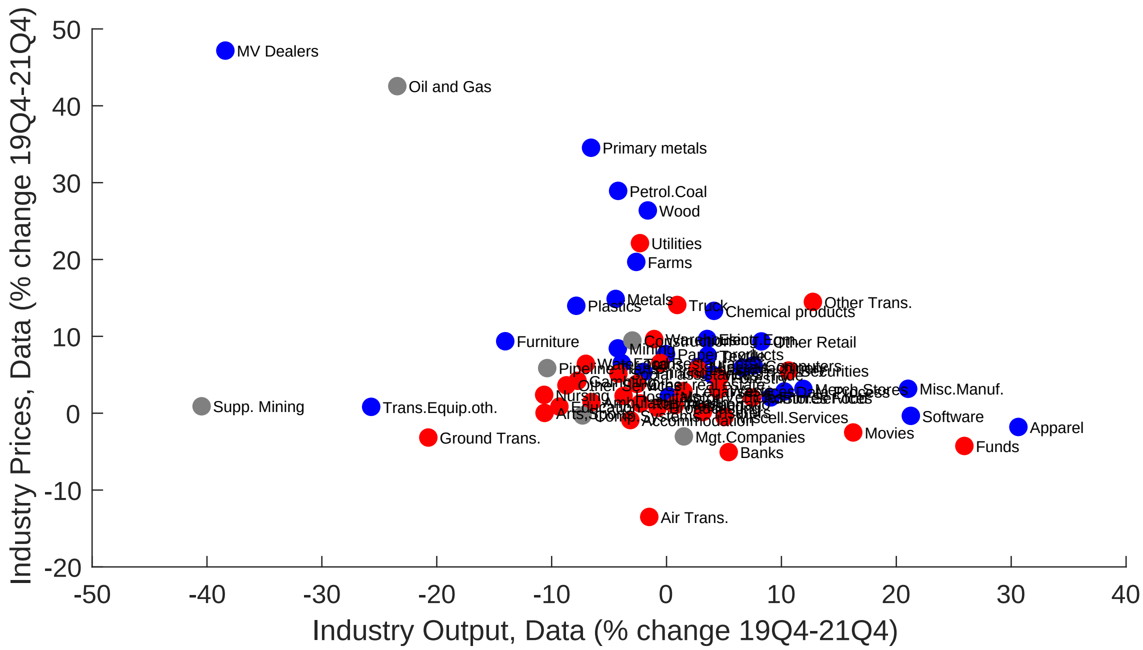
This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter. Solid lines denote the baseline model. Dotted lines denote the response of variables if price adjustment costs were homogeneous across industries. For clarity, we only plot sectoral variables in the model with homogeneous price adjustment costs. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 5: Model and Data: Sectoral Responses to Demand Reallocation Shock



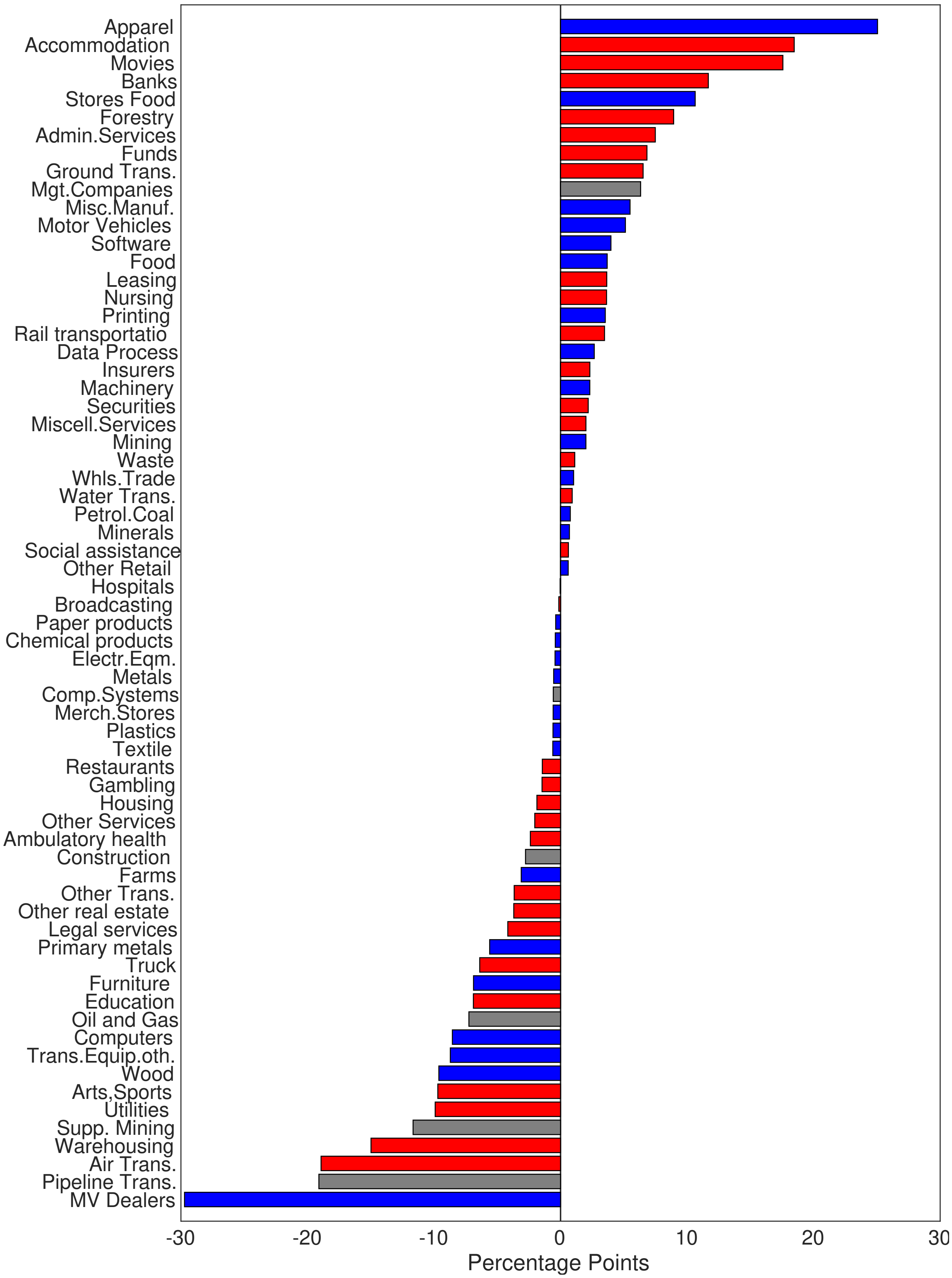
This Figure compares the cross-sectional implication of the model with the data in response to a demand reallocation shock that increases preferences for goods. Each dot is one industry. The x-axis plot inflation rates (percent change in the industry chain-type price price index) and real gross output 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. Gray dots denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 6: Sectoral Price and Quantity Dynamics between 2019 and 2021



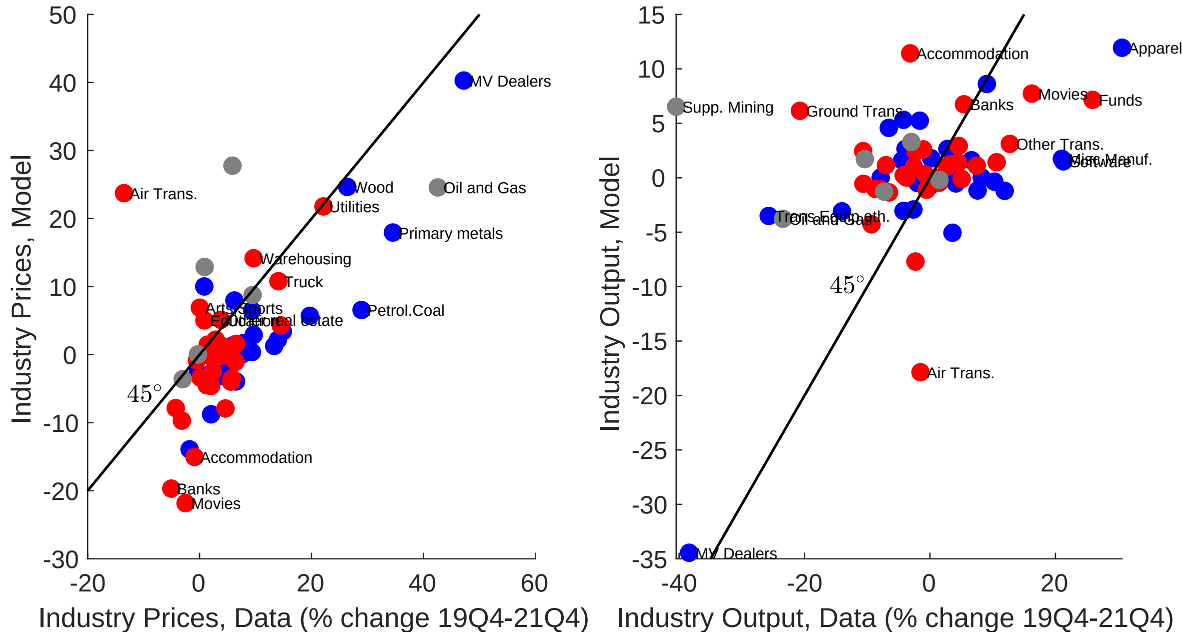
This Figure plots the change in prices in each sector against the change in sectoral output, from 2019Q4 to 2021Q4. Services-producing industries are shown in red and goods-producing industries are shown in blue. Gray dots denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 7: Measured Idiosyncratic TFP Shocks



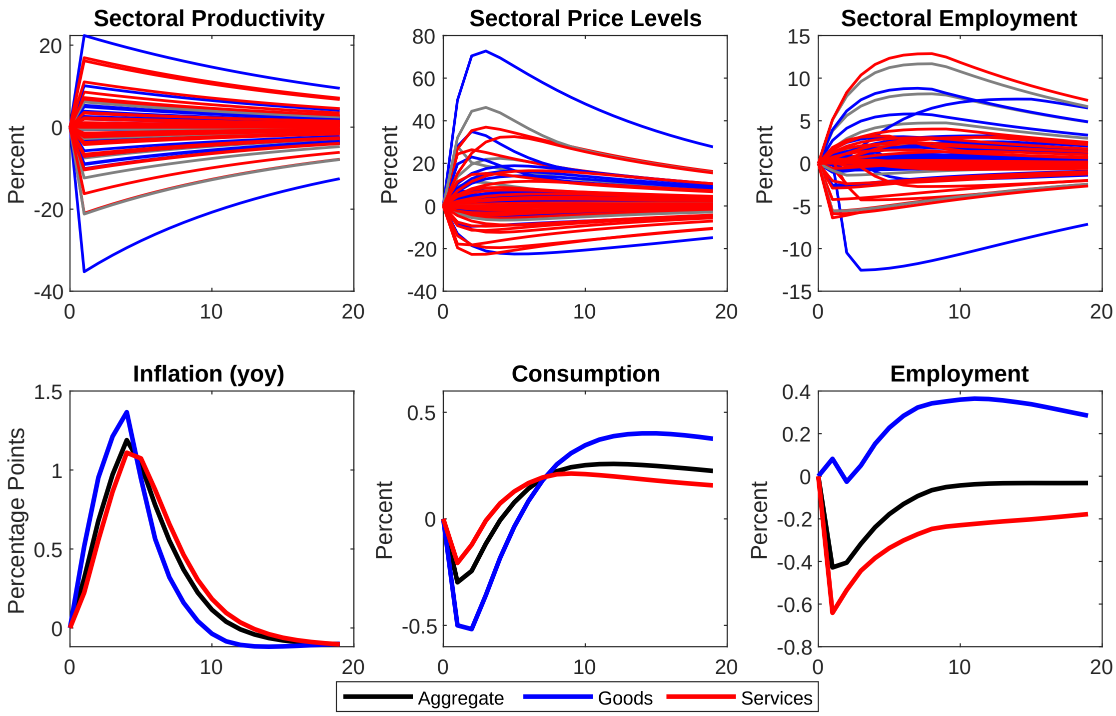
This Figure shows the change in measure productivity in each sector. Services-producing industries are shown in red and goods-producing industries are shown in blue. Gray bars denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 8: Model and Data: Sectoral Responses to Idiosyncratic TFP Shocks



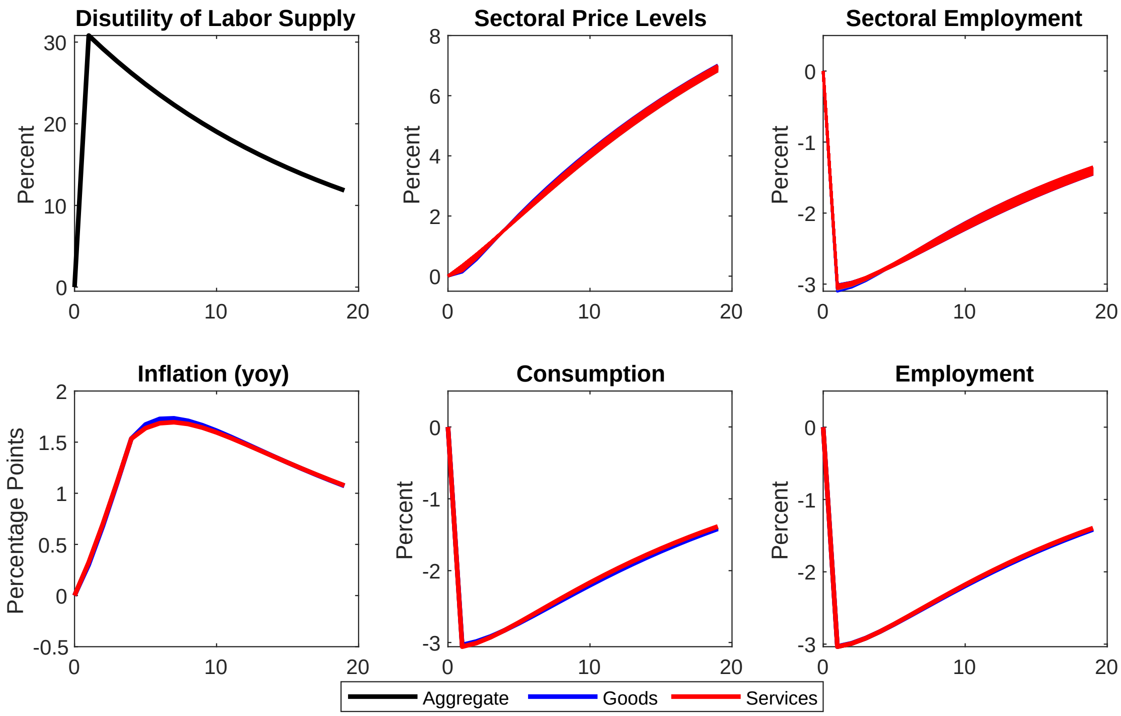
This Figure compares the cross-sectional implication of the model with the data in response to an estimated idiosyncratic TFP shocks at the industry level. Each dot is one industry. The x-axis plot inflation rates (percent change in the industry chain-type price price index) and real gross output growth 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. Gray dots denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 9: Aggregate Effects of Idiosyncratic TFP Shocks



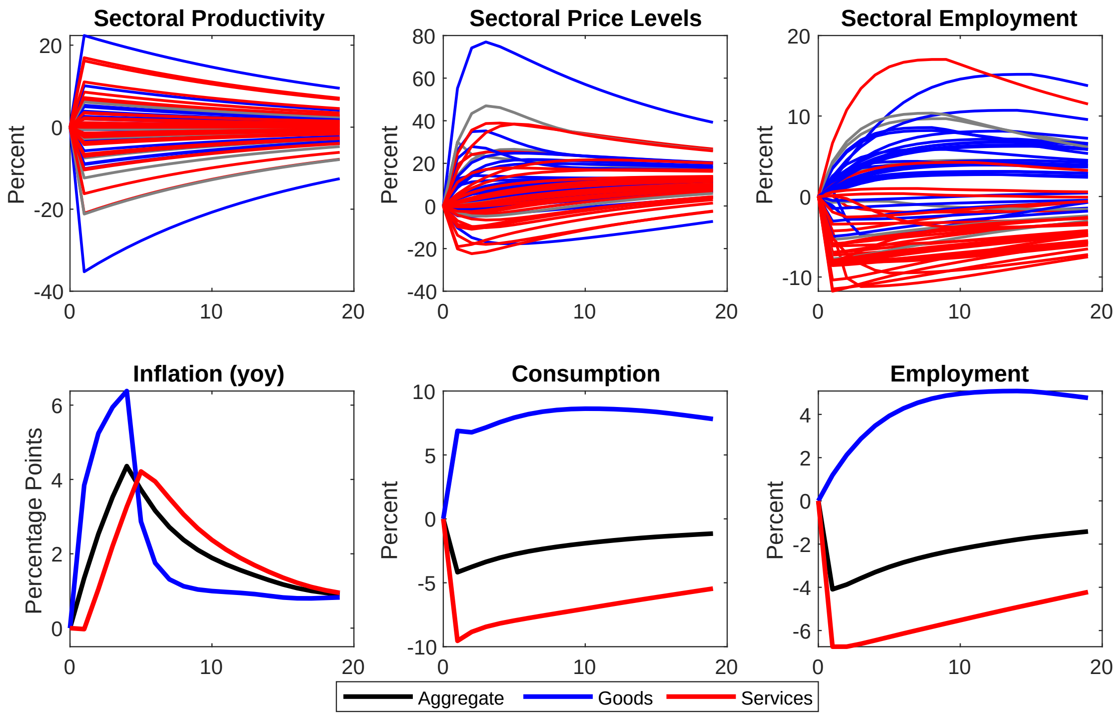
This Figure plots the impulse response of key variables to estimated idiosyncratic productivity shocks (using industry level data on output, added value and employment) in period 1. Each period is one quarter. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 10: Aggregate Effects of Labor Supply Shocks



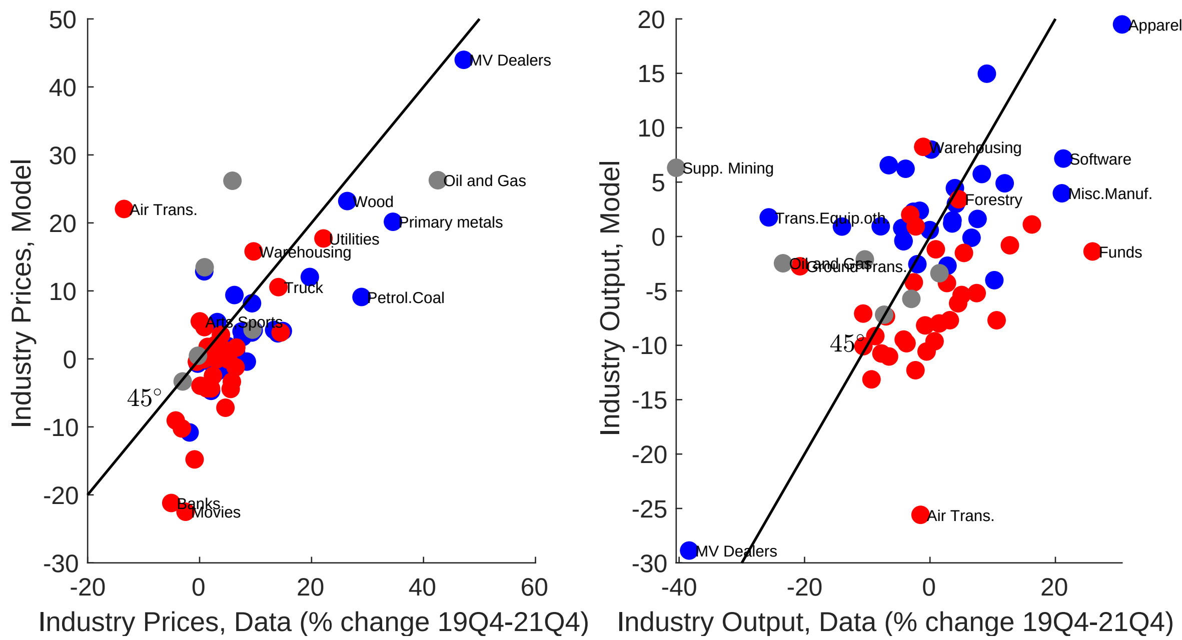
This Figure plots the impulse response of key variables to a labor supply shock that increases the disutility of labor in period 1. Each period is one quarter. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 11: Aggregate Effects of All Shocks



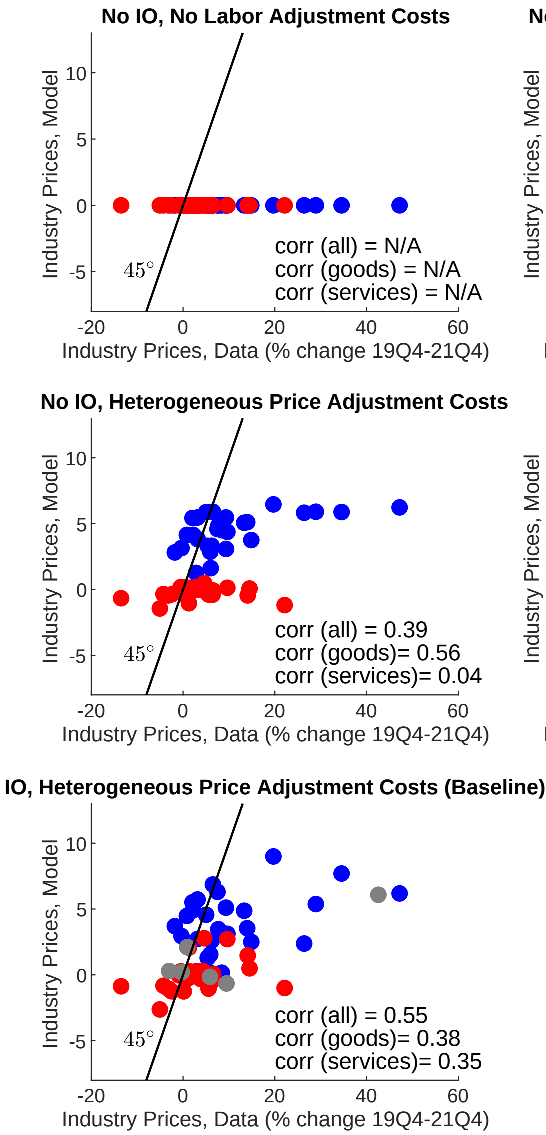
This Figure plots the impulse response of key variables to three combined shocks: (1) a demand reallocation shock that increases preferences for goods, (2) estimated idiosyncratic TFP shocks at the industry level, and (3) a negative labor supply shock. Each period is one quarter. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 12: Model and Data: Sectoral Responses to All Shocks



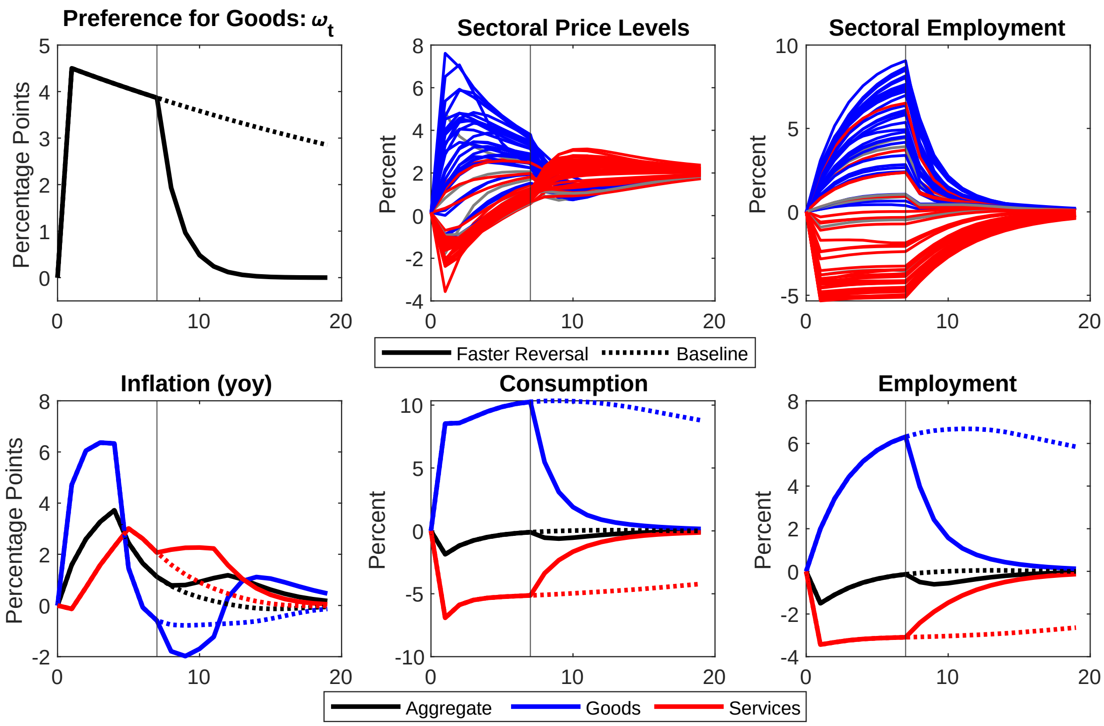
This Figure compares the cross-sectional implication of the model with the data in response to three combined shocks: (1) a demand reallocation shock that increases preferences for goods, (2) estimated idiosyncratic TFP shocks at the industry level, and (3) a negative labor supply shock. Each dot is 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. Gray dots denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 13: Sectoral Inflation Response to Demand Reallocation Shock in Alternative Models



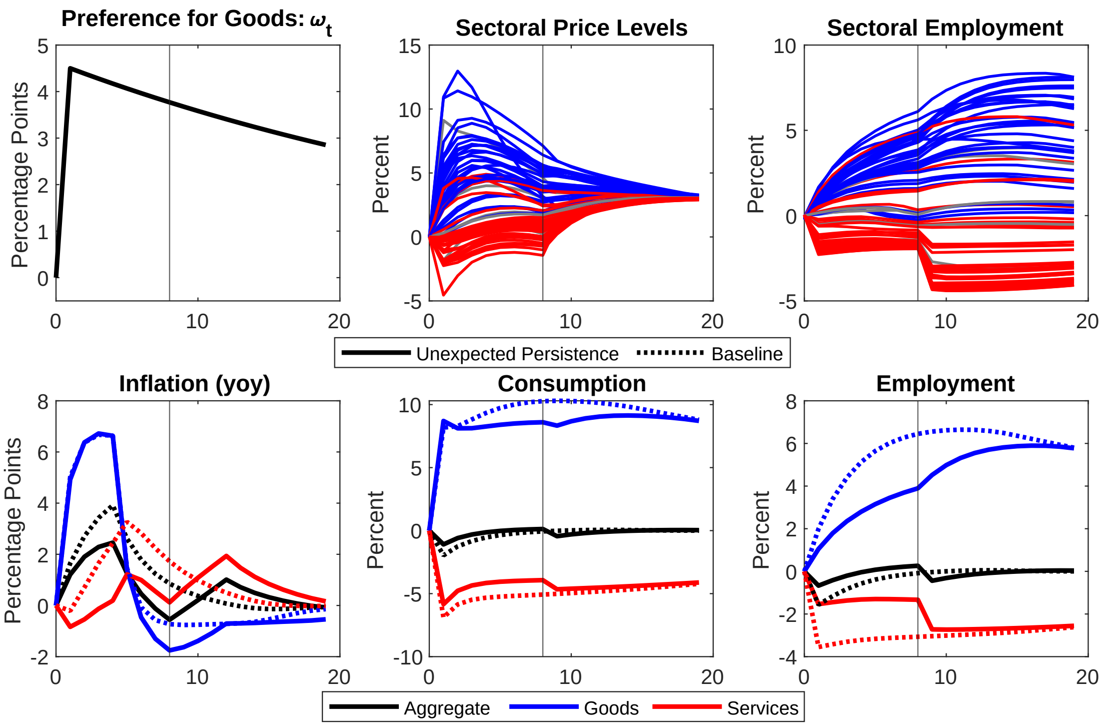
This figure compares the cross-sectional implications of different models for sectoral inflation against actual inflation between 2019Q4 and 2021Q4. The first panel reports the response of a model without input-output linkages or costly labor re-allocation. The second panel reports the response of a model with labor adjustment costs but no input-output linkages and with homogeneous price stickiness across 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. Services-producing industries are shown in red and goods-producing industries are shown in blue. Gray dots denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 14: Aggregate Effects of Reversal of 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. The dotted lines shows the baseline persistence. The solid lines show outcomes if the persistence unexpectedly declines from 0.95 to 0.5 after two years (denoted by the vertical line). Each period is one quarter. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure 15: Aggregate Effects of Unexpected Persistence of 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. The dotted lines shows the baseline persistence. The solid lines show outcomes if agents expect the shock to have a lower persistence of 0.5 for the first two years and are repeatedly surprised. After two years agents learn the true persistence (denoted by the vertical line). Each period is one quarter. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

References

Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry. 2012. "Measuring the upstreamness of production and trade flows." *American Economic Review*, 102(3): 412–16.

Anzoategui, Diego, Diego Comin, and Robert Johnson. 2022. "Supply Chain Constraints and Inflation."

Atalay, Enghin. 2017. "How important are sectoral shocks?" *American Economic Journal: Macroeconomics*, 9(4): 254–80.

Baqaee, David, and Emmanuel Farhi. 2022. "Supply and demand in disaggregated Keynesian economies with an application to the covid-19 crisis." *American Economic Review*, 112(5): 1397–1436.

de Soyres, François, Ana Maria Santacreu, and Henry L Young. 2022. "Demand-Supply imbalance during the Covid-19 pandemic: the role of fiscal policy." *International Finance Discussion Paper*, , (1353).

di Giovanni, Julian, Sebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A Yildirim. 2022. "Global Supply Chain Pressures, International Trade, and Inflation." National Bureau of Economic Research Working Paper 30240.

Fernald, John, and Huiyu Li. 2022. "The Impact of COVID on Productivity and Potential Output."

Fornaro, Luca, and Federica Romei. 2022. "Monetary policy during unbalanced global recoveries."

Gertler, Mark, and Antonella Trigari. 2009. "Unemployment fluctuations with staggered Nash wage bargaining." *Journal of political Economy*, 117(1): 38–86.

Ghassibe, Mishel. 2021. "Monetary policy and production networks: an empirical investigation." *Journal of Monetary Economics*, 119: 21–39.

Gorodnichenko, Yuriy, and Michael Weber. 2016. "Are sticky prices costly? Evidence from the stock market." *American Economic Review*, 106(1): 165–99.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning. 2021. "Monetary policy in times of structural reallocation." *University of Chicago, Becker Friedman Institute for Economics Working Paper*, , (2021-111).

La'O, Jennifer, and Alireza Tahbaz-Salehi. 2022. "Optimal Monetary Policy in Production Networks." *Econometrica*, 90(3): 1295–1336.

Merz, Monika, and Eran Yashiv. 2007. "Labor and the Market Value of the Firm." *American Economic Review*, 97(4): 1419–1431.

Ozdagli, Ali, and Michael Weber. 2017. "Monetary Policy through Production Networks: Evidence from the Stock Market." National Bureau of Economic Research Working Paper 23424.

Pasten, Ernesto, Raphael Schoenle, and Michael Weber. 2020. "The propagation of monetary policy shocks in a heterogeneous production economy." *Journal of Monetary Economics*, 116: 1–22.

Streitwieser, Mary L. 2010. "Measuring the nation's economy: An industry perspective." *Bureau of Economic Analysis.*

Vom Lehn, Christian, and Thomas Winberry. 2022. "The investment network, sectoral comovement, and the changing US business cycle." *The Quarterly Journal of Economics*, 137(1): 387–433.

A Data Appendix

Our estimation exercise uses industry data on 66 private industries for which the BEA publishes quarterly data on real gross output, prices, and real intermediate inputs dating back to 2005:Q1.[2] The industry names, BEA codes, nominal shares of gross output in 2021, and PCE category-based expenditures allocated to each industry are listed in Table A.1.

For each industry, we measure percent changes in prices, gross output, employment, and productivity between the end of 2019 and the end of 2021, relative to their pre-pandemic trend. We log and linearly detrend each variable using an industry-specific trend calculated for 2005-2019 sample. The percent change in prices between 2019:Q4 and 2021:Q4 relative to the pre-pandemic trend is shown in Table A.2.

- **Prices:** We measure prices using the published BEA series on Chain-Type Price Indexes for Gross Output by Industry. Farms prices rose 19.7 percent relative to their pre-pandemic trend in the 2020-2021 period, while Air Transportation prices fell 13.5 percent.
- **Output:** We measure output using the published BEA series on chained Real Gross Output.
- **Employment:** Non-farm Employment data are published at the 3-digit NAICS code level by the Bureau of Labor Statistics in the monthly "B" tables of the Employment Situation News Release.[3] We aggregate these data at the BEA industry level using the concordance described in `https://www.uspto.gov/sites/default/files/documents/oce-ip-economy-supplement.pdf`.[4] For the farm sector, we have no data and assume no change in employment.[5]
- **Productivity:** For each industry, we follow Vom Lehn and Winberry (2022) and calculate productivity using a Solow residual approach. Lacking quarterly data on capital, we ignore variations in the capital stock and assume a simplified industry constant-returns-to-scale production function with employment and intermediates inputs only. The intermediate inputs share for each industry is an average (between 2005 and 2021) of the ratio of intermediate inputs to gross output. The employment share is, accordingly, one minus the intermediate share. Sector level productivity is then calculated as log output minus the weighted average of log employment and log intermediates, using as weights the industry-specific shares calculated above.

  The BLS publishes yearly estimates of total factor productivity at the level of three- and four-

[2] See the BEA website (`https://www.bea.gov/data/gdp/gdp-industry`) as well as Streitwieser (2010).

[3] See `https://www.bls.gov/ces/data/employment-situation-table-download.htm`

[4] As a disproportionate amount of the employment margin between 2019 and 2021 was driven by the extensive margin, we ignore fluctuations in measured hours and equate number of employees in the data with labor input in our model.

[5] This is consistent with agricultural employment, as published in the Household Survey: `https://fred.stlouisfed.org/series/LNS12034560`

digit NAICS industries [6]. As of this writing, estimates for 2021 have not been published yet. For the year 2020, our estimates of productivity growth by industry have a high correlation (around 0.7) with published data on labor productivity from the BLS.

For our estimation exercise, we de-mean the sectoral productivity changes for two reasons. First, while the BLS estimates of sectoral total factor productivity at the sectoral level are not yet available, estimates for the total economy suggest no deviation of aggregate TFP from the pre-pandemic trend.[7] Second, there is currently elevated uncertainty over the level of aggregate productivity due to the divergence between the income-side and expenditure-side measures of real GDP.[8]

Our calibration relies on consumption data for each of the 66 sectors in the model. We calculate values of γ_i^g and γ_i^s using the PCE Bridge provided by the BEA, which allocates PCE category-level consumption expenditures to NAICS industries.[9] This is possible for all industries apart from those in the wholesale/retail trade sectors. For these industries we calculate consumption expenditures from the BEA Input-Output tables and allocate all such spending to goods rather than services. This is consistent with the fact that the wholesale and retail margins reported in the PCE bridge are only present for goods spending.[10]

B Robustness

B.1 Alternative Estimation Strategies

We perform estimation of alternative versions of the model. Table A.3 reports the estimated parameters and selected properties of each of these versions. Column 1 reports the estimated parameters and basic properties of the benchmark model. The reallocation shock can account for an increase in inflation of 3.7 percentage points, while all shocks combined lead to a total rise in inflation of 4.4 percent. As shown in column 2, the important role of reallocation shocks in accounting for the rise in inflation also remains in a version of the model with 14 sectors and a less granular level of sectoral aggregation.

Column 3 shows that when we allow for the estimation of a separate cost of cutting employment (*cneg*), we find that this cost is estimated to be close to zero, while other parameters are largely unaffected. However, adding this extra parameter increases the uncertainty in the value of the

[6] See https://www.bls.gov/news.release/prin.toc.htm and https://www.bls.gov/news.release/prin2.toc.htm

[7] BLS TFP estimates are available at https://www.bls.gov/productivity/tables/. Sectoral TFP estimates for 2021 are scheduled for release in November 2022.

[8] This is discussed in further detail in Fernald and Li (2022).

[9] The PCE Bridge is available at https://www.bea.gov/industry/industry-underlying-estimates.

[10] Specifically, we use the "Use of Commodities by Industries, Before Redefinitions" table to calculate consumption expenditures for the wholesale/retail trade sectors.

estimated parameters. Consequently, in column 4 we modify the estimation strategy by targeting the increase in goods and the increase in services inflation separately. The estimated cost of cutting employment remains close to zero and the precision of the estimates improves substantially.

In column 5 we modify the weighting scheme so that the estimation places an arbitrarily small weight (100 times smaller) on the cross-sectional standard deviations and correlations. The precision of the estimates deteriorates, thus bolstering our confidence in using cross-sectional moments to infer information about the parameters of our model. The price stickiness in our model is roughly equivalent to a model with staggered price adjustment a-la Calvo in which prices change on average every 2 quarters. In column 6 we estimate a version of the model where we scale up the Rotemberg price adjustment costs so that they correspond, to a first order, to a Calvo model where prices change every 4 quarters, as in many new-keynesian models of the business cycle. While the estimated cost of increasing labor is slightly larger, and the effect of reallocation shocks is slightly smaller, the basic properties of the model are largely invariant to this modification.

Finally, in column 7 we estimate a version where we restrict the production function elasticities, ϵ_M and ϵ_Y, to be equal to 1. This version of the model fits the data slightly worse, and features a slightly smaller effect of reallocation shocks on inflation.

B.2 Effect of Complementarities in Production

In this section we consider the importance of the estimated complementarities in the production function. We feed the same demand reallocation shock into the model holding all parameters constant apart from the production function elasticities, ϵ_M and ϵ_Y, which we set to 1.

Figure A.2 compares the response in this calibration to the baseline model. The amount of inflation caused by the demand reallocation shock is around 25% lower. While firms still face hiring costs when increasing their labor, higher production function elasticities now increase their ability to increase output using intermediate inputs from other industries. One effect of this is that there is slightly less labor reallocation than seen in the baseline model.

Table A.1: Summary Statistics for the Industries in our input-output model

BEA Code	Industry	Output Share	Goods Spending	Services Spending
111CA	Farms	1.52	83,607	705
113FF	Forestry, fishing, and related activities	0.16	3,603	5,765
211	Oil and gas extraction	1.65	0	0
212	Mining, except oil and gas	0.31	57	0
213	Support activities for mining	0.19	0	0
22	Utilities	1.58	0	285,419
23	Construction	4.24	0	0
321	Wood products	0.28	5,458	0
327	Nonmetallic mineral products	0.33	5,881	4,480
331	Primary metals	0.74	535	0
332	Fabricated metal products	1.01	17,348	463
333	Machinery	1.14	7,723	0
334	Computer and electronic products	1.35	94,980	24
335	Electrical equipment, appliances, and components	0.39	41,619	0
3361MV	Motor vehicles, bodies and trailers, and parts	2.11	243,648	0
3364OT	Other transportation equipment	0.75	20,827	0
337	Furniture and related products	0.17	56,822	0
339	Miscellaneous manufacturing	0.59	100,199	0
311FT	Food and beverage and tobacco products	2.85	612,836	18,393
313TT	Textile mills and textile product mills	0.14	23,218	0
315AL	Apparel and leather and allied products	0.06	150,460	0
322	Paper products	0.52	19,864	0
323	Printing and related support activities	0.23	5,358	5
324	Petroleum and coal products	2.75	176,634	0
325	Chemical products	2.40	327,999	0
326	Plastics and rubber products	0.65	41,173	0
42	Wholesale trade	6.38	615,608	0
441	Motor vehicle and parts dealers	0.82	169,781	0
445	Food and beverage stores	0.72	250,025	0
452	General merchandise stores	0.86	230,902	0
4A0	Other retail	3.60	874,540	0
481	Air transportation	0.80	0	165,837
482	Rail transportation	0.22	0	1,527
483	Water transportation	0.15	0	25,506
484	Truck transportation	1.12	0	12,719
485	Transit and ground passenger transportation	0.25	0	52,324
486	Pipeline transportation	0.14	0	0
487OS	Other transportation and support activities	0.78	0	25,447
493	Warehousing and storage	0.52	0	94
511	Publishing industries, except internet (includes software)	1.69	97,565	0
512	Motion picture and sound recording industries	0.67	7,163	17,981
513	Broadcasting and telecommunications	3.09	0	340,686
514	Data processing, internet publishing, and other information services	2.15	44,145	33,179
521CI	Federal Reserve banks, credit intermediation, and related activities	2.30	0	331,266
523	Securities, commodity contracts, and investments	1.81	0	251,927
524	Insurance carriers and related activities	4.14	0	430,919
525	Funds, trusts, and other financial vehicles	0.45	0	157,331
HS	Housing	5.76	0	2,220,452
ORE	Other real estate	3.92	0	6,768
532RL	Rental and leasing services and lessors of intangible assets	1.25	15,318	101,274
5411	Legal services	0.94	0	111,136
5415	Computer systems design and related services	1.69	0	0
5412OP	Miscellaneous professional, scientific, and technical services	5.15	0	73,239
55	Management of companies and enterprises	2.27	0	0
561	Administrative and support services	3.49	0	74,546
562	Waste management and remediation services	0.32	0	29,304
61	Educational services	0.96	0	301,718
621	Ambulatory health care services	3.41	13,173	1,128,380
622	Hospitals	2.67	0	1,133,302
623	Nursing and residential care facilities	0.65	0	244,870
624	Social assistance	0.62	0	148,275
711AS	Performing arts, spectator sports, museums, and related activities	0.52	0	70,352
713	Amusements, gambling, and recreation industries	0.41	0	205,585
721	Accommodation	0.79	0	167,673
722	Food services and drinking places	2.50	0	822,730
81	Other services, except government	1.89	2,089	502,347

Note: The table shows key summary statistics for the industries used in our input-output model. Goods and services spending are for the year 2019 and expressed in millions of dollars.

Table A.2: Summary Statistics for the Industries in our Sample

			% Change from 2019:Q4 to 2021:Q4			
BEA Code	Industry	Share	Prices	Output	Empl.	Product.
111CA	Farms	1.52	19.7	-2.6	0.0	-1.0
113FF	Forestry, fishing, and related activities	0.16	4.6	4.6	-6.8	9.1
211	Oil and gas extraction	1.65	42.6	-23.4	-17.0	-4.5
212	Mining, except oil and gas	0.31	8.4	-4.2	-3.8	3.3
213	Support activities for mining	0.19	0.9	-40.5	-35.0	-8.2
22	Utilities	1.58	22.1	-2.3	-1.6	-6.7
23	Construction	4.24	9.5	-3.0	-0.2	-0.7
321	Wood products	0.28	26.4	-1.6	5.7	-6.5
327	Nonmetallic mineral products	0.33	6.0	2.8	-0.3	2.2
331	Primary metals	0.74	34.5	-6.6	-4.8	-3.1
332	Fabricated metal products	1.01	14.9	-4.4	-4.3	1.2
333	Machinery	1.14	5.9	6.6	-4.4	3.6
334	Computer and electronic products	1.35	6.2	7.6	2.0	-5.6
335	Electrical equipment, appliances, and components	0.39	9.7	3.5	1.3	1.3
3361MV	Motor vehicles, bodies and trailers, and parts	2.11	2.2	0.2	1.1	5.9
3364OT	Other transportation equipment	0.75	0.8	-25.7	-2.8	-5.7
337	Furniture and related products	0.17	9.4	-14.0	4.1	-4.2
339	Miscellaneous manufacturing	0.59	3.2	21.0	1.5	6.2
311FT	Food and beverage and tobacco products	2.85	6.5	-3.9	-1.9	4.7
313TT	Textile mills and textile product mills	0.14	7.5	3.6	0.4	1.1
315AL	Apparel and leather and allied products	0.06	-1.8	30.6	-2.3	22.7
322	Paper products	0.52	7.7	0.0	0.3	1.3
323	Printing and related support activities	0.23	5.4	-2.0	-6.3	4.6
324	Petroleum and coal products	2.75	28.9	-4.2	-6.3	2.3
325	Chemical products	2.40	13.3	4.1	2.9	1.3
326	Plastics and rubber products	0.65	14.0	-7.9	1.1	1.1
42	Wholesale trade	6.38	5.0	4.0	-3.0	2.5
441	Motor vehicle and parts dealers	0.82	47.2	-38.4	-5.7	-23.4
445	Food and beverage stores	0.72	2.1	9.1	-0.1	10.6
452	General merchandise stores	0.86	3.2	11.9	3.5	1.1
4A0	Other retail	3.60	9.3	8.3	-1.6	2.1
481	Air transportation	0.80	-13.5	-1.5	-0.1	-14.3
482	Rail transportation	0.22	1.3	-2.3	-11.6	4.6
483	Water transportation	0.15	6.4	-7.0	-19.1	2.4
484	Truck transportation	1.12	14.1	0.9	-0.3	-3.7
485	Transit and ground passenger transportation	0.25	-3.2	-20.7	-27.4	7.1
486	Pipeline transportation	0.14	5.9	-10.4	-6.5	-14.4
487OS	Other transportation and support activities	0.78	14.5	12.7	7.6	-1.5
493	Warehousing and storage	0.52	9.6	-1.1	20.0	-11.0
511	Publishing industries, except internet (includes software)	1.69	-0.3	21.3	6.1	5.0
512	Motion picture and sound recording industries	0.67	-2.5	16.2	-5.0	16.4
513	Broadcasting and telecommunications	3.09	0.7	-0.8	-3.9	1.5
514	Data processing, internet publishing, and other information services	2.15	2.8	10.3	3.1	3.9
521CI	Federal Reserve banks, credit intermediation, and related activities	2.30	-5.1	5.4	3.0	11.5
523	Securities, commodity contracts, and investments	1.81	5.6	10.6	0.4	3.5
524	Insurance carriers and related activities	4.14	0.2	3.2	-3.2	3.6
525	Funds, trusts, and other financial vehicles	0.45	-4.3	25.9	0.4	7.4
HS	Housing	5.76	1.0	0.7	0.5	0.1
ORE	Other real estate	3.92	3.8	-2.6	0.5	-1.5
532RL	Rental and leasing services and lessors of intangible assets	1.25	5.8	2.7	-11.7	4.7
5411	Legal services	0.94	2.9	1.5	1.7	-1.9
5415	Computer systems design and related services	1.69	-0.3	-7.3	-2.3	1.1
5412OP	Miscellaneous professional, scientific, and technical services	5.15	-0.5	5.0	2.0	3.3
55	Management of companies and enterprises	2.27	-3.0	1.5	-7.9	7.0
561	Administrative and support services	3.49	2.0	7.4	-3.3	7.9
562	Waste management and remediation services	0.32	3.0	4.5	-2.1	2.6
61	Educational services	0.96	0.9	-9.3	-6.1	-4.2
621	Ambulatory health care services	3.41	1.4	-6.5	-3.4	-0.4
622	Hospitals	2.67	2.3	-3.7	-4.1	1.6
623	Nursing and residential care facilities	0.65	2.4	-10.7	-15.2	4.7
624	Social assistance	0.62	5.1	-4.2	-9.4	2.1
711AS	Performing arts, spectator sports, museums, and related activities	0.52	0.0	-10.6	-20.4	-6.5
713	Amusements, gambling, and recreation industries	0.41	4.2	-7.7	-14.8	0.4
721	Accommodation	0.79	-0.9	-3.2	-29.0	17.2
722	Food services and drinking places	2.50	6.6	-0.5	-12.8	0.4
81	Other services, except government	1.89	3.6	-8.7	-6.9	-0.1

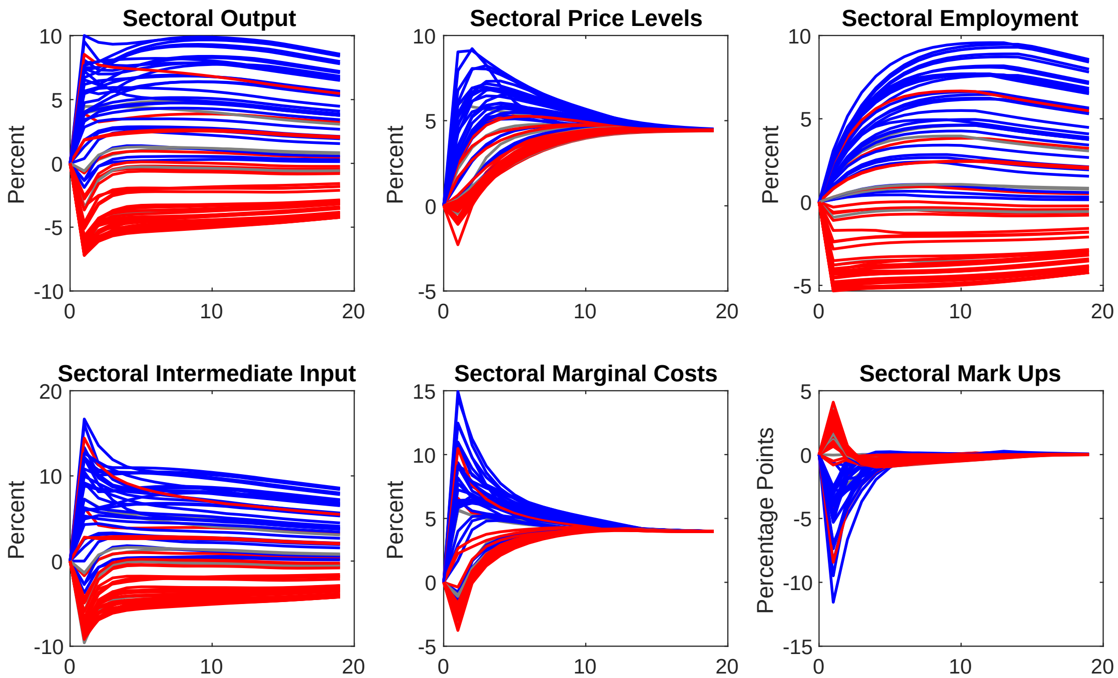
Note: The table shows key summary statistics for prices, output, employment and TFP for the industries used in our input-output model.

Table A.3: Estimation Results for the Benchmark and for Alternative Models

	1	2	3	4	5	6	7
	Benchmark	14 sectors	Asymm. Cost	Asymm.Cost Separate P	No cross section	Stickier Prices	Unit Elasticity
c	31.31	134.38	29.83	14.46	233.76	43.17	33.55
(SE)	17.41	136.97	189.48	10.5	8540.09	27.11	19.38
$cneg$			0.85	0.01			
(SE)			90.96	1.39			
ϵ_M	0.01	0.41	0.01	0.01	0.01	0.01	1
(SE)	0.27	0.21	0.48	0.3	25.45	0.32	
ϵ_Y	0.58	0.32	0.58	0.57	0.62	0.42	1
(SE)	0.05	0.04	0.07	0.05	9.85	0.04	
$\Delta\chi$	0.11	0.12	0.11	0.12	0.13	0.12	0.11
(SE)	0.04	0.05	0.48	0.04	0.91	0.04	0.04
Infl.: Reallocation	3.7	3.5	3.4	3.1	2.8	2.8	3
Infl.: All Shocks	4.4	4.2	3.9	4.3	2.9	4.2	3.4
Std(L) Data	8.72	5.82	8.72	8.72	8.72	8.72	8.72
Std(L) Model	5.87	4.62	5.84	6.53	4.16	6	4.46
Std(P) Data	10.42	9.76	10.42	10.42	10.42	10.42	10.42
Std(P) Model	12.27	10.09	12.28	12.04	12.81	12.27	7.09
Std(Y) Data	12.18	7.33	12.18	12.18	12.18	12.18	12.18
Std(Y) Model	8.61	7.76	8.61	8.88	7.73	8.71	7.82
Total Loss	100		99.78			89.7	103.59

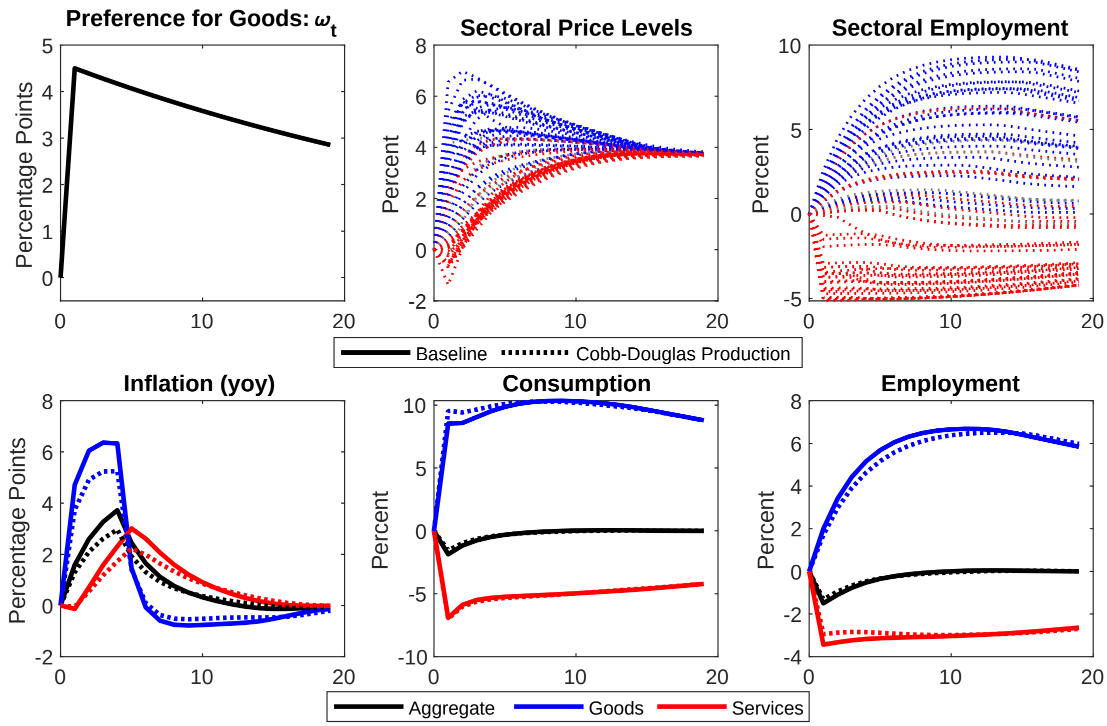
Note: See text for a description of the models. The total loss (squared norm of the distance between model and data moments) is normalized to 100 for the benchmark model, and expressed relative to the benchmark model for the estimated versions of the model that are directly comparable to the benchmark one.

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



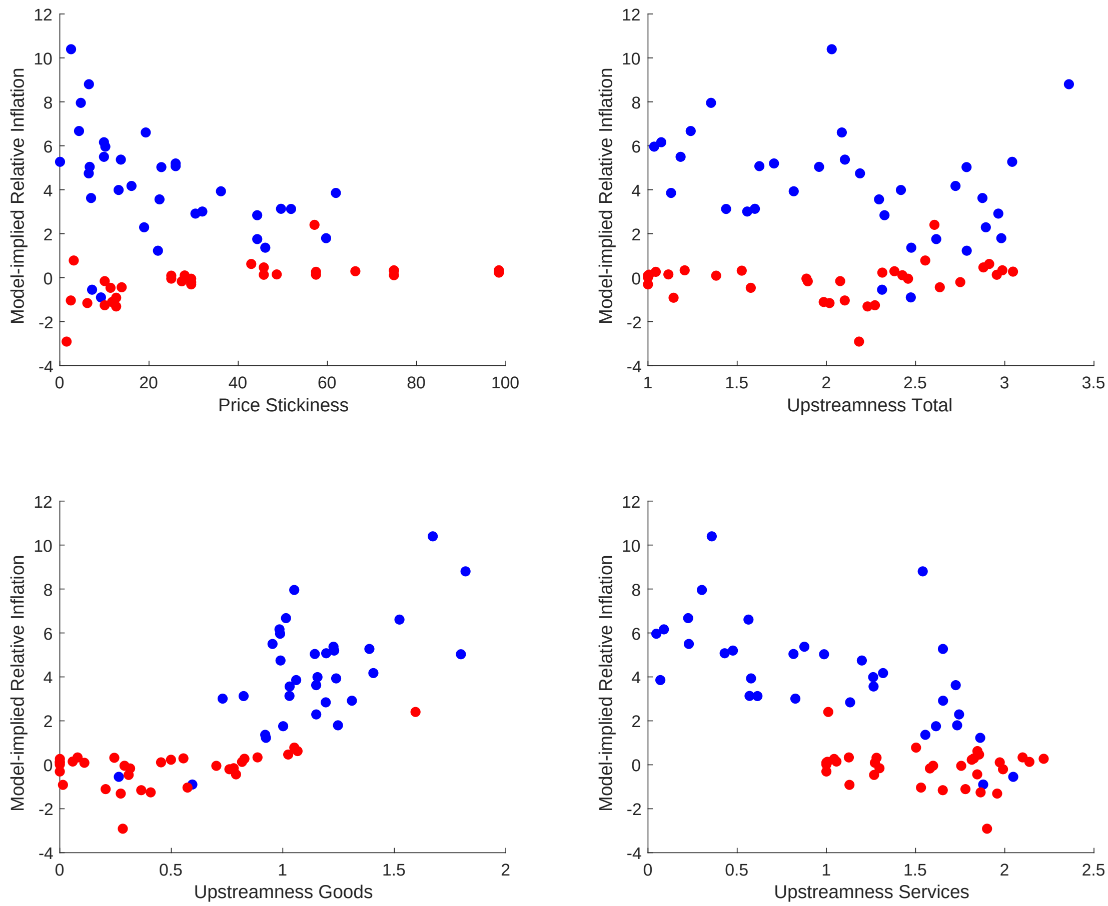
This Figure plots the dynamic response of sectoral variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter. Services-producing industries are shown in red and goods-producing industries are shown in blue. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

Figure A.2: Demand Reallocation Shock: Baseline v Cobb-Douglas Production



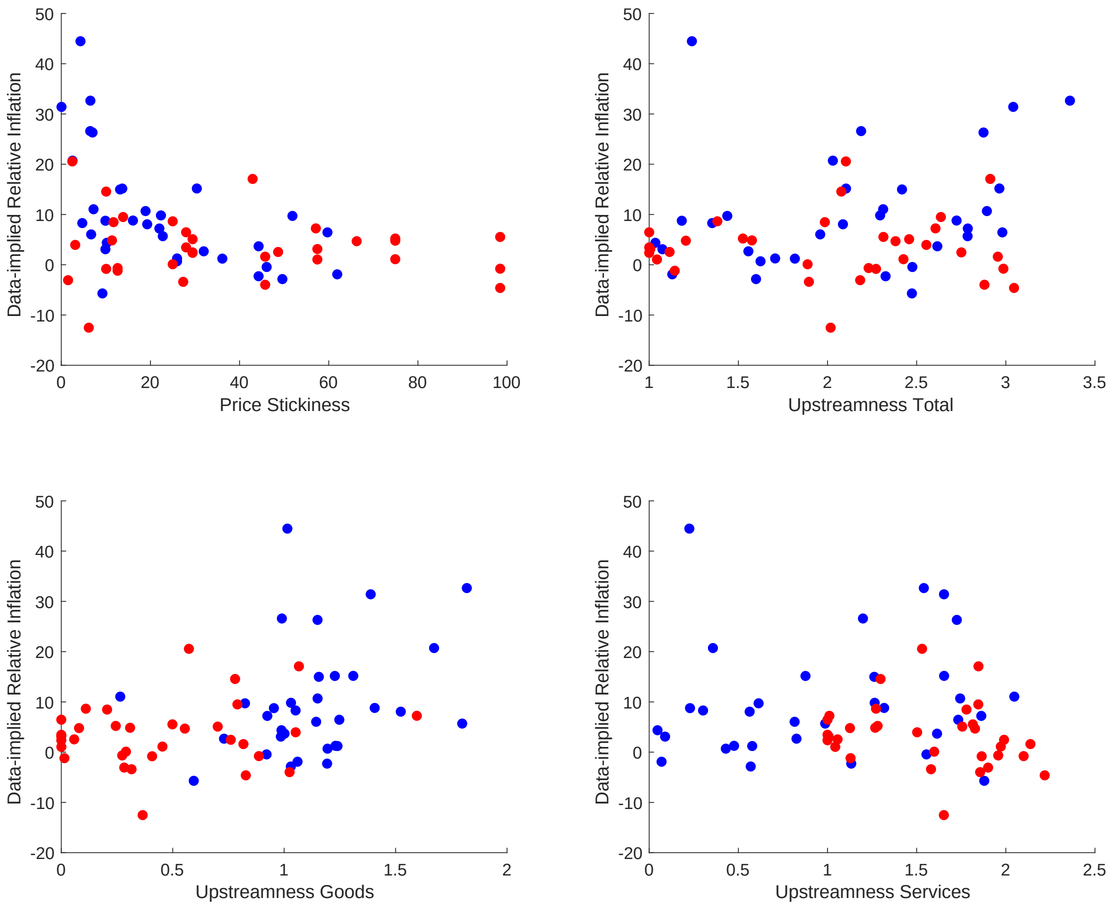
This Figure plots the impulse response of key variables to the demand reallocation shock that increases the value of the preference parameter for goods (ω_t) in period 1. Each period is one quarter. Solid lines denote the baseline model. Dotted lines denote the response of variables with Cobb-Douglas production ($\epsilon_M = \epsilon_Y = 1$). For clarity, we only plot sectoral variables in the model with Cobb-Douglas production. Gray lines denote sectors for which no output is directly consumed. Such sectors are classified as producing neither goods nor services.

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



This Figure compares the sectoral change in inflation implied by the model 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 upstreamness 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.4: Data Implied Sectoral Inflation vs Sector Characteristics



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.