

Pandemic-Era Inflation Drivers and Global Spillovers*

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Abstract

We estimate a multi-country multi-sector New Keynesian model to quantify the drivers of the pandemic-era inflation. The model incorporates a rich set of sectoral and aggregate shocks that transmit through the global trade and production network. This framework allows us to match observed headline inflation rates across countries as well as changes in sector-level prices, wages, and exchange rates. Estimating the model for a world economy consisting of the United States, Euro Area, Russia, China+RoW, and up to 44 sectors, yields four key findings. First, negative supply shocks to factors of production – labor and intermediate inputs – that can be of domestic or foreign origin, initially sparked inflation in 2020–2021. Second, positive aggregate demand shocks widened demand-supply imbalances and amplified inflation during 2021–2022. Third, the reallocation of consumption between goods and service sectors transmitted the demand-supply imbalances across countries, impacting current accounts. Fourth, energy shocks had differential impacts on the Euro Area relative to other countries’ inflation rates, due to a higher foreign factor content of trade combined with complementarities between foreign and domestic factors of production. Our findings quantifies the inflationary impact of positive aggregate demand shocks under global sectoral supply shocks relative to a counterfactual of only aggregate demand shocks.

JEL Codes: E2, E3, E6, F1, F4

Key words: Inflation, international spillovers, global production network

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“Many viewed the sudden upturn in inflation as mostly a function of pandemic-related shifts in the composition of demand, a disruption of supply chains, and a sharp decline in labor supply. The resulting supply and demand imbalances led to large increases in the prices of a range of items, especially goods ... But in the fourth quarter of 2021, the data clearly changed ... with only gradual progress in restoring global supply chains, and relatively few workers rejoining the labor force ... A new shock arrived in February 2022, when Russia invaded Ukraine, resulting in a sharp increase in energy and other commodity prices ... it was clear that bringing down inflation would depend both on the unwinding of the pandemic-related demand and supply distortions and on our tightening of monetary policy, which would slow the growth of aggregate demand, allowing supply time to catch up.”

Remarks from Jay Powell, 24th Jacques Polak Annual Research Conference, IMF, 2023.

1 Introduction

The Covid-19 pandemic shocked the world economy along several dimensions. Notably, it led to inflation rates in advanced countries that we had not seen in four decades. Given the multitude of economic shocks, diverse domestic policy responses, and spillovers across countries over the pandemic period, the underlying causes and the evolution of inflation together with the impact of monetary policy are still debated. To contribute to this debate, we develop a New Keynesian open-economy network model and use the model to quantify the key drivers of aggregate inflation across several countries, including the United States. Our model-based inflation match observed headline inflation as well as observed changes in sector-level prices, wages, together with multilateral exchange rates and current accounts.

The model’s success depends on allowing for a variety of shocks at the sector and aggregate levels, driven by an effort to mimic the real-world events. Accounting for sector-level supply and demand shocks and their interactions through the global production network has important implications for the domestic employment/output-inflation trade-off, since this trade-off can deteriorate or improve when supply and demand shocks coincide with different signs. In this sense, our paper builds on the *closed-economy* papers of [Baqae and Farhi \(2022\)](#) and [Rubbo \(2023a\)](#). By extending those models to an open economy setup, we can better map the model to the data since an open economy framework allows us to track both domestic and foreign sectoral shocks, as well as their interactions, in driving inflation.

We estimate our N-country, J-sector model as a 4 region-by-4 sector and a 4 region-by-44 sector global model, which we refer to as the 4×4 or 4×44 model going forward. The four regions/economic areas are the US, the Euro area, Russia, and China + the rest of the world, which we refer to as

China+. The 4×4 model breaks each economy down into the durables, non-durables, services, and energy sectors. The 4×44 model further disaggregates the 4 sectors. We show that going from 4 to 44 sectors helps us to match better the observed inflation.

We quantify the following narrative of three distinct phases in the rise of global inflation, as highlighted in our opening quote. In the early phase of 2020–2021, supply shocks arising from pandemic-induced scarcity in factors of production, such as constrained imported intermediates and domestic labor, sparked inflation. This period was characterized by local and global supply chain bottlenecks, rising factor costs including prices of imported intermediate inputs together with slack in domestic labor markets. The initial rise in product prices – also highlighted by [Blanchard and Bernanke \(2023\)](#) and [Lorenzoni and Werning \(2023\)](#) – is an important feature of this episode that our model matches. Further, the model is able to match the observed rise in real wages during early 2020, before they fell in 2021, an important feature of the data and hard to match by the standard models. Importantly, by exploiting the global network structure of the model, we can connect labor and other factor markets, differently than other papers, and hence measure the relative contribution of both domestic and foreign sectoral factor supply shocks’ to domestic inflation, since the pass-through of these shocks depends on foreign factors of production used in domestic production, which the input-output structure captures.

There were also large fiscal packages and loose monetary policy during the first phase, especially in advanced countries. The aggregate demand shock resulting from easy policies, along with the re-opening of economies, intensified the original supply chain bottleneck problem, widening demand-supply imbalances, leading to rising inflation during the second phase over 2021–2022.¹ We model all the stimulative policies as an aggregate demand shock through inter-temporal demand shifters. The final phase (2022–2023) was characterized by the Russian invasion of the Ukraine with a sizeable impact on energy prices, modeled as productivity of the energy sector in the energy exporting Russia.

The model features two frictions: downward nominal wage rigidity and segmented factor markets.² Downward nominal wage rigidity helps us to match the initial rise in unemployment. Seg-

¹As [di Giovanni, Kalemli-Özcan, Silva, and Yıldırım \(2023\)](#) show, the three fiscal package in the US drives 60 percent of the US inflation during 2021–2022. The dates of the US fiscal packages are December 2020, March 2021, December 2021.

²As shown by [Fernald and Li \(2022\)](#), during 2020–2022, the contribution of labor reallocation from low to high wage/productivity sectors is very small, 0.18 percent, whereas labor productivity grew 1.1 percent.

mented factor markets, especially for the non-traded factors such as labor, helps us to match sectoral wages, factor and product prices. We embed the global production structure into a standard two-period open-economy macroeconomics model, which allows us to pin down endogenous changes in nominal exchange rates relative to world currency, as well as current account adjustments to demand and supply shocks. We assume that each country issues a nominal bond, which can only be traded domestically and are in net zero supply. We further allow for the trade of an international bond that is denominated in a common world currency and is in zero net supply globally. Home households can save in both; domestic bond is needed for domestic monetary policy. Nominal exchange rate changes are solved for given standard asset market conditions and households' Euler equations. Current accounts adjust endogenously to shocks such that capital flows across countries equilibrate world financial markets and the world bond's interest rate move to its new equilibrium value. The model is non-linear and needs to be solved computationally.

For estimation, we use data on sector-level employment (hours) and consumption shares, aggregate expenditures, and energy prices at the quarterly level in order to construct our series of sectoral supply, demand and aggregate demand shocks. The baseline analysis includes empirically estimated values for the exogenous parameters of the model. For example, given the short-run complementarity between factors of production in the data (e.g., [Boehm, Levchenko, and Pandalai-Nayar, 2023](#)), the effect of any input shortage (sector level supply shock) in a given country-sector is amplified to production worldwide in model calibrations that use data-consistent elasticities. This feature is particularly important in terms of the complementarity between oil as an input and domestic labor, as also highlighted by [Gagliardone and Gertler \(2023\)](#). We use detailed *pre-pandemic* cross-country input-output tables in order to first solve the model at an initial steady-state and then shock this pre-pandemic steady-state with sector-level and aggregate shocks and solve for prices, wages, rental rates of capital and output together with exchange rates and current accounts. We do this for each quarter to find out deviations in all endogenous variables from their steady-states. We then compute year-on-year inflation rates for aggregate prices each quarter, which provides a time series for the evolution of inflation.

To summarize how well model-generated inflation rates compare to the data at the annual level, we take the arithmetic average of quarter-specific year-on-year inflation rates for the given year. The baseline model generates inflation rates of (in percent) 1.38, 6.96, and 6.86 in the United States

for 2020, 2021, and 2022, while actual headline inflation during these years was 1.23, 4.98, and 7.72 percent, respectively. Thus, the model predicted-inflation rates broadly match those observed in data on average, which is surprising given the parsimonious nature of the model and that we do not target any moments in the data.³

Next, to quantify the sources of inflation, we feed each shock into the model *separately* to calculate their contribution to inflation. This exercise yields an interesting historical decomposition of the drivers of inflation. For example, for the US in 2020, allowing for only sector-level supply shocks would have generated 3.13 percent inflation (higher than reality); including only sector-level demand shocks would have generated 0.32 percent inflation (lower than reality); including only aggregate demand shocks would have generated -1.31 percent inflation (much lower than reality), and having only energy shocks would have led to -0.02 percent inflation (much lower than reality). These findings suggest that supply shocks were more important initially and aggregate demand shocks were disinflationary. In 2021, sector-level supply shocks would have generated an inflation rate of -1.93 percent; only sector-level demand 0.14, only aggregate demand 8.5, and only energy 0.11, suggesting that aggregate demand shocks were more important in 2021 given that actual inflation was approximately 5 percent. During 2022, sector-level supply shocks only would have generated an inflation rate of -0.87 percent, sector-level demand an inflation rate of -0.06 percent, aggregate demand an inflation rate of 9.04 percent, and energy an inflation rate of 0.20 percent. Therefore, actual inflation would have been much higher without the improvement in supply chains that acted as a disinflationary force (measured via the sector-level supply shock) in the last part of 2021 and throughout 2022. Notice that these supply shocks are distinct from the energy shock and energy shock alone is not enough to match the inflation in 2022. Euro area inflation is also well matched by the model with similar contributions of each shock with an exception of energy shocks that played a bigger role in 2022 Euro area inflation.

The model also allows us to examine the quantitative importance of complementarities in production. These complementarities play an important role in the response of prices to shocks insofar as these elasticities dictate how much a fall in the supply of goods from one country-sector can be substituted with varieties from other countries. When these elasticities are low, the impact of in-

³The model overshoots 2021 inflation, but as discussed in Section 4, this is due to base effects impact of the massive rebound arising from the reopening of the economy.

ternational shocks becomes more pronounced. Notably, we show that our model exercises produce inflation rates that farther from the data when using high trade elasticities of substitution – values of 5, which are common for “long-run” trade analysis – rather than our baseline elasticities of 0.6, which capture short-run complementarities and the inability to shift trading partners.

The baseline quantification exercise generates exchange rate changes and current account dynamics that are consistent with the data. First, the US’s current account-to-GDP ratio that is generated by feeding in all shocks into the model tracks the time series of the data quite well, with a 0.89 correlation between model-based and observed CA/GDP ratios. In the case of the Euro Area, while the model does not perform as well in matching the CA/GDP in the data relative to the US, we are still able to capture the overall trends in the data – the correlation between the model-generated and data CA/GDP is 0.6 (when dropping an outlier quarter, 2022Q3). Second, the baseline quantification exercise, which omits the impact of monetary policy shifts over the period, is able to match the initial depreciation of the USD broad exchange rate index.⁴

A key contribution of our paper is to show how international spillovers operate through several channels in amplifying or mitigating domestic inflation in the model. Using a first order approximation, we formally show that the degree to which supply shocks spillover over from foreign countries to impact domestic inflation depends on domestic consumption’s exposure, not only to foreign goods but to foreign factors of production. This exposure depends both on the consumption of foreign *final* goods, but also on the degree to which any consumption good embeds foreign factors of production. In particular, final goods are produced using intermediate goods, which may be sourced from multiple countries and pass through several stages of production. Therefore, the degree to which domestic consumption depends on foreign factors in turn depends on network effects arising from global production linkages, which will amplify shocks to foreign factors. This dependency varies greatly from country to country – for example, the US shows relatively less dependency on foreign factors leading to large differences in contribution of foreign supply shocks to domestic inflation: A 1 percent decline in all foreign factors would result in 10 basis points increase in the CPI for the US compared to 60 basis points increase in the CPI of Ireland. Euro area in general will suffer from a much higher inflation given their high foreign factor share.⁵

⁴We believe, the later period exchange rate movements can be explained by the differential timing in monetary policy tightening across countries, that is the interest rate differentials, a feature that can be added to the model.

⁵Europe’s higher energy dependence from Russia vis-à-vis the US is a typical example, however for different factors

As global network connects labor markets to foreign factors, we can also quantify the importance of local vs global slackness/tightness on home inflation. Our exercises on tracing the impact of Chinese lockdowns and US fiscal stimulus show that both aggregate demand shocks and factor supply shocks can travel between countries. A fiscal stimulus in the US might increase inflation in the rest of the world if the global factor markets are constrained. The strength of this effect will depend on trade elasticities: under empirically estimated short-run complementarity between foreign and domestic factors of production, effects of foreign shocks are amplified, to different degrees: 100 basis points higher inflation in US vs 400 basis points higher inflation in Euro Area. Similarly, Chinese lockdowns add 50 vs 70 basis points additional inflation to US and Euro Area. These differences capture both the importance of import demand and foreign factor content of production. While the US increased demand for goods relatively more than the Euro Area over the pandemic, the Euro Area's foreign content of consumption (both final and intermediate goods in production) is larger than that of the US.

Related Literature

Our paper relates to the rapidly growing literature studying the inflation of 2021–2023. As in closed economy papers of [Baqaee and Farhi \(2022\)](#), [Rubbo \(2023b\)](#), [Guerrieri et al. \(2021\)](#), [Lorenzoni and Werning \(2023\)](#), we emphasize a multi-sector approach to modelling pandemic-era inflation, input-output linkages, production complementarities and downward nominal wage rigidities. As in [Gagliardone and Gertler \(2023\)](#) and [Blanchard and Bernanke \(2023\)](#), we highlight the role of oil shocks, product price increases and labor market tightness. As in [Comin, Johnson, and Jones \(2023\)](#), [Amiti, Heise, Karahan, and Şahin \(2023\)](#) and [Ferrante, Graves, and Iacoviello \(2023\)](#), we emphasize the role of global supply chains. We differ from these other open economy papers in that we allow for a full global trade and production network input-output structure, so that all sector and aggregate price changes are endogenous to shocks across country-sectors in the world. These papers instead limit their analysis to two sectors in a small open economy setting and, hence, have to take foreign import prices as exogenous. In addition, they work with aggregate shocks to labor instead of sectoral as we do. This is an important feature of our work to capture the interaction between labor market dynamics in services vs good sectors and prices in these

of production these dependencies might differ across countries and hence the entire network needs to be taken into account for the precise measurement of international spillovers.

sectors. We also relate to studies that emphasize a non-linear Phillips curve, such as [Eggertson and Kohn \(2023\)](#) and [Benigno and Eggertsson \(2023\)](#), that link the slope of the non-linear Phillips curve to labor market slackness and tightness. In contrast to these models, our non-linear sector-level approach can account for variety of shocks explaining inflation at different times in different countries together with the co-existence of slack and tight labor markets.

Our paper fits in the literature that focuses on inflation and monetary policy with input-output linkages such as [Basu \(1995\)](#), [Erceg et al. \(2000\)](#), [Aoki \(2001\)](#), [Woodford \(2003\)](#), [Blanchard and Gali \(2007\)](#), [La'O and Tahbaz-Salehi \(2022\)](#), [Carvalho \(2006\)](#), [Klenow and Kryvtsov \(2008\)](#), [Nakamura and Steinsson \(2008, 2010, 2013\)](#), [Carvalho and Nechio \(2011\)](#), [Bouakez, Cardia, and Ruge-Murcia \(2014\)](#), [Pasten et al. \(2020, 2023\)](#), [Castro \(2019\)](#), [Höynck \(2020\)](#), [Baqae and Farhi \(2022\)](#) and [Rubbo \(2023a\)](#). Our difference is open economy and quantification of the pandemic-era inflation. We do not study optimal monetary policy. There are also reduced-form empirical studies that seeks to identify the different drivers of inflation with sign restrictions in VAR such as [Jordá, Liu, Nechio, and Rivera-Reyes \(2022\)](#), [Shapiro \(2022a,b\)](#); [de Soyres et al. \(2024\)](#), and [Jordá and Nechio \(2022\)](#).

The contribution of our work over the existing literature that tries to understand the Covid-era inflation is the ability to quantify the role of four sets of shocks (aggregate and sector-level) to the different phases of inflation over 2020–2023 and study the transmission of these shocks across sectors and countries given our global trade and production network structure.⁶ The model's micro-structure is rich enough to study how different assumptions on production and consumption substitutability impact the contribution of different shocks to inflation, both domestically and abroad, which is central to cost of fragmentation and re-shoring debates.

Outline of the Paper

Section 2 outlines the multi-country multi-sector model that we use to quantify the drivers of inflation. Section 3 describes the data and shock construction that we use for the quantification exercises. Section 4 presents the quantitative results. Section 5 concludes.

⁶The policy extension of our paper focusing only on US and Europe in 2021 that was prepared for the 2022 ECB-Sintra conference embeds a fixed-exchange rate regime.

2 Model

We extend the [Baqaee and Farhi \(2022\)](#) model to an open-economy setting by incorporating cross-country and cross-sector input output linkages, as well as endogenous exchange rate and current account adjustments. The model allows for a rich set of shocks, including country-level aggregate demand shocks, country-sector level demand shifts, and country-sector level factor supply and productivity shocks. We now describe the full model in turn.

Environment. There are two time periods, which we label as $t = \{0, 1\}$. We call $t = 0$ “the present” and $t = 1$ “the future”. We denote countries with indices $m, n = 1, \dots, \mathcal{N}$, where \mathcal{N} is the number of countries, and use $i, j, k = 1, \dots, \mathcal{J}$ as sector indices. A sector in a country is identified by a pair of indices corresponding to countries and sectors, respectively.

2.1 Households

In each country n , there is a representative household with perfect foresight. We divide the household problem into an intertemporal and an intratemporal part, which we describe in turn.

Intertemporal problem. The household maximizes the present value of lifetime utility:

$$(1 - \beta)\phi_n(0)\frac{(C_n(0))^{1-\sigma} - 1}{1 - \sigma} + \beta\phi_n(1)\frac{(C_n(1))^{1-\sigma} - 1}{1 - \sigma},$$

where we assume a CRRA utility function each period, β is the subjective discount factor, and $\{\phi_n(0), \phi_n(1)\}$ are intertemporal preference shifters that may differ in the present and future period. Note that while the discount factor is assumed to be homogeneous across countries, the intertemporal shifters may differ and capture heterogeneous aggregate demand shocks.

The household has access to two bonds: (i) a nominal domestic bond, B_n , which pays off in domestic consumption units and is priced in *local currency*, and (ii) a nominal world bond, B_n^W , that is traded across countries and pays off in units of world GDP (the model’s numéraire), which are denominated in a world (common) fictitious currency⁷. We introduce a domestic bond policy

⁷This notion of a “fictitious currency” is not a new concept and appears recently in different papers under different names and assumptions. For example, it is similar to the “star currency” introduced in [Aggarwal et al. \(2023\)](#), the setup in [Gourinchas et al. \(2021\)](#) where there is a “global nominal risk-free rate” that all countries take as given when taking their intertemporal decisions and the real tradable bond introduced in [Fornaro and Romei \(2023\)](#) (although in the latter case, the bond is real, while ours is nominal).

to account for the impact of domestic monetary policy. The world bond is in zero net supply across countries, so $\sum_n B_n^W = 0$. International markets are frictionless, so the nominal return on the bond is equal across all countries.⁸ To simplify notation, we further assume that initial holdings of the domestic and world bonds are zero across all countries. Given these assumptions, the present and future budget constraints of the household in local currency units can be written as

$$P_n(0)C_n(0) + B_n(0) + \mathcal{E}_n(0)B_n^W(0) \leq \mathcal{E}_n(0) \sum_i (W_{ni}(0)L_{ni}(0) + R_{ni}(0)K_{ni}(0)), \quad (1)$$

$$P_n(1)C_n(1) \leq \mathcal{E}_n(1) \sum_i (W_{ni}(1)L_{ni}(1) + R_{ni}(1)K_{ni}(1)) + (1 + i_n(0))B_n(0) + \mathcal{E}_n(1)(1 + i^W(0))B_n^W(0), \quad (2)$$

where $P_n(t)$ is the price of the consumption bundle at time t , $\mathcal{E}_n(t)$ is the exchange rate between country n at the world currency at time t . This exchange rate transforms units of world currency into local currency. An increase in \mathcal{E}_n implies a depreciation of the local currency relative to this world currency. $W_{ni}(t)$ is the wage in sector i of country n at time t , $L_{ni}(t)$ is the quantity of labor in sector i country n at time t , $R_{ni}(t)$ is the price of capital in sector i of country n at time t , $K_{ni}(t)$ is the quantity of capital in sector i country n at time t , $i_n(0)$ is the nominal interest rate in local currency, and $i^W(0)$ is the interest rate on the world bond.

We can then write the household's intertemporal optimization problem as:

$$\max_{\{C_n(0), C_n(1), B_n(0), B_n^W(0)\}} (1 - \beta)\phi_n(0) \frac{(C_n(0))^{1-\sigma} - 1}{1 - \sigma} + \beta\phi_n(1) \frac{(C_n(1))^{1-\sigma} - 1}{1 - \sigma} \quad \text{s.t.} \quad (1), (2).$$

The first-order conditions of this problem, assuming interior solutions, are

$$C_n(0) : \quad (1 - \beta)\phi_n(0)(C_n(0))^{-\sigma} = \mu(0)P_n(0), \quad (3)$$

$$C_n(1) : \quad \beta\phi_n(1)(C_n(1))^{-\sigma} = \mu(1)P_n(1), \quad (4)$$

$$B_n(0) : \quad \mu(0) = (1 + i_n(0))\mu(1), \quad (5)$$

$$B_n^W(0) : \quad \mu(0)\mathcal{E}_n(0) = (1 + i^W(0))\mathcal{E}_n(1)\mu(1), \quad (6)$$

$$\mu(0) : \quad P_n(0)C_n(0) + \mathcal{E}_n(0)B_n^W(0) + B_n(0) = \mathcal{E}_n(0) \sum_i (W_{ni}(0)L_{ni}(0) + R_{ni}(0)K_{ni}(0)), \quad (7)$$

$$\mu(1) : \quad P_n(1)C_n(1) - (1 + i_n(0))B_n(0) - \mathcal{E}_n(1)(1 + i^W(0))B_n^W(0) = \mathcal{E}_n(1) \sum_i (W_{ni}(1)L_{ni}(1) + R_{ni}(1)K_{ni}(1)), \quad (8)$$

where the Lagrange multipliers for the present- and future-period budget constraints are denoted

⁸This two bonds characterization follows recent work on understanding endogenous trade imbalances in dynamic international trade models such as [Reyes-Heroles \(2016\)](#) and [Dix-Carneiro et al. \(2023\)](#). It is also a well-known device in two-country models, pervasive in the international macroeconomics literature; see, for example, [Benigno and Thoenissen \(2008\)](#).

by $\mu(0)$ and $\mu(1)$, respectively.

This system of first-order conditions can be reduced by (i) combining (3) and (4) to obtain the Euler equation, and (ii) combining (5) and (6) to write a no-arbitrage condition between bonds:

$$(1 - \beta)\phi_n \frac{(C_n(0))^{-\sigma}}{P_n(0)} = \beta\phi_n(1)(1 + i_n(0)) \frac{(C_n(1))^{-\sigma}}{P_n(1)} \quad (\text{Euler Equation}), \quad (9)$$

$$(1 + i_n(0)) = (1 + i^W(0)) \frac{\mathcal{E}_n(1)}{\mathcal{E}_n(0)} \quad (\text{No arbitrage condition}). \quad (10)$$

Note further that we can combine (9) and (10) to re-write the Euler equation as

$$(1 - \beta)\phi_n(0) \frac{(C_n(0))^{-\sigma}}{P_n(0)} = \beta\phi_n(1)(1 + i^W(0)) \frac{\mathcal{E}_n(1)}{\mathcal{E}_n(0)} \frac{(C_n(1))^{-\sigma}}{P_n(1)}. \quad (11)$$

This concludes the characterization of the intertemporal problem.

Intratemporal problem. We next turn to the household's intratemporal problem, where we omit the time index to ease notation. While the intertemporal problem provides the time path for aggregate consumption, $C_n(0)$ and $C_n(1)$, this section models how household allocates the aggregate consumption across goods each period. We omit the time index whenever it causes no confusion. To begin, we model C_n as a Cobb-Douglas aggregate of *sector-level* consumption bundles:

$$C_n = \prod_{j=1}^{\mathcal{J}} C_{n,j}^{\Omega_{n,j}^C} \quad \text{with} \quad \sum_{j=1}^{\mathcal{J}} \Omega_{n,j}^C = 1,$$

where $C_{n,j}$ denotes country n 's consumption bundle of sector j 's goods (or services), and $\Omega_{n,j}^C \geq 0$ represents the household's consumption share of this sector. The sector-level consumption bundles are in turn aggregates of varieties of goods from different countries in a given sector. Let $C_{n,mj}$ denote the consumption of output of sector j in country m by consumers in country n . Then the country n -sector j consumption bundle is formed by the following CES aggregation⁹:

$$C_{n,j} = \left[\sum_{m=1}^{\mathcal{N}} (\Omega_{n,mj}^{CB})^{1/\xi_j^c} C_{n,mj}^{\frac{\xi_j^c - 1}{\xi_j^c}} \right]^{\frac{\xi_j^c}{\xi_j^c - 1}} \quad \text{with} \quad \sum_{m=1}^{\mathcal{N}} \Omega_{n,mj}^{CB} = 1,$$

⁹All our CES functions are calibrated CES functions. For expositional simplicity, we do not show the normalization parameters.

where $\Omega_{n,mj}^{CB} \geq 0$ is the weight of country-sector mj in country n 's consumption of sector j , and ξ_j^c captures the elasticity of substitution between these varieties.

The household solves standard cost minimization problems, which define country-level price indices that are used to construct the model-predicted inflation rates at the country and sectoral levels. Having defined the household's side, we now turn to the production side of the economy.

2.2 Production

Goods are produced at the sector level by combining different factors of production and intermediate inputs. We assume that factors are sector-specific labor and capital, and to help with notation we combine these to create a *value-added* bundle. Each sector in each country uses goods from other countries to construct their sector-specific intermediate bundles.

Sector i in country n , therefore, uses sector specific value-added, VA_{ni} , and an intermediate bundle, Z_{ni} , to produce final output, Y_{ni} , using the following CES production function:

$$Y_{ni} = A_{ni} \left[(\Omega_{ni,VA}^Y)^{1/\theta} VA_{ni}^{\frac{\theta-1}{\theta}} + (\Omega_{ni,Z}^Y)^{1/\theta} Z_{ni}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \quad \text{with} \quad \Omega_{ni,VA}^Y + \Omega_{ni,Z}^Y = 1,$$

where A_{ni} is a sector-specific productivity parameter, θ determines the elasticity of substitution between the value added and the intermediate bundle, and $\Omega_{ni,VA}^Y$ and $\Omega_{ni,Z}^Y$ are the shares of value added and the intermediate good used in the final good's production, respectively.

The value-added bundle for country-sector ni consists of sector-specific labor and capital. We assume that capital is always fully utilized and is always at its steady-state value, K_{ni}^* . Labor levels, on the other hand, may potentially fluctuate from their steady-state value when the economy experiences shocks. The value-added bundle is defined as:

$$VA_{ni} = \left[(\Omega_{ni,L}^{VA})^{1/\eta} (L_{ni})^{\frac{\eta-1}{\eta}} + (\Omega_{ni,K}^{VA})^{1/\eta} (K_{ni})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \quad \text{with} \quad \Omega_{ni,L}^{VA} + \Omega_{ni,K}^{VA} = 1,$$

where η is the elasticity of substitution between labor and capital, and $\Omega_{ni,L}^{VA}$ ($\Omega_{ni,K}^{VA}$) is the weight of value-added that is attributed to labor (capital).

Similar to consumption bundles, the intermediate bundles are constructed from country-specific

sector bundles given the following CES aggregator with an elasticity of substitution of ε :

$$Z_{ni} = \left[\sum_{j=1}^{\mathcal{J}} (\Omega_{ni,j}^Z)^{1/\varepsilon} X_{ni,j}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \quad \text{with} \quad \sum_{j=1}^{\mathcal{J}} \Omega_{ni,j}^Z = 1,$$

where $\Omega_{ni,j}^Z \geq 0$ is sector j 's weight in producing country-sector good ni and $X_{ni,j}$ is the amount of sector-level bundle $X_{n,j}$ used by ni . These sector-level bundles are formed using the following CES aggregator of country-specific varieties:

$$X_{n,j} = \left[\sum_{m=1}^{\mathcal{N}} (\Omega_{n,mj}^X)^{1/\xi_j^s} X_{n,mj}^{\frac{\xi_j^s-1}{\xi_j^s}} \right]^{\frac{\xi_j^s}{\xi_j^s-1}} \quad \text{with} \quad \sum_{j=1}^{\mathcal{N}} \Omega_{n,mj}^X = 1,$$

where $X_{n,mj}$ is the amount of output of country-sector mj used by country n , ξ_j^s is the elasticity of substitution between sector-level varieties, and $\Omega_{n,mj}^X$ is the weight of country-sector mj in the sector bundle for j in country n .

Given the production structure of the economy outlined above, it follows that the bilateral flow of intermediate goods produced by country-sector mj and used by country-sector ni is given by:

$$X_{ni,mj} = X_{n,mj} \frac{X_{ni,j}}{X_{n,j}}.$$

2.3 Monetary Policy, Exchange Rate Determination and the Current Account

Future variables and steady-state characterization. We assume that future period variables, where $t = 1$, are equal their steady-state values, which we denote with a bar. That is, \bar{X} is the steady-state value of any variable X . This assumption implies that the economy reverts to its initial steady-state after any shock to the present period. We now focus on the behavior of the exchange rate and the current account determination.

2.3.1 Exchange rate determination

The framework described above is, in essence, a canonical international macroeconomic model that embeds a disaggregated production and trade structure. Interestingly, however, we can show that under certain assumptions, the behavior of nominal bilateral exchange rates only depends on the

stance of monetary policy. In contrast, the multilateral exchange rate (vis-à-vis the world currency) depends on the ratio of the world interest rate relative to the nominal interest rate of the country.

We start by solving for the world interest rate, i^W . Since this is a multi-country general equilibrium model, this object is endogenous. Setting $\sigma = 1$, as we will do in our quantitative exercise, and adding up the equation (11) across all countries, we can show that the world interest rate is a weighted-sum of the intertemporal shifters across all countries and the size of world expenditures relative to its steady-state value:

$$(1 + i^W(0)) = \frac{(1 - \beta) \sum_n \alpha_n(1) \phi_n(0) E(1)}{\beta \sum_n \alpha_n(0) \phi_n(1) E(0)} = \frac{(1 - \beta)}{\beta} \sum_n \bar{\alpha}_n \phi_n(0) \left(\frac{\bar{E}}{E(0)} \right), \quad (12)$$

where $\alpha_n(t) = \frac{P_n(t)C_n(t)/\mathcal{E}_n(t)}{E(t)}$ is the expenditure share of country n on world expenditure $E(t) = \sum_m P_m(t)C_m(t)/\mathcal{E}_m(t)$ at time $t = \{0, 1\}$. The last equality follows from the fact that the economy reverts back to the steady state in the future, where $\alpha_n(1) = \bar{\alpha}_n$, $\phi_n(1) = \bar{\phi}_n = 1$, $\sum_n \bar{\alpha}_n = 1$, and $E(1) = \bar{E}$.

Combining the equation (12) with the no-arbitrage condition (10) implies that the nominal exchange rate's deviation from its steady-state value is:

$$\frac{\mathcal{E}_n(0)}{\bar{\mathcal{E}}_n} = \frac{(1 - \beta) \sum_m \bar{\alpha}_m \phi_m(0)}{\beta (1 + i_n(0))} \left(\frac{\bar{E}}{E(0)} \right). \quad (13)$$

Equation (13) holds for all countries. Therefore, there are \mathcal{N} equations that relate $2\mathcal{N}$ variables – each country's exchange rate vis-à-vis the world currency and their domestic interest rates. We solve the model by setting world GDP as the numéraire, so we can pin down the last term on the right-hand side, $(\bar{E}/E(0))$, which is the deviation of this numéraire from its steady-state value. However, without making any further assumptions, there is nothing in the rest of the model that allows us to solve for exchange rates and domestic interest rates independently. For example, we have not specified domestic countries' monetary policy rules that would allow us to close the system. Therefore, to proceed, and as we discuss in more detail in the quantitative section, we assume that domestic nominal interest rates are fixed and at their zero lower bound. This assumption implies that exchange rates are fixed absent domestic aggregate demand shocks (intertemporal shifters) or world aggregate demand shocks (changes in world expenditure). To see this result, set

$i_n(0) = (1 - \beta)/\beta$ and $\phi_n(0) = 1$ for all n in (13), which implies that $\mathcal{E}_n(0) = \bar{\mathcal{E}}_n$.

Utilizing (13), we can further derive the deviation in the bilateral exchange rate between countries n and n' from its steady-state value. Defining the bilateral exchange rate $\mathcal{E}_{nn'}(0) = \mathcal{E}_n(0)/\mathcal{E}_{n'}(0)$, we can show that:

$$\frac{\mathcal{E}_{nn'}(0)}{\bar{\mathcal{E}}_{nn'}} = \frac{\mathcal{E}_n(0)/\bar{\mathcal{E}}_n}{\mathcal{E}_{n'}(0)/\bar{\mathcal{E}}_{n'}} = \frac{(1 + i_{n'}(0))}{(1 + i_n(0))},$$

which implies that bilateral nominal exchange rate changes are only a function of domestic nominal interest rates, $i_n, i_{n'}$, and if they are at their zero lower bound, the bilateral exchange rate does not deviate from its steady-state value.

2.3.2 Current account

Given our assumption that initial bond holdings are zero, the period-0 current account equals a country's trade balance, since in an open economy households can consume more/less than what is produced domestically and there is no net income payments derived from initial holdings of the world bond.¹⁰ Specifically, first recall from the consumer's budget constraint that country n 's period-0 holdings of the world bond, $B_n^W(0)$, which is equal period-0 current account is equal to

$$B_n^W(0) = (E_n(1) - nGDP_n(1))/(1 + i^W(0)) = nGDP_n(0) - E_n(0), \quad (14)$$

where $nGDP_n(t) = \sum_i (W_{ni}(t)L_{ni}(t) + R_{ni}(t)K_{ni}(t))$ represents country's n GDP in units of the numéraire at time t .

Then, note from (14) that a country's current account depends on the world interest rate, $i^W(0)$, and plugging in the solution for the world interest rate from (12) into (14) yields

$$\frac{B_n^W(0)}{E(0)} = \frac{\beta}{(1 - \beta)} \frac{(\bar{\alpha}_n - \bar{\gamma}_n)}{\sum_n \bar{\alpha}_n \phi_n(0)}, \quad \bar{\alpha}_n = \frac{\bar{E}_n}{\bar{E}}, \quad \bar{\gamma}_n = \frac{\overline{nGDP}_n}{\bar{E}}.$$

Hence, the current account of country n (normalized by total world expenditure) can fluctuate due to aggregate demand shifts only, $\{\phi_n(0)\}_n$. For countries that were net savers at the initial steady

¹⁰Note that we do not impose balanced trade as is assumed in a majority of papers that use a multi-country multi-sector framework.

state ($\bar{\alpha}_n - \bar{\gamma}_n < 0$), an increase in the world interest rate reduces the present value of its future surplus, which reduces (in absolute value) its current account deficit in the present period. The converse is true for net debtors ($\bar{\alpha}_n - \bar{\gamma}_n > 0$): an increase in the world interest implies a lower present value of future deficits, thus lowering the need for saving in the present period.

2.4 Market Clearing

We assume that all goods' markets clear. Goods can be used as final (consumption) goods and intermediate inputs in all countries. Therefore, we write the goods market clearing condition for country-sector ni as:

$$Y_{ni} = \sum_{m \in \mathcal{N}} (C_{m,ni} + X_{m,ni}),$$

where country m is the consuming country.

For the factor markets, we take both labor and capital to be sector-specific. Capital is fully utilized and assumed to be at its steady-state level with:

$$K_{ni} = \bar{K}_{ni}.$$

Labor, on the other hand, is subject to shocks. In addition, we assume that there is a downward wage rigidity relative to the steady-state wage. Denoting the amount of available labor for country-sector ni at the time of the shock with \tilde{L}_{ni} and given the sector-specific labor assumption implies that:

$$\tilde{L}_{ni} \leq \bar{L}_{ni}.$$

Given the downward wage rigidity, there might be slack conditions in a sector's labor market during the shock period. Therefore, the shock-period employment, L_{ni} , maybe be lower than available labor:

$$L_{ni} \leq \tilde{L}_{ni}. \tag{15}$$

Finally, the downward wage rigidity necessitates that the wage in a given country sector (W_{ni}) cannot go below its steady-state level (\bar{W}_{ni}) in local currency. The downward wage rigidity condition

is then given by:

$$\underbrace{\mathcal{E}_n W_{ni} \geq \bar{W}_{ni}}_{\text{In local currency}} \Rightarrow \underbrace{W_{ni} \geq \frac{\bar{W}_{ni}}{\mathcal{E}_n}}_{\text{In world currency}}. \quad (16)$$

Optimality implies that at least one of the inequalities in (15) and (16) is binding:

$$\left(\tilde{L}_{ni} - L_{ni}\right) \left(W_{ni} - \frac{\bar{W}_{ni}}{\mathcal{E}_n}\right) = 0. \quad (17)$$

The world assets and domestic assets markets are in zero net supply:

$$\sum_n B_n^W = 0, \quad (18)$$

$$B_n = 0 \quad \text{for all } n, \quad (19)$$

[Appendix A](#) describes the solution methodology in detail. Starting from the pre-shock equilibrium, we solve for the changes in prices and Domar weights to arrive at a new equilibrium. Although we solve for levels, our methodology yields solutions akin to the hat-algebra methodology often used in the trade literature, since we start by calibrating CES functions with equilibrium prices set to 1. However, given the non-linearities of the model arising from the rigidities in the factor market, we cannot simply use the hat-algebra approach.

2.5 Approximating Inflation in an Open Economy

We provide an analytic first-order approximation of a country's inflation as a function of domestic and foreign shocks. We utilize the Ω matrix that we define to solve the model in [Appendix A](#) in order to capture all necessary information in deriving the approximation to inflation. We briefly sketch out the solution and refer the interested reader to [Appendix B](#) for a formal proof.

First, we define the Leontief inverse matrix:

$$\Psi = [I - \Omega]^{-1},$$

where I is the appropriately sized identity matrix. The Leontief inverse captures the direct and indirect dependencies between entities. For country n , its consumption dependencies are captured

by the n^{th} row of the Ψ matrix, which corresponds to the households of this country. The entries of this row reflect how much of the output of the corresponding entity accounts for direct and indirect expenditures in country n . These constitute the basis for country-specific Domar weights, which capture the influence of a sector or a factor in the consumption basket of a country. Formally, we define the country-specific Domar weights for each country-sector as:

$$\lambda_{mj}^n = \Psi_{n,mj} \quad \text{for } mj \in Y.$$

Similarly, for any factor f (including labor and capital), with some abuse of notation we define:

$$\Lambda_f^n = \Psi_{n,f} \quad \text{for } f \in F,$$

where F is the set of all factors in the world. Global factor share of each factor is given by:

$$\Lambda_f \equiv \frac{W_f L_f}{E} = \sum_n \frac{E_n}{E} \Lambda_f^n$$

We write the corresponding column vector for these Domar weights by dropping the subscripts. Note that households are the terminal nodes of the input-output networks. Starting from the households, we can thus trace back the origin of the goods that are consumed in country n . The Leontief inverse operation captures this path of production to consumption. Applying this Leontief logic, define the share of the output of country-sector mj directly or indirectly (i.e., through supply chains) to satisfy the consumption of households in country n with Y_{mj}^n . Then, the country-specific Domar weight can be written as:

$$\lambda_{mj}^n \equiv \frac{P_{mj} Y_{mj}^n}{E_n}.$$

For each sector, we know the share of the sector-specific labor in its value-added. Then, we can interpret the country-specific factor shares of the different labor factors as:

$$\Lambda^n = \Omega^{\text{VA}} \Omega^Y \lambda^n.$$

Therefore, Λ_f^n captures the factor share that directly or indirectly satisfies the consumption in n . With these definitions in hand, we calculate the first-order approximation to the CPI in country n

via the following proposition:

Proposition 1. *The first-order approximation to CPI in country n is:*

$$d \log CPI_n = \underbrace{d \log \mathcal{E}_n}_{\text{Exchange rate changes}} - (\lambda^n)^T \underbrace{d \log A}_{\text{Productivity shock}} - (\Lambda^n)^T \underbrace{d \log L}_{\text{Factor changes}} + \underbrace{(\Lambda^n)^T d \log \Lambda}_{\text{Local-global mismatch}},$$

\mathcal{E}_n is the exchange rate in country n , λ^n (Λ^n) is the vector of country-specific Domar weights for country-sector pairs (factors), A is the vector of sector-specific productivities, L is the vector of factor levels, Λ is the global factor shares.

Proof. See [Appendix B](#). □

This first-order approximation captures the importance of international linkages since all terms (λ^n , Λ^n , $d \log A$, $d \log L$, $d \log \Lambda$) are calculated globally.

Proposition 1 implies positive productivity changes, $d \log A$, are deflationary in nature, and shocks to productivity in country-sector mj impact inflation in country n in proportion to λ_{mj}^n . Meanwhile, factor shortages, at home and abroad, are inflationary domestically. The shocks to labor supply in factor f impact domestic inflation in proportion to Λ_f^n , the country's n ultimate exposure to changes in the price of factor f . Without wage rigidity, the labor supply shock would be exogenous. However, with downward wage rigidity present in the system, the decline in factor shortages is also endogenously determined, potentially depending on other shocks, such as sectoral demand and aggregate demand changes.

The local-global mismatch term captures the discrepancies between local and global changes. Note that if $d \log \Lambda = d \log \Lambda^n$, then

$$(\Lambda^n)^T d \log \Lambda^n = \sum_f \Lambda_f^n d \log \Lambda_f^n = \sum_f d \Lambda_f^n = d \underbrace{\sum_f \Lambda_f^n}_{=1} = 0.$$

Hence, if the global factor shares changes are completely aligned with the local changes, the inflationary effect of this channel would be zero. But if these changes are not aligned, then there might be a non-zero contribution to CPI. Hence, shocks around the world can potentially trigger price changes differentially in different countries due to countries different exposure to these mismatches,

as captured by the Λ^n vector.¹¹

We finally note that positive aggregate demand shocks in the form of increases in intertemporal shifters $\{\phi_n\}$ affect country n 's inflation due to three channels. A rise in ϕ_n induces a change in the exchange rate by equation (13), creating inflation to the first order in country n . Note that this channel also has a spillover component: since equation (13) applies to all countries, a rise in, say, ϕ_m will raise the world interest rate, leading to a depreciation of country n 's currency (higher \mathcal{E}_n), ultimately raising inflation in country n . The aggregate demand shock also affects factor quantity levels, $d \log L$, due to downward wage rigidities and the global-local mismatch term due, $d \log \Lambda$ to changes in factor demands worldwide.

To quantify the potential impact of factor shortages in foreign countries in creating inflation in country n , we define Λ_{FOR}^n , as the share of foreign factors in satisfying household consumption in country n :

$$\Lambda_{\text{FOR}}^n \equiv \sum_{f \in F - F_n} \Lambda_f^n \equiv 1 - \Lambda_{\text{DOM}}^n, \quad (20)$$

where F_n is the set of factors in country n . The last equality comes from the fact that sum over all factors are equal to 1.

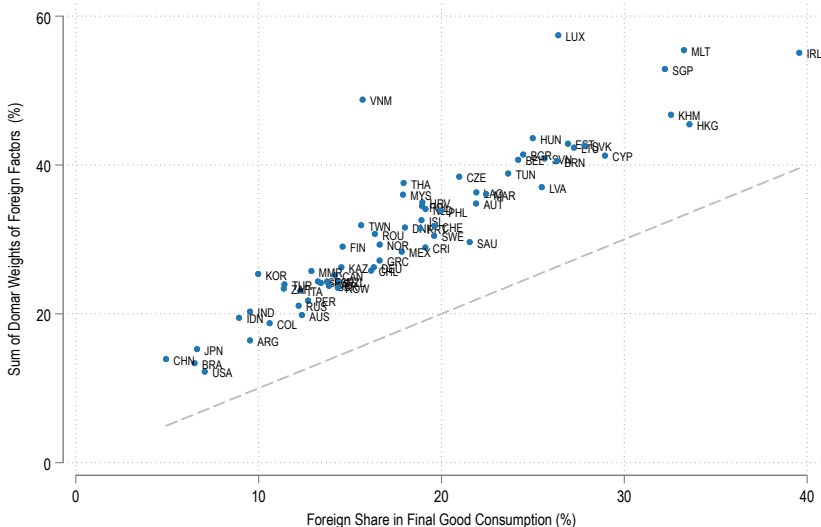
Figure 1 shows the values for Λ_{FOR}^n for all countries present in the OECD's ICIO Tables.¹² The share of foreign factors is higher compared to the direct share of imports in final goods for all countries. Intuitively, this captures the fact that total domestic consumption of foreign goods includes both final goods as well as foreign factors that are "embedded" in all consumption goods (both domestic and foreign) arising from the use of intermediate goods in production. However, these shares vary significantly between countries. For instance, a 1 percent decline in factor levels in foreign countries would potentially result in 0.12 percent increase in the CPI for the US compared to 0.55 percent increase in the CPI of Ireland.

Finally, we also use the Domar weights, λ_{mj}^n , to ask how productivity shocks $d \log A$ impact domestic inflation (to a first-order) using Proposition 1. According to the proposition, the impact of any country-sector productivity shock will impact aggregate domestic inflation in proportion to

¹¹Another way to understand this term is to go back to its definition $\Lambda_f = W_f L_f$. Since we are already considering changes in factor quantities in the proposition, $d \log L_f$, we can interpret these mismatches as the change in factor prices around the world for *given levels of factor quantities*. As these changes in factor prices are endogenous, they depend on our aggregate demand shocks, productivity, and sectoral demand changes, the model's primitives.

¹²See Section 3.1.5 for the description of ICIO Tables

Figure 1. Foreign Share of the Factor Domar Weights



Notes: This figure shows the share of the foreign factors of the Domar weights (Λ_{FOR}^n defined in Equation 20) and foreign share of the final good consumption. Dashed gray line show the 45° line.

that country-sector’s Domar weight. This Domar weight captures the direct and indirect use of a given country-sector input into the production of final goods of the ultimate customer, so embeds global supply chain linkages’ importance in transmitting foreign sector-level productivity shocks on domestic inflation. This term plays an important role in transmitting the impact of the energy price shocks resulting from the Ukraine-Russian war as we model the change in energy prices as originating from a negative technology shock in Russia’s fossil fuels sector. The Domar weight of Russia’s energy sector for German consumption is 0.0031, Euro Area consumption as a whole is 0.0025, and for the US consumption is 0.0006. Therefore, the expected effect of an increase in Russian energy price is approximately 5 times higher for Germany and 4 times higher for the Euro Area compared to the US.

3 Data Description and Construction of Shocks

The model-based quantitative exercises require four sets of shocks: country-level aggregate demand changes, country-sector level factor supply changes, country-sector level demand changes, and global energy price changes. The analyses use data on four “countries”: the United States, the Euro

Area,¹³ Russia, and a Rest of the World composite (ROW) that importantly includes China; and four sectors: durables, non-durables, services, and energy.

We focus on these four countries and sectors given data constraints on sector-level data for ROW countries. Nevertheless, even with this level of aggregation, we are able to capture the key shocks during our analysis period, and how they vary in the cross section. For example our measured shocks are able to capture the stringency of the Chinese lock downs in 2020-2021 (measured by the shocks to the China+ labor supply), the US and European fiscal stimuli of 2021–2022, and the Russia-Ukraine War in early 2022 and its impact on energy prices worldwide. We include Russia and also an “energy” sector to be able to speak to the role of higher energy prices and their implications for the US and, importantly, for the Euro Area, which was the region that, *a priori*, appeared to be one of the country groups that would be the most affected by the energy shock. We map the energy price shock to a decline in Russia’s energy sector productivity and study the inflation spillovers of such a shock to other countries. We next describe our data sources and explain details of how we construct the shock series using these data before showing how the shocks evolved over time.

3.1 Data

3.1.1 Aggregate Demand

The model-implied measure of an aggregate demand shock is an intertemporal shifter at the country-level, $\phi_n(0)$. Using data on expenditures and nominal interest rates, we can back out these intertemporal shifters. To see this, rewrite the Euler equation for country n and solve for the present period intertemporal shifter to get

$$\frac{\phi_n(0)}{\bar{\phi}_n} = \frac{E_n(0)}{\bar{E}_n} \frac{(1 + i_n(0))}{\beta/(1 - \beta)} \implies \phi_n(0) = \frac{E_n(0)}{\bar{E}_n} (1 + i_n(0)).$$

where the last line follows since we set $\bar{\phi}_n = 1$ and $\beta = 1/2$. Hence, with information on expenditures and nominal interest rates, we get the implied intertemporal shifter.

In this version, we do not consider changes in nominal interest rates $(1 + i_n(0))$. As a result, the intertemporal shifter only depends on changes in the country’s nominal expenditure. We,

¹³Note that we rely on Euro Area countries’ underlying data and aggregate up.

therefore, collect cross-country data on nominal expenditures or absorption ($E_n(0)$), depending on data availability, at the quarterly frequency. We then compute growth rates of these series each quarter relative to the base (steady-state) year 2018 $\left(\frac{E_n(0)}{\bar{E}_n}\right)$ to use as shocks in the model.¹⁴

United States. We use gross national income (codename: A023RC1Q027SBEA) available from the Bureau of Economic Analysis (BEA). These data are available at a quarterly frequency from 2010 to 2022.

Euro Area. Gross national income is only available at a yearly frequency for the Euro Area, which is not appropriate for our empirical application. For this reason, we instead collect data on absorption from EuroStat, which we use as the Euro Area measure of E_n . Aggregate absorption includes household and consumption expenditures, gross fixed capital formation, and imports.

Russia and China+. For Russia, we construct a measure of domestic absorption from Russia’s national accounts. We measure China+’s aggregate expenditure by adding consumption on durables, non-durables, and services from the OECD quarterly national accounts for all countries except the United States and those in the Euro Area.

3.1.2 Country-Sector Level Factor Supply: Total Hours Worked

The growth rates of total hours, defined as log-deviations from pre-pandemic steady-state values, are used as shocks to potential sector-specific labor *supply*, \bar{L}_{ni} . Of course, observed changes in total hours observed in the data are an equilibrium objects and depend on labor demand and labor supply in each sector. Given our modeling assumption of nominal downward wage rigidity, negative changes in equilibrium labor can be rationalized by a decline in labor demand or labor supply. In contrast, positive changes in equilibrium labor can only be rationalized by a combination of labor demand and supply shifts, where a necessary condition is that labor supply shifts at least in the same amount as labor demand. In an extreme case, if labor supply does not shift up while labor demand does, this only creates wage inflation with no effect on the equilibrium level of employment

¹⁴We choose 2018Q4 as our base period to be able to construct year-on-year model-based inflation rates for 2020. To do so, we require model-predicted price levels for 2019. We could have alternatively used actual data for 2019 instead to calculate the inflation rates, but we wanted to use a consistent methodology throughout the three years of analysis.

and cannot possibly rationalize increases in total hours worked in equilibrium. As we explain in detail when discussing the results in the next section, we use the model structure in conjunction with the other set of shocks to disentangle changes in total hours worked into supply and demand. The results support our assumption that changes in observed hours work best capture labor supply shocks.

United States. We use Tables B1 and B2 provided by the Bureau of Labor Statistics (BLS) to collect information to construct our measure of labor supply. These tables contain information on employment and average weekly hours at a monthly frequency, respectively. Since hours in Table B2 are at a higher level of aggregation than those for employment in Table B1, we construct measures of L in the model by multiplying employment in a disaggregated sector by the hours of the aggregate sector. For example, the ‘Information sector’ contains six sub-sectors in Table B1, but it is only available as an aggregate information sector in Table B2. We thus multiply each sub-sectors employment by the hours of the aggregate sector in Table B2 to obtain a measure of total hours worked in each of the six sub-sectors separately. Our final sample contains information from 2006 to 2022 for 66 sectors that we aggregate up to 4 sectors.

In addition, we also collect information on total private employment (code CES0500000001) and hours (code CES0500000002) from the BLS and construct total hours worked for the aggregate economy as we did for the sector-level numbers.

Euro Area. We collected data from Eurostat, which contains information on hours and employment at the sectoral level at a quarterly frequency. We follow the same procedure as in the US to construct changes in total hours worked in each sector.

Russia. For Russia, we collected information on hours and employment from the International Labor Organization (ILO). This data is available for 6 broad sectors, which allows us to construct the total hours worked for the goods, services, and energy sectors. Since the goods sector cannot be disentangled into durables and non-durables in this case, we assume that changes in the hours worked in the durables and non-durables sectors are the same as those in the overall goods sector.

China+ Since sector-level and time series data are not readily available for China+ for the time span analyzed, we take an indirect approach to construct total hours worked changes for these countries. To construct hours worked at the sectoral level for China+, we first regress total hours worked shocks computed at the sector level for the US on the US stringency index from [Hale et al. \(2021\)](#), which aims to capture the strictness of countries’ government policies against Covid. Formally, we run the following specification for the period 2020m1 to 2022m12:

$$\hat{\varepsilon}(hw)_{st}^{US} = \beta_{0s} + \beta_s S_t^{US} + \nu_{st}^{US},$$

where $\hat{\varepsilon}(hw)_{st}^{US}$ are the total hours worked “shock” in sector s in the United States at time t , constructed as we explained in the previous section, S_t^{US} is the stringency index in the US at time t , and ν_{st}^{US} is an error term. From this regression, we recover the estimated coefficients $(\hat{\beta}_{0s}, \hat{\beta}^{US})$.

We then project the stringency index of China+ using these estimated parameters to get predicted values of total hours worked in each sector for both countries:

$$\hat{\varepsilon}(hw)_{st}^c = \hat{\beta}_{0s} + \hat{\beta}_s S_t^c,$$

where $\hat{\varepsilon}(hw)_{st}^c$ is the series total hours worked shocks in country c , sector s at time t and $c = \{\text{China+}\}$.

The China+ stringency index is a population-weighted average of the stringency index in [Hale et al. \(2021\)](#), where we take the mean across all available countries except the United States, Russia, and countries belonging to the Euro Area. Importantly, China appears in the stringency index. As a result, our predictions for the Rest of the World will contain their strict lockdown policies that were a focal point in creating the early supply chain disruptions in 2020.

3.1.3 Country-Sector Level Demand: Consumption Expenditure

Sector-level demand shocks – changes in $\Omega_{n,j}^C$ in the model – are computed as the change in sector-level consumption expenditure shares across non-durable goods, durable goods, services, and the energy sector. Computing the shocks therefore requires cross-country information on disaggregated sector-level consumption patterns at the quarterly frequency.

United States. We use information on personal consumption expenditures from Table 2.3.5U of the Bureau of Economic Analysis version May 2023. This data set contains disaggregated sector-level information on personal consumption expenditures from 1959 to 2022 at a quarterly frequency. In particular, we use durable, non-durable, services, and energy sector consumption from this table.

Euro Area. We use the information on durables, non-durables, and services from the OECD quarterly national accounts. These data are available from 2010 to 2022 at a quarterly frequency. Unfortunately, the data set does not have information on consumption in the energy sector separately. Since energy consumption is part of non-durable consumption, we assign the change in non-durables to the energy sector.

China+ and Russia. We use information from the OECD quarterly national accounts to construct sector-level consumption shares for the Rest of the World. We consider all countries except the United States and those belonging to the Euro Area. Consumption series are denominated in local currency for all countries, so to construct a China+ aggregate, we convert all series to US dollars using the average exchange rate between 1990 and 2022 per country that we source from the IMF. Finally, we aggregate each consumption series across countries. As in the case of the Euro Area, we assume energy consumption experienced the same changes as non-durables. Since data for sectoral expenditure is not available for Russia, we use the same changes as for China+.

3.1.4 Energy Prices

We proxy energy prices using the energy commodity price index constructed by the IMF (code: PRNG). This index contains information on crude oil, natural gas, coal price, and propane price indices and is available at a monthly frequency from 1992 to 2022. We choose this broad index to better capture the potential impact of the Russian-Ukraine War, on countries' inflation rates, and particularly the Euro Area, which heavily depended on Russian natural gas.

3.1.5 Input-Output Matrices, Factor and Consumption Shares

Since we assume two sector-specific factors (capital and labor) in each sector in our quantitative exercise, we need to compute each factor's respective share in nominal GDP. To simulate the model,

note that we only need to construct these shares, along with intermediate input expenditure and consumption shares for the initial steady state (the year 2018).

Input-Output Matrices. We use the 2018 inter-country input-output (ICIO) tables from OECD, which contain information for 45 sectors and 66 countries. Given data constraints on other sector-level data (e.g., sector-level hours worked or consumption shares) as well as country coverage for other data series, we aggregate the ICIO tables into our four countries and four sectors of interest. These input-output tables allow us to construct intermediate input linkages at the country-sector level.

Factor Shares. The ICIO tables do not contain information on capital and labor payments at the country-sector level. We therefore supplement the ICIO tables with the structural analysis (STAN) database for the year 2018. This database contains information on labor compensation (labor payments) and gross operating surplus (capital payments). These data allow us to construct the fraction of value added that is paid to labor at the country-sector level for the United States and Euro Area. We aggregate all countries outside of the Euro Area and the United States into a single Rest of the World composite country, sector by sector. Due to data availability, we use information from the “Socioeconomic Accounts” release 2016 in the World Input-Output tables to compute the sector-level labor shares in Russia. [Table C.1](#) in the appendix shows the numbers we use for each country-sector.

3.2 Aggregate and Sector-level Facts

As explained above, we feed in actual data on expenditures, aggregate and sector-level, hours worked, and global energy prices as shocks to our model to recover changes in the sector-level prices and wages, and sector-level expenditure shares together with aggregate prices. It is therefore useful to first examine the time series of the data series used to construct the shock series.

[Figure 2](#) begins by plotting aggregate data, where panel (a) plots the aggregate of log hours worked relative to its 2018Q4 value across countries, and panel (b) plots aggregate demand – log deviation relative to 2018Q4 – across countries.¹⁵ We can see that hours worked declined in all

¹⁵As explained in the earlier section, we construct measures of aggregate demand using nominal expenditures. For the US, we use gross national income. For the Euro Area, we use domestic absorption. For China+, we add

countries to slowly recover their 2018Q4 levels by the end of 2021 for the United States and 2022 for the other countries. Panel (b) of [Figure 2](#) shows the aggregate demand changes (nominal expenditures) for the Euro Area, United States, and the Rest of the World. Consistently across countries, aggregate demand plummeted during early 2020 to recover its level in early 2021.

[Figure 3](#) shows the sector-level demand changes as the cumulative growth of nominal expenditures relative to 2018Q4. Several interesting facts jump out. First, services consumption uniformly plummeted across countries at the onset of the pandemic, and barely started to recover in the Euro Area by the end of 2022 and was far below its pre-pandemic level in both the United States and the Rest of the World during the pandemic period. Second, we observe the initial shift in consumption from services to durable goods during early 2020. This shift occurred across all countries, but was by far the largest in the United States. Meanwhile, non-durable consumption growth was relatively larger compared to the growth in durables outside the US.

[Figure 4](#) plots the time series of the energy price shocks. As explained above, the energy index used to construct the shocks contains information on oil as well as natural gas prices. We can see that at the beginning of the pandemic, energy prices were lower than their level in 2018Q4, and began to increase, return to pre-pandemic levels by mid-2021 and then continuing to rise. This pattern is consistent with that described in [Gagliardone and Gertler \(2023\)](#), where oil prices started to rise in mid-2021 and into 2022.

4 Results

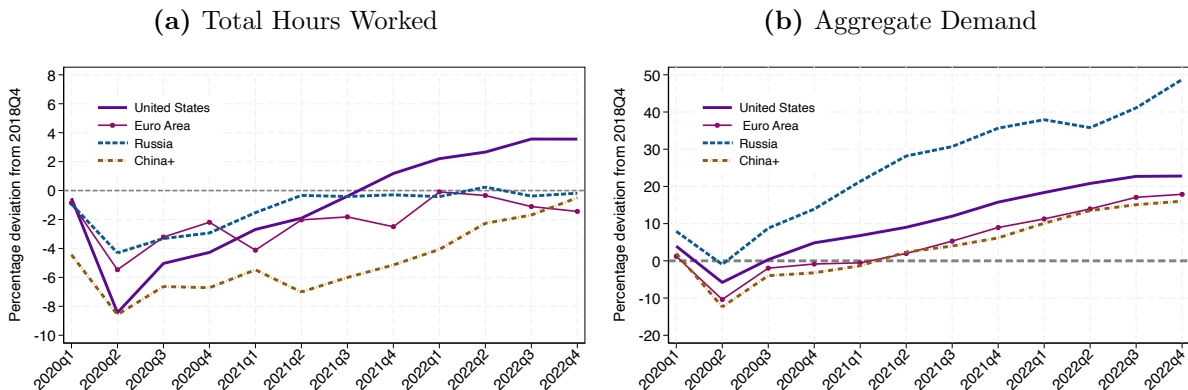
This section presents results for model quantification exercises using the data and shock series described above.¹⁶ Given the model’s rich consumption and production structures, we must choose several parameters in order to perform our calibrations. Importantly, several of these parameter choices will allow us to control how substitutable factors and goods used for production are with each other, both within and across countries.

Our baseline quantification exercises use the parameter values presented in [Table 1](#). A key assumption that we make in our baseline choice of parameters, based on the recent empirical

up durables, non-durables, and services expenditures from the OECD quarterly national accounts for all countries except the US and those belonging to the Euro Area. For Russia, we domestic absorption from its national accounts.

¹⁶In [appendix E](#), we provide a more disaggregated model that features 44 sectors for both the United States and the Euro Area. Preliminary results suggest that disaggregated details matter in the recent inflationary period.

Figure 2. Aggregate Hours Worked and Expenditures



Note: These figures plot the log deviations of aggregate time series relative to their 2018Q4 value. Panel (a) plots total hours worked across countries, while panel (b) plots aggregate demand. See the main text for definitions and data sources of each series. Note that aggregate demand is constructed such that it is equal for Russia and the Rest of the World, so we include only the series for China+.

Table 1. Baseline parameter values

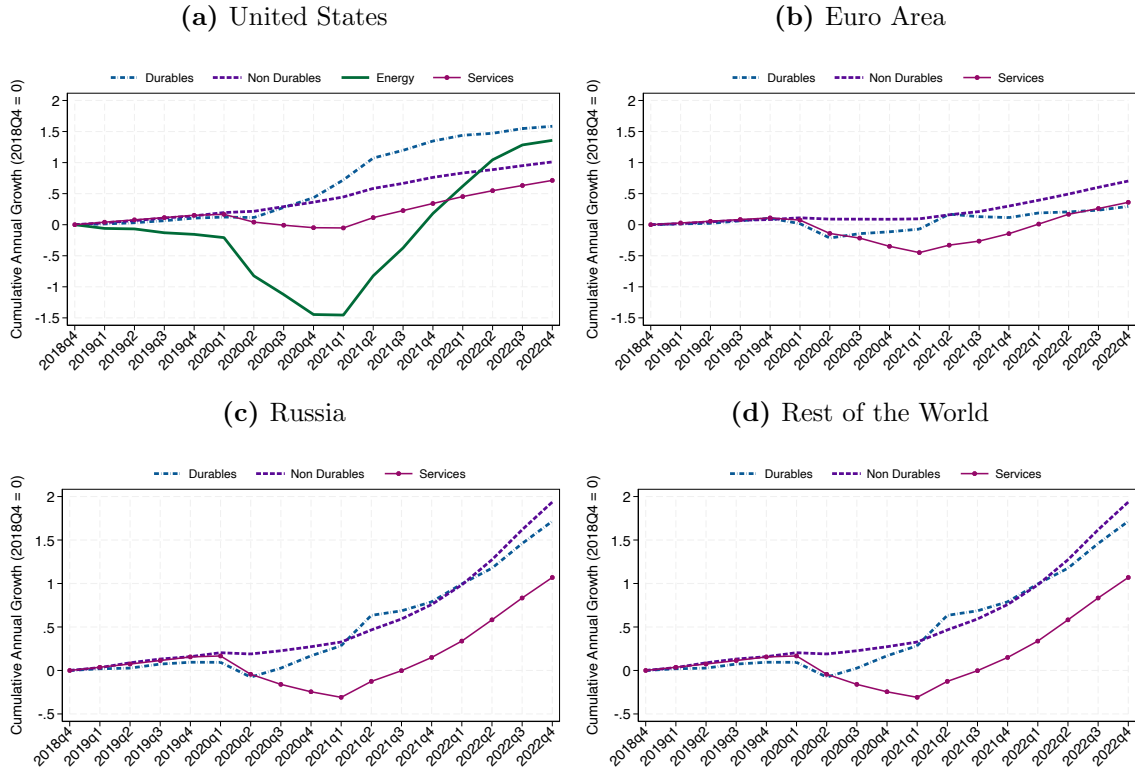
Parm.	Value	Source	Related to
θ	0.6	Atalay (2017)	EoS between intermediates and VA
η	0.6	Oberfield and Raval (2021)	EoS across factors
ε	0.2	Boehm et al. (2019)	EoS among intermediate inputs
ξ^s	0.6	Consistent with η, ε	Country-sector level input bundle EoS
ξ^c	0.6	Consistent with η, ε	Country-sector level consumption bundle EoS

Note: ‘EoS’ stands for elasticity of substitution.

literature, is that inputs to production have a low degree of substitutability in the short run. We assume complementarities across factors (η) and between factors of production and intermediate inputs (θ). Further, intermediates themselves are difficult to substitute for each other along the whole production process, which is meant to capture the difficulty in substituting between types of inputs (e.g., steel vs. plastic, ε) as well as source of inputs (e.g., Chinese vs. US steel, ξ^s). Similarly, we assume that the elasticity of substitution for sector-level consumption across countries is also low in the short run (ξ^c). We will vary the degrees of substitutability in further exercises to highlight how these elasticities impact the importance of shock transmission to domestic inflation.

Besides elasticities, we also need to take a stand on what kind of shocks we feed into the model

Figure 3. Sector-level Consumption Expenditures



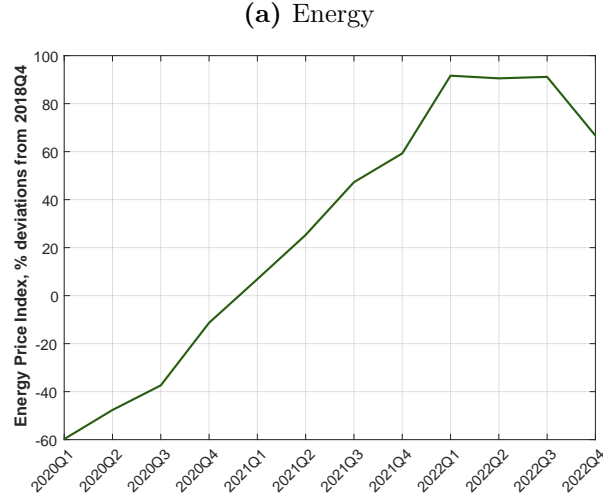
Note: This figure plots nominal consumption growth in each quarter vis-à-vis 2018Q4 and cumulated for four different consumption series: durables, non-durables, services, and energy. The blue dot-dashed line represents durable consumption. The dashed purple line represents nondurable consumption. The green line represents energy consumption. Finally, the pink dot line represents service consumption. Since we source sector-level consumption for the Euro Area and the Rest of the World from the OECD quarterly national accounts, it only contains information for durables, non-durables, and services. Due to data availability, we use the same behavior of sector-level consumption shares for Russia as that of the Rest of the world. Thus, Panel (c) and (d) are the same.

each time we estimate it. [Table 2](#) shows the scenarios we consider in this section. In particular, we consider eight different model quantification exercises. We explain these as we present their results. Before moving on to discussing the results of the different exercises, we first explain how we use the model structure and quantification exercises to confirm the assumptions we make on the mapping between sector-level supply shocks and the data-shocks we feed into the model.

Sector-level Supply-Only Shock Scenario and Downward Nominal Wage Rigidities.

Our model-to-data assumption implies that we consider changes in hours worked at the sector level as if these were shocks to potential sector-level labor supply. In the data, however, changes in sector-level hours worked come from supply and demand forces. We use the model solutions after

Figure 4. Energy Prices



Note: This figure shows the energy price index relative to its value in 2018Q4.

feeding in shocks to assess if a shock is to labor supply. To help build intuition on this approach, we describe two examples of how the model assesses a labor supply change in a given sector in our quantitative exercises.

Figure 5 presents simple diagrammatic analysis of the forces driving the labor market dynamics in the context of our model over two phases of the pandemic. Panel (a) plots the early phase of the pandemic. The y-axis, W_f , is the wage in the sector, while the x-axis represents the labor quantity, L_f . \underline{W}_f is the lower bound on the nominal wage, \bar{L}_f is the potential labor supply, and L_f^d represents the labor demand. To solve the model, we need to take a stand on the initial equilibrium. Point A represents such equilibrium where labor supply meets labor demand. Starting from point A, an observed fall in hours worked may have been driven by inward shifts in potential sector-level labor supply or labor demand combined with the nominal downward wage rigidity. In the example depicted in the figure, demand shifted by more than supply, thus driving the wage to hit the lower bound at point B. In this case, employment is demand-determined, and there are infinite combinations of potential labor supply shifts, i.e., changes in \bar{L}_f , consistent with the economy moving from point A to point B.

Panel (b) shows the late 2021 to 2022 phase, where employment started to recover in some sectors relative to the initial equilibrium. Within our framework and in contrast to the early phase of the pandemic, sector-level employment may only have increased because demand and supply

Table 2. Shocks and Scenarios

Scenario	Shocks	Countries
Baseline	All	All
Sector-level Supply	Sector-level supply only	All
Sector-level Demand	Sector-level demand only	All
Aggregate Demand	Aggregate demand only	All
Energy	Energy shock only	Russia Energy Sector
Domestic	All	Domestic country
International	All	Foreign countries
China Supply	Sector-level supply China only	China+

Note: This table shows the different shocks we use in each scenario.

move in tandem. For example, an increase in \bar{L}_f without an accompanying increase in labor demand, L_f^d , puts downward pressure on wages. Since wages cannot fall below \underline{W}_f , the rise in \bar{L}_f does not affect wages and employment in equilibrium. Similarly, an increase in labor demand without changes in \bar{L}_f implies that wages must rise without affecting equilibrium employment.

In both cases, we use the model to tell us what the shocks to potential employment, \bar{L}_f , are: whenever the full model, where we feed all shocks series, gives a solution where the nominal downward wage rigidity is binding in that sector, we set the potential sector-level supply shock to zero. Otherwise, we assume that hours worked changes in the data maps directly to changes in \bar{L}_f . Taking such an approach is conservative: it decreases the role of potential labor supply shocks when hours worked decline in the data relative to 2018Q4. Thus, our numbers on sector-level supply changes have to be considered as a lower bound on the role of sector-level supply on inflation under this approach.

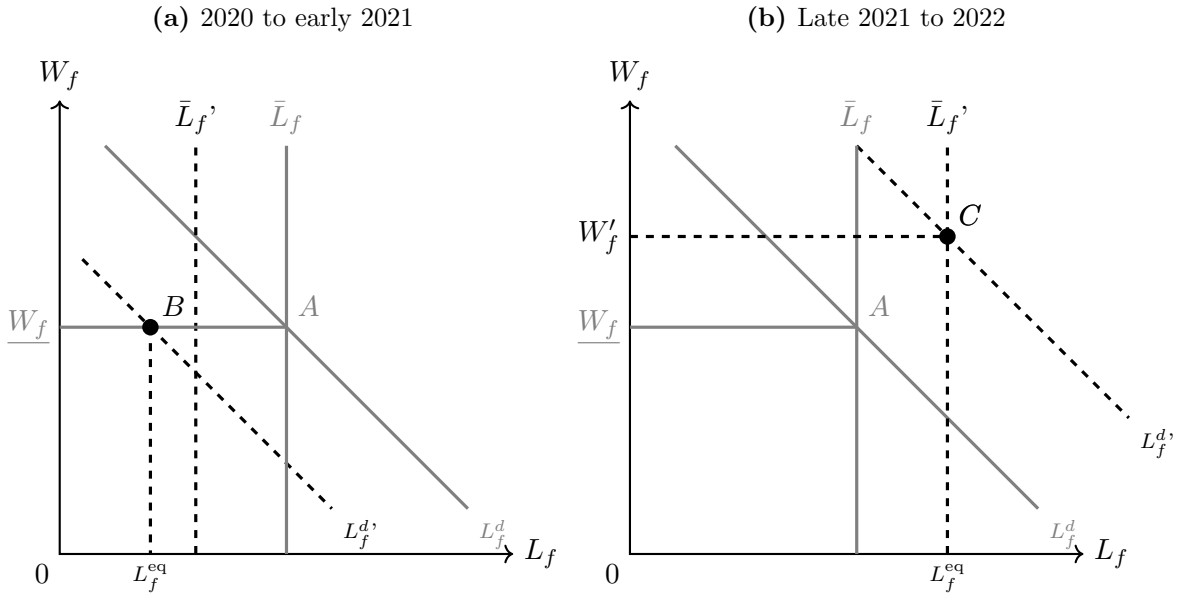
4.1 Baseline Quantification Exercise

Figure 6 begins by plotting quarterly CPI inflation rates for the model calibration, using all shocks to all countries, and data for the United States and the Euro Area, in panels (a) and (b) respectively. Both sets of inflation rates are calculated as year-on-year annual growth rates.¹⁷

We plot actual inflation with the solid black line while the blue diamonds are the model-

¹⁷The model gives the price level in deviation from steady-state. We convert them to year-on-year annual growth by taking the annual (log) difference between the model-predicted post-shock price levels. The resulting series is our model-based inflation.

Figure 5. Sector-level Labor Markets under Nominal Downward Rigidity



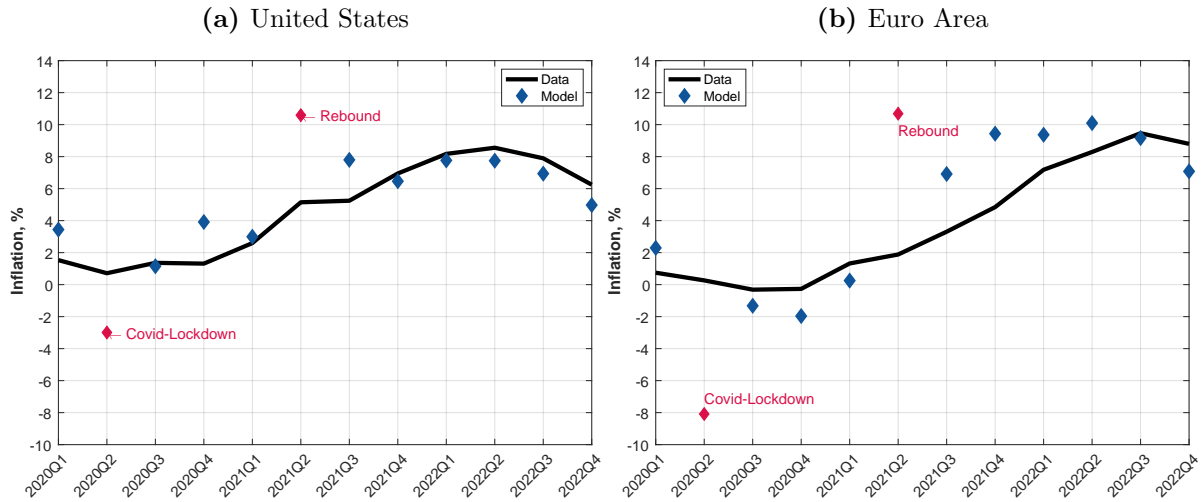
generated inflation rates that are calculated by feeding in the shock series quarter-by-quarter. We further highlight two periods with pink diamonds: (i) the Covid Lockdown, and (ii) the Rebound resulting from economies reopening. The magnitude of shocks during these periods, particularly aggregate demand, are an order of magnitude larger than economic shocks witnessed in recent memory (e.g., compared to the Global Financial Crisis), and we therefore put less weight in the model being able to match observed inflation during these periods.¹⁸ The model still performs remarkably well in matching observed inflation over the 2020q1–2022q4 period for both the US and the Euro Area.

Figure 7 next shows that our model calibration produces USD Broad Dollar index exchange rate dynamics similar to those observed in the data during 2020 and early 2021 but fall short of reproducing the dollar appreciation vis-à-vis the rest of the world of 2022.

Figure 8 plots the model and data current-account-to-GDP ratio over time for the US. As can be seen, the current account deficit widened in 2020, improved in 2021, and then widened again in late 2021–2022. This pattern matches well with the pattern of movements in US aggregate demand and savings, which originally increased during the lockdown but then started to fall given aggregate demand stimulus (See Aggarwal et al. (2023), Gourinchas et al. (2021) for similar current account dynamics).

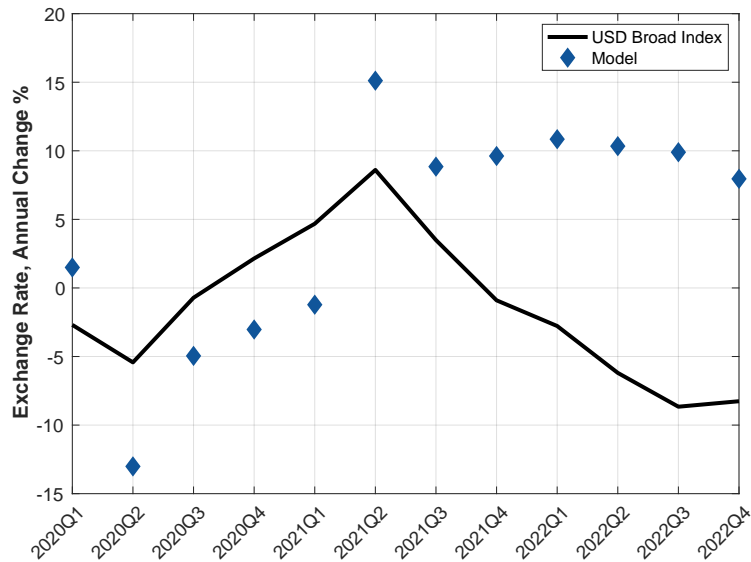
¹⁸It is also debatable how well national statistical agencies were able to measure economic series, such as GDP or aggregate expenditures, during the Covid lockdown.

Figure 6. United States and Euro Area Inflation Rates: Baseline Model vs. Data



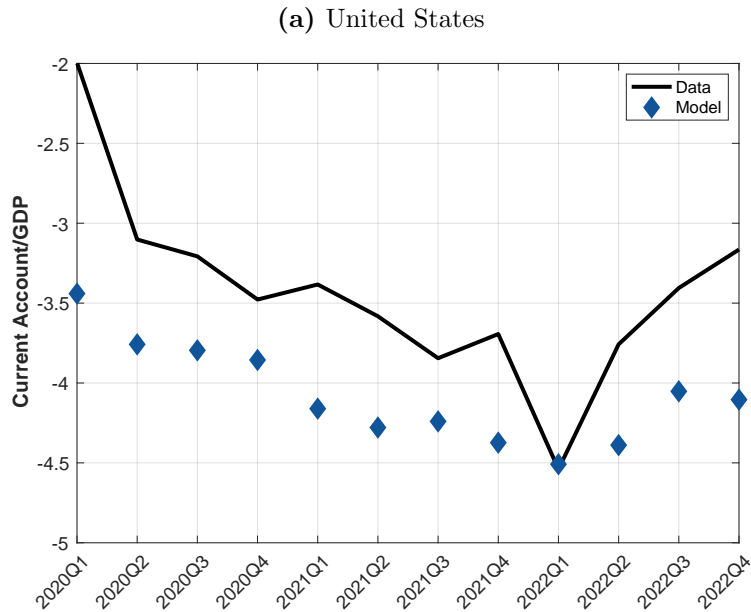
Note: This figure shows annual inflation implied by the model (blue diamonds) relative to the headline CPI inflation in the data (black solid line) when feeding the model with all shocks. The pink diamond in 2020Q2 highlights the Covid lockdown period, while the pink diamond in 2021Q2 highlights a “base effect” that exist in macroeconomic time series, as economic activity had a huge rebound relative to the Covid lockdown phase once the economy reopened.

Figure 7. USD Broad Exchange Rate: Model vs. Data



Note: This figure plots the annual percentage change in the USD broad index exchange rate implied by the baseline model (blue diamonds) and the observed change in the data (black solid line) for comparison. The broad index we show corresponds to the negative of that in the data to be consistent with our exchange rate convention of local currency per unit of world currency.

Figure 8. Current Account-to-GDP Ratio: Model vs. Data



Note: This figure shows the current account-to-GDP ratio implied by the baseline model (blue solid line). We also plot the current account-to-GDP ratio as in the data (black solid line) for comparison.

4.2 Shock Decomposition

We next provide a decomposition of the “all shock” inflation numbers that were generated by the model shown in Figure 6. To do so, we re-estimate the model by applying each shock one-by-one (for all countries). Figure 9 shows the output for these exercises for the US and Euro Area in panels (a) and (b), respectively. Before describing the full sets of results, it is worth noting that the sum of predicted inflation rates of the different “shock experiments” need not equal the inflation rate of the “all shock” model results reported above, since the solution to that model captures non-linear interactions generated by applying all shocks simultaneously.

We begin by considering the impact of sector-level supply shocks (the purple dots) in isolation. Two main patterns emerge, both for the US and Euro Area. First, sector-level supply shocks were inflationary early in the pandemic. Thus, in the absence of these shocks, there would have been more disinflation early on than observed in the data. Second, we see that without the expansion of sector-level supply in early 2022 as supply chain bottlenecks began to clear up and workers began returning more to the labor market, inflation would have been even higher in both the US and the Euro Area.

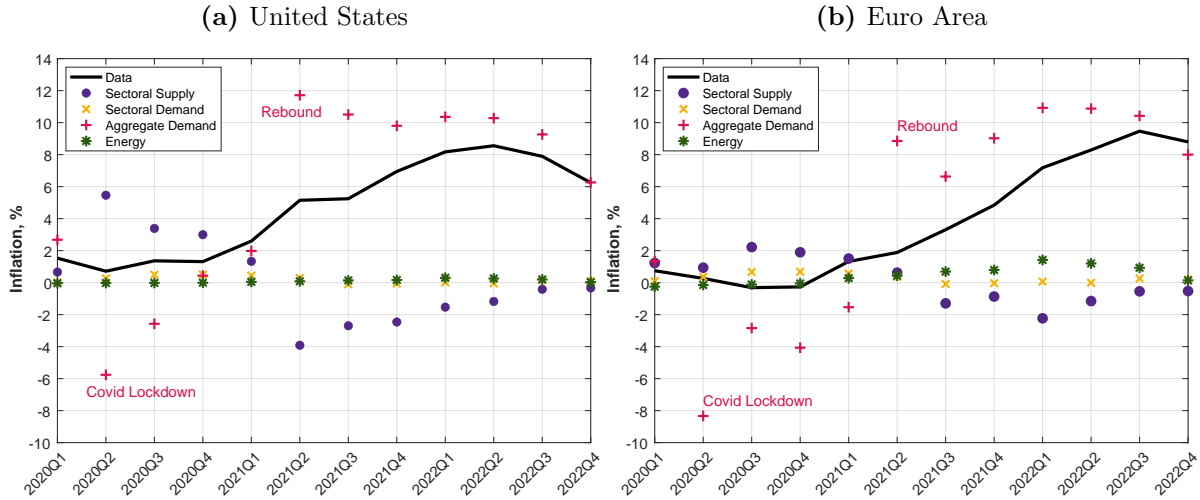
Second, we examine the role of sector-level demand shocks (the yellow crosses). The shocks capture the consumption switching across sectors that took place as economies closed and then reopened. Interestingly, the substitution to goods consumption early in the pandemic had an inflationary effect, but the rebalancing later as the economy reopened did not have a disinflationary effect.

Third, we explore the role of aggregate demand shocks (pink plus signs) in the evolution of inflation across countries. According to our quantification exercises, these shocks clearly played an important role in driving inflation over the period. Notably, the model captures the impact of the fall in aggregate demand and its disinflationary forces early on in the US, as is also found in [Baqae and Farhi \(2022\)](#). Interestingly, these negative aggregate demand shock forces appear to have played an even greater role in the Euro Area early on (irrespective of including in the ‘Covid Lockdown’ point). The reopening rebound and various expansionary policies then had a large inflationary impact in both countries. The model results show that the positive aggregate demand shock has a larger impact in the US vs. the Euro Area, which matches well with the narrative of the differential impact of stimulative policies in the two regions over this period. Looking at the end of the sample period, a fall in the aggregate demand shock explains the fall in inflation at the end of 2022.

Finally, the green stars denote the model-predicted inflation arising from energy shocks. These shocks play a minor role early on in the pandemic and are, if anything, disinflationary. Moving into 2021 and the Russia-Ukraine War, we see that energy shocks start to exert upward pressure on prices. Looking at the period where this effect was at its peak, 2022Q1, we find that the model predicted energy inflation is almost five times larger for the Euro Area than in the US; 1.4 vs. 0.3 percent.

International Spillovers. We next investigate the role of international spillovers, under our baseline flexible exchange rate regime, on domestic inflation in [Figure 10](#). Comparing the domestic (orange dots) and international (purple diamonds) points in the US and the Euro Area, we see that model-based inflation is mostly a domestic shock-driven phenomenon. This result differs from our earlier work, where the model was solved under fixed exchange rates, and we found that external shocks played a larger role for the Euro Area: we found that two-thirds of inflation in Europe

Figure 9. United States and Euro Area Sources of Inflation: Shock Decomposition

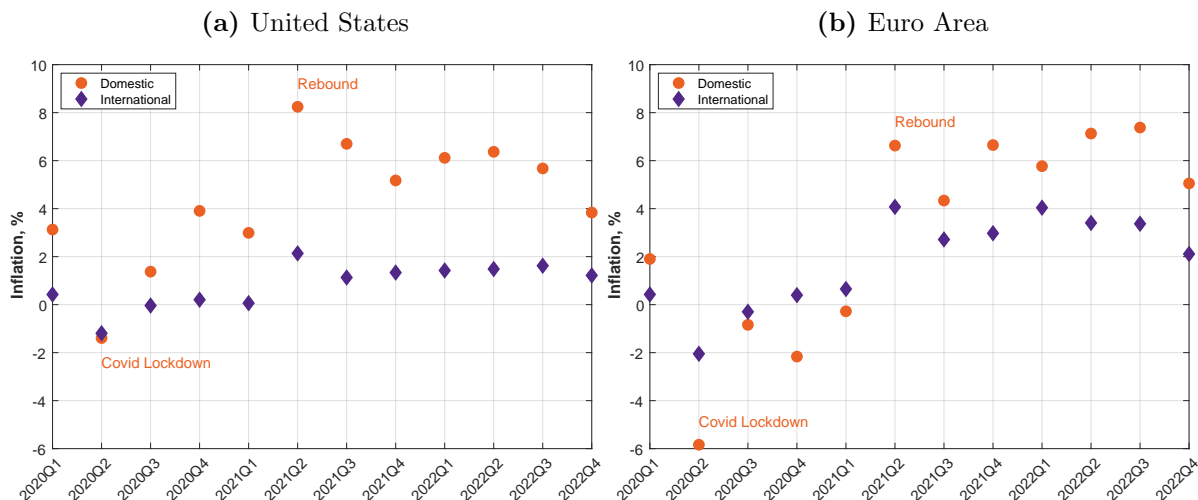


Note: This figure shows annual inflation in the data (black line) relative to the data when feeding the model with all shocks and counterfactual scenarios where we feed in one type of shock at a time. The pink + in 2020Q2 highlights the Covid lockdown period, while the pink + in 2021Q2 highlights a “base effect” that exist in macroeconomic time series, as economic activity had a huge rebound relative to the Covid lockdown phase once the economy reopened.

was explained by external shocks (di Giovanni, Kalemli-Özcan, Silva, and Yıldırım, 2022). The effect of international shocks is still more important for Euro Area countries compared to the US, which is consistent with the differences in the foreign-factor component of consumption depicted Figure 1 (as well as our earlier findings under a fixed exchange rate modeling assumption). In other words, the foreign factor content of European output is larger than that of the US, so the Euro Area inflation is more impacted by shocks to foreign factors (i.e., foreign supply shocks that are transmitted by the global production network). This result is notable in 2022Q1, which picks up Europe’s reliance on imported petroleum products in production.

The Role of Chinese Lockdown Shocks. Chinese lockdown policies played an important role in generating supply chain bottlenecks worldwide, helping to generate supply-demand imbalances that arguably helped fuel inflation across countries. We examine the impact of the “Chinese supply shocks” using the model by feeding in China-specific labor supply shocks in the model while omitting other shocks. Specifically, we apply the China sector-level labor supply shocks to all countries in the China+ aggregate and simulate the model. Figure 11 presents results of this quantification exercise of the US and the Euro Area in panels (a) and (b), respectively. The lockdowns during 2020 contributed to generating inflation in the United States and the Euro Area, with a more

Figure 10. United States and Euro Area Sources of Inflation: Domestic and International Shocks



Note: This figure shows annual inflation when feeding only domestically originated shocks (orange x) relative to international shocks only (purple $+$). 2020Q2 highlights the Covid lockdown period, while 2021Q2 highlights a “base effect” that exist in macroeconomic time series, as economic activity had a huge rebound relative to the Covid lockdown phase once the economy reopened.

significant impact on the latter. For instance, during 2020 the average inflation generated by the China Supply shocks was 0.55 percent in the United States, while it was 0.77 percent in the Euro Area. This captures the fact that while the US increased demand for goods relatively more than the Euro Area over the pandemic, the Euro Area’s foreign content of consumption (see Figure 1) is larger than that of the US, so it was more impacted by negative supply shocks to factors in China. This result corresponds to the overall results we found on international spillovers in Figure 10.

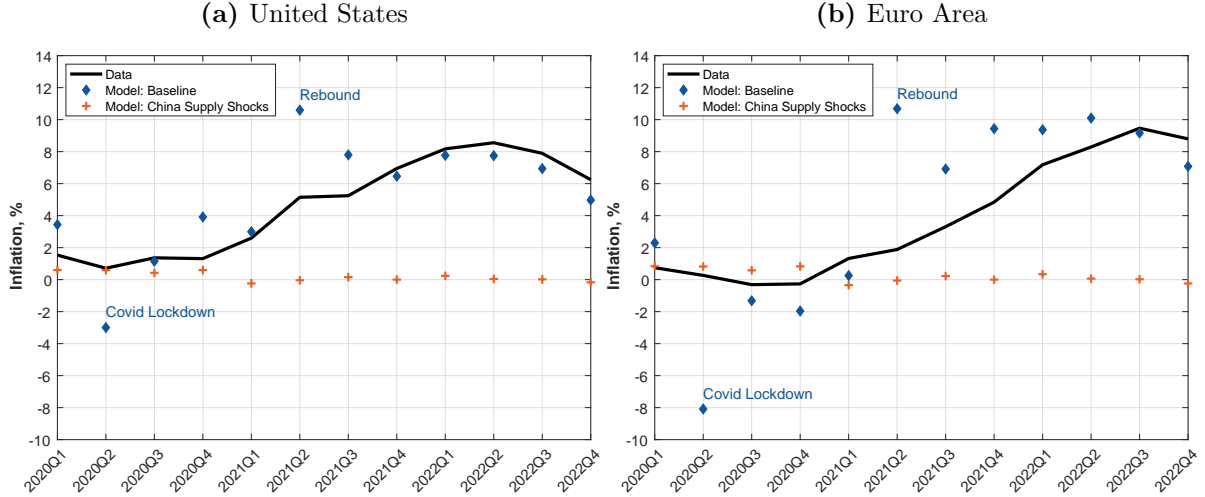
4.3 Production and Trade Elasticities

We next investigate the quantitative importance of varying elasticities of substitution within the global network on the amplification of shocks on domestic inflation. We first examine how changing the elasticities of production impacts the amplification of shocks to domestic inflation and then move on to conduct a similar exercise for trade elasticities.

We focus on how varying the elasticities of substitution in production impacts the effects of shocks on the energy sector. To do so, we vary the elasticity of substitution and reallocation of factors across sectors commonly used in the literature. The new higher-substitutability elasticities we feed into the model are $(\eta, \varepsilon, \theta) = (1.5, 1.5, 1.5)$.¹⁹

¹⁹We choose 1.5 for these elasticities because it represents the upper end of available short-run estimates in the

Figure 11. United States and Euro Area Inflation Rates: The Role of China



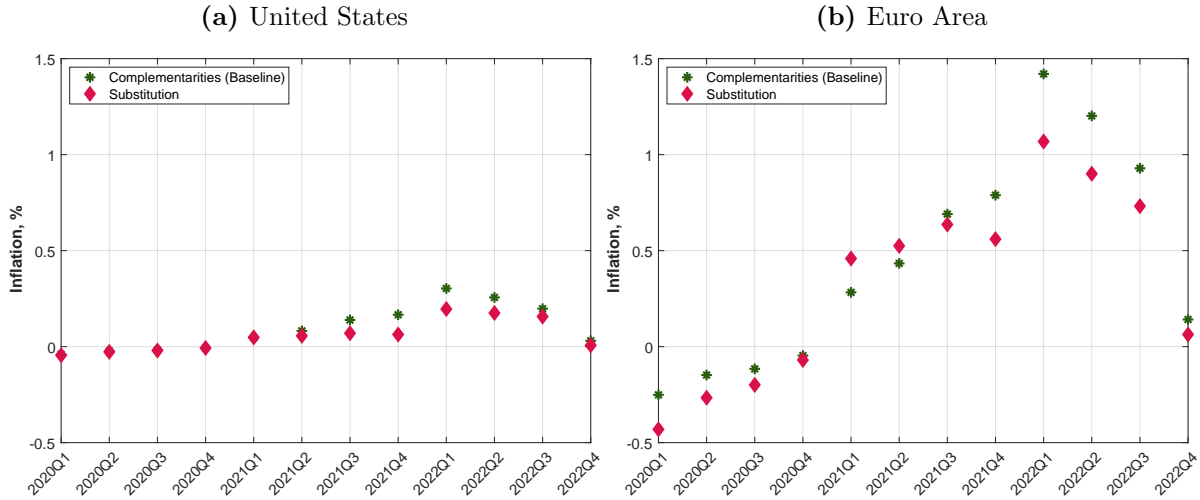
Note: This figure shows annual inflation implied by the baseline model (blue diamonds) relative to the headline CPI inflation in the data (black solid line) when feeding the model with all shocks and when feeding all shocks but sector-level supply (orange plus). 2020Q2 highlights the Covid lockdown period, while 2021Q2 highlights a “base effect” that exist in macroeconomic time series, as economic activity had a huge rebound relative to the Covid lockdown phase once the economy reopened.

Figure 12 presents simulation results when we vary production elasticities. We plot our baseline (‘Complementarities’) calibration with the one that imposes a higher elasticity of substitution across factors used in production (‘Substitution’) – note that these substitution parameters impact allocation across country-sector pairs. As can be seen, allowing producers to more easily substitute across factors substantially dampens the impact of energy shocks on inflation in both the US and the Euro Area. The impact of this difference in elasticities on inflation is notably larger in the Euro Area during the Russia-Ukraine War, which is unsurprising given the Euro Area’s higher exposure to the energy price shock.

We next analyze the role of trade elasticities. To do so, we vary the trade elasticity parameters ξ over three possible values, $\{0.6, 1, 5\}$, for both the importing of consumption and intermediate goods. Varying these elasticities, conditional on holding production elasticities at their baseline values, is meant to capture how a change in the ease of access to different markets impacts the transmission of shocks to domestic inflation. These experiments help to further gauge the impact

literature. $\theta = 1.2$ in the baseline of [Carvalho, Nirei, Saito, and Tahbaz-Salehi \(2021\)](#) and $\eta = 1.5$ in Table 1 specification (vi) of [Karabarbounis and Neiman \(2014\)](#). Estimates of ε are typically below one at any horizon. For example, [Peter and Ruane \(2023\)](#) find this elasticity to be 0.6 at a 7-year horizon, and [Boehm, Flaaen, and Pandalai-Nayar \(2019\)](#) estimate this to be 0.03 in the short run. We take the extreme symmetric assumption $(\eta, \varepsilon, \theta) = (1.5, 1.5, 1.5)$ for parsimony to highlight the importance of complementarities in production.

Figure 12. Production Complementarities and Energy Shocks Transmission to Inflation



Note: This figure shows annual inflation implied by the baseline model (green *) relative to the model with high elasticities of substitution (pink diamonds).

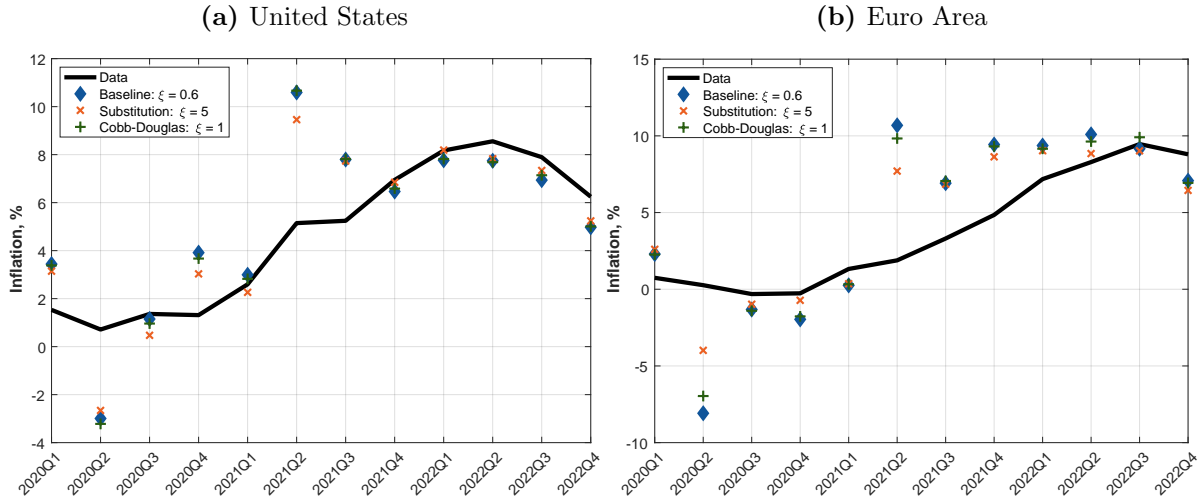
of global supply chain bottlenecks on inflation. Specifically, varying the elasticities from low (short-run) to high (long-run) values will capture the ability of countries to substitute between suppliers for goods and services.

Figure 13 presents the resulting inflation patterns from varying trade elasticities in the US and Euro Area. Unsurprisingly, allowing for greater substitution of consumption and intermediate goods from source countries along the global supply chain dampens the impact of shocks on domestic inflation. The impact of increasing elasticities is quite small for the US but has a larger impact on the model exercises for the Euro Area. The higher elasticity dampening effect on the propagation of shocks to Euro Area inflation captures Europe’s higher exposure to foreign factors of production that are embedded in domestic consumption, as measured in the foreign Domar weights in Figure 1.

4.4 Real Wages

This subsection examines how closely the model is able to match real wages movements, both in the aggregate and across sectors. We focus on the US since detailed wage data at the sector-level level is more readily available for this country. Specifically, we use the non-farm business sector hourly compensation to measure nominal wages. These data come from FRED (code COMPNFB). We deflate the series using headline CPI to obtain our measure of real wages from the data. We

Figure 13. United States and Euro Area Inflation Rates: The Role of Trade Elasticities



Note: This figure shows inflation numbers when we introduce all shocks under different trade elasticities $\xi^c = \xi^s = \xi$. Blue diamonds represent our baseline model. Orange x use a high trade elasticity $\xi = 5$. Green $+$ assumes a unitary trade elasticity, $\xi = 1$.

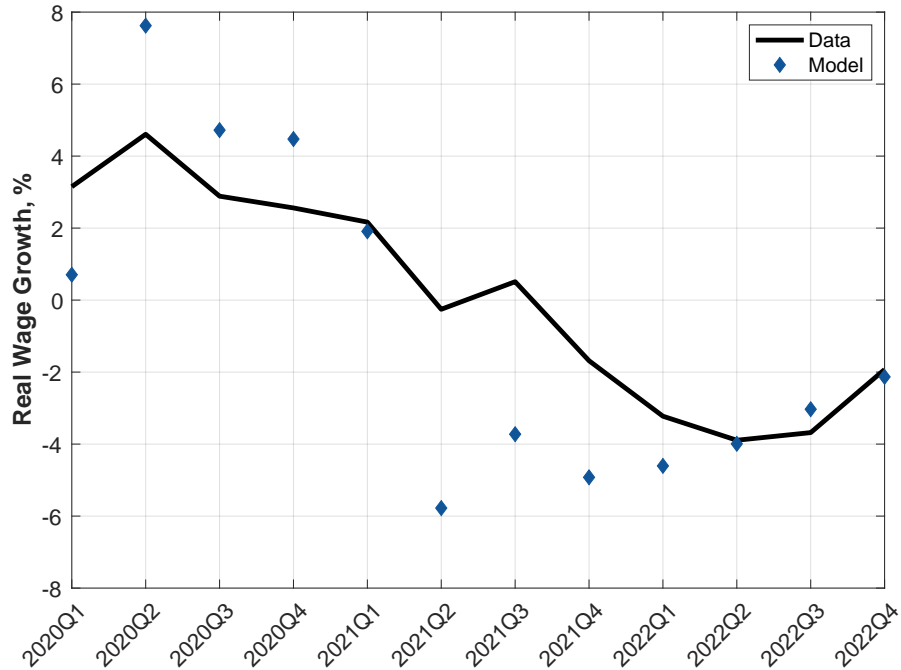
similarly compute the real wage from the model by deflating the aggregate nominal wage by the overall price index.

Figure 14 compares the behavior of real wages in the data and those generated by baseline model quantification exercise by plotting the year-on-year growth rate of real wages. The black line represents the data, and the blue diamonds depict model predictions. The model-generated series tracks the evolution of real wages observed in the data quite closely over the analyzed period for the United States, and it is consistent with the large increase in the real wage during 2020 and its subsequent decline over 2021–2022.

We next take advantage of the model structure to examine its performance at the disaggregated level. This would not be possible without modeling the supply side across several sectors of the economy (along with the input-output structure) – an advantage of our methodological approach absent in much of the other literature focusing on the pandemic inflation period. Specifically, we are able to study how well the model matches the evolution of sector-specific real wages. Performing this exercise is important because when labor is sector-specific and immobile across sectors, a key relative price is the real wage in units of the sector-specific price. For ease of exposition, we aggregate sectors into goods (durables, non-durables, and energy) and services.²⁰ Figure 15

²⁰We do this for the model and data based on each sector’s nominal wage and price levels.

Figure 14. Real Wage Changes



Note: This figure shows year-on-year real wage growth rate. Nominal wage corresponds to total private sector hourly earnings series from the Bureau of Labor Statistics, codes CES0500000003. We deflate this measure using headline CPI. The black line represents the data. Blue diamonds are model-based predictions.

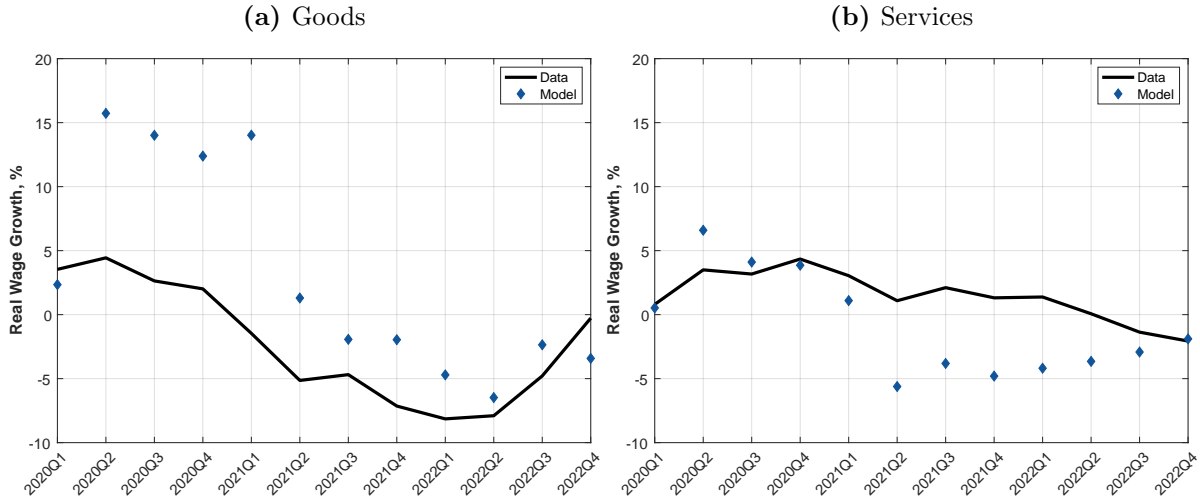
compares the model to the data for sector-level real wages in the goods sector in panel (a) and the service sector in panel (b).²¹

Overall, in the model and the data, goods and services real wage growth was positive during 2020 before declining over the 2021–2022 period. The model matches the overall behavior of real wages in the goods sector, as shown in panel (a), with an initial positive growth and subsequent fall in the real wage. While we over-predict real wage growth from 2020 until mid-2021, the model captures the magnitude of the decline in real wage growth from mid-2021 onward. In contrast, panel (b) shows that the model results closely track the real wage growth in the service sector in 2020 but underpredict this sector’s real wage growth starting in 2021. This result suggests that the service sector price increases faster than its wage. In our model, this means that other factor prices — wages and, notably, the price of capital in other sectors — went up more than wages in the service sector.

Figure D.4 in the appendix plots the nominal wages for the goods and services sector. The

²¹Figure D.3 shows each sector nominal wages deflated by the overall price level instead of sector-specific prices. We find similar results.

Figure 15. Sector-Specific Real Wages Growth



Note: This figure shows sector-specific real wage growth. Black lines represent the data, while blue diamond represents the model. We compute real wages by deflating nominal wages in that sector by the sector-level price. All numbers are year-on-year growth; each panel shows the real wage growth for a different sector. In the model, we aggregate nominal wage growth across the durables, non-durables, and energy sectors to construct nominal wage growth in the goods sector. We subtract goods inflation from nominal wage growth to construct real wage growth in the goods sector. We source sector-level nominal wages from the Bureau of Labor Statistics average hourly earnings series with codes: CES0600000003 (goods) and CES0800000003 (services). We source sector-level prices from FRED with codes: CUSR0000SAC (goods) and CUSR0000SASLE (services).

model predicted behavior of nominal wages in the service sector (reported in panel (b)) closely tracks the time series of nominal wages observed in the data. Thus, the reason why the model does not track real wages for services is due to the model overstating increases in the service sector’s price growth, especially during 2021. As we analyze in the following subsection, the services sector price indeed increased more in our model than in the data. We believe this is due to missing granularity in sector-level prices in the data as the latter combines the increase in, for example, grocery delivery prices with the decrease in restaurant prices, leading to a flat pattern of the service sector price.

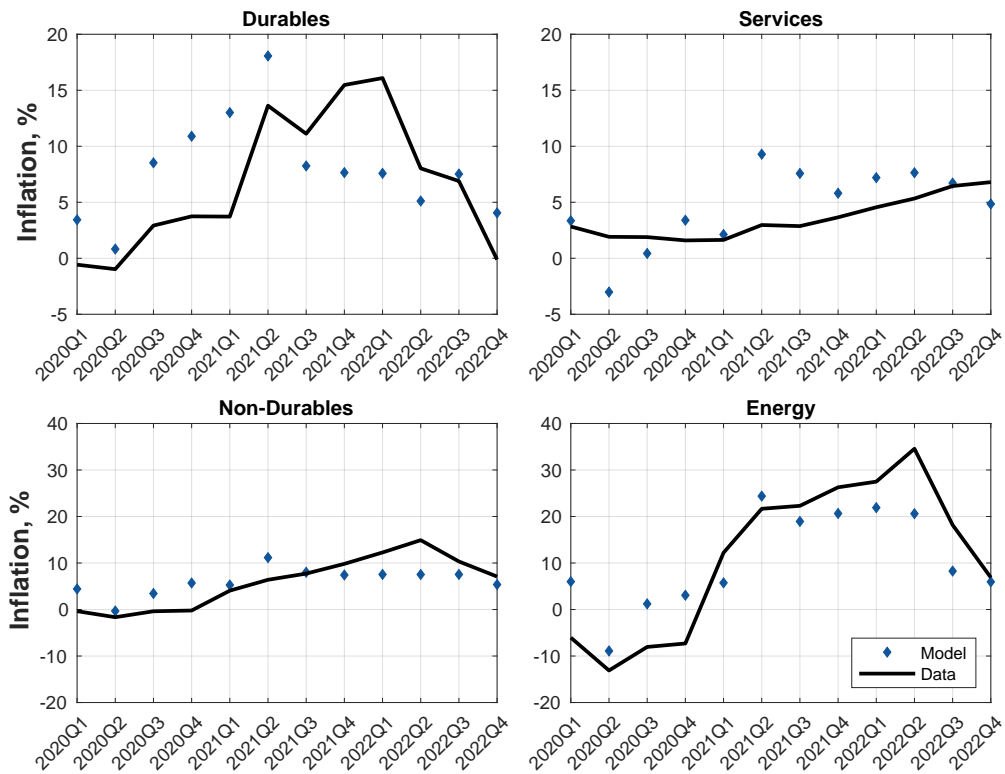
To sum up, the sector-specific real wage growth patterns are consistent with sector-level labor supply declines that initially put upward pressure on sector-level real wages during the initial phase of the pandemic, coupled with increases in labor demand driven by positive aggregate demand shocks starting at the end of 2020. The story in 2021 and 2022 is a recovery in sector-level employment supply and demand, with a corresponding decline in real wages. These findings suggest that sector-level labor supply played a key role in real wage dynamics during 2020–2022.

4.5 Sector-level Price Inflation

We next examine how well the model matches observed sector-level price movements, focusing on the US again. [Figure 16](#) plots US sector-level price inflation. Overall, the model-predicted inflation rates match the data well for the US. However, as in the case of aggregate CPI inflation presented above, the model tends to over-predict inflation quite a lot during the reopening period.²² Goods inflation (durables, non-durables, and energy) was initially weakly positive and increased to stabilize around 2021 in both the non-durables and energy sectors, while it declined in the durables sector during this period. The continuous increase in the non-durables and energy sector prices helps to explain the real wage growth decline in the goods sector we observed since 2021 in panel (a) of [Figure 15](#). Conversely, the model predicts a significant and persistent increase in service inflation, which is larger than in the data from 2021 onwards. As we have articulated in the above section, we believe this is due to the missing granularity in sector prices data where higher prices of shelter and online services and lower prices in contact-intensive services sectors are averaged out in service sector prices. These dynamics in service prices help explain why the model-predicted real wage growth in the services sector reported in panel (b) of [Figure 15](#) was negative during the latter half of the sample period.

²²See [Figure D.5](#) for the shock decomposition of the sector-level price inflation series.

Figure 16. United States Sector-level Price Inflation



Note: These figures plot year-on-year sector-level model-based inflation rates implied for all shocks (blue diamonds) and actual inflation (black lines) for the US. Data comes from FRED. Codes: Durables CUSR0000SAD, Non-durables CUSR0000SAN, Services CUSR0000SASLE, Energy CPIENGLS.

5 Conclusion

This paper estimates a multi-country multi-sector general equilibrium model to quantify the drivers of global and domestic inflation during 2020–2023. Given the global nature of the model, we also measure inflation spillovers across countries. The baseline quantification exercise produces aggregate inflation rates that match those observed in the data across countries, as well as being able to explain movements in sector-level prices and wages that are similar to those observed in the data. The model is also able to match endogenous exchange rates and current accounts in the data. This is an important feature given the open economy dimension of our work that takes into account both trade and production linkages globally.

The model further allows us to conduct a shock decomposition exercise, which quantifies the drivers of inflation in each phase of the pandemic-inflation period. This exercise shows that inflation began due to pandemic-related supply shocks in factor markets and increased further due to expansionary fiscal and monetary policies that stimulated aggregate demand. The reallocation of consumption across sectors combined with energy shocks also played important roles in the global amplification of shocks together with the complementarities in production. We highlight this narrative that we quantify in the introduction by a quote from Chairman Powell. The overarching policy implication of our paper is that, in a world with more supply shocks (fragmentation), at sector or at the aggregate level, we will see more inflation.

References

- Aggarwal, Rishabh, Adrien Auclert, Matthew Rognlie, and Ludwig Straub. 2023. “Excess savings and twin deficits: The transmission of fiscal stimulus in open economies.” *NBER Macroeconomics Annual* 37 (1): 325–412.
- Amiti, Mary, Sebastian Heise, Fatih Karahan, and Ayşegül Şahin. 2023. “Inflation Strikes Back: The Role of Import Competition and the Labor Market.” May. [10.3386/w31211](https://doi.org/10.3386/w31211), NBER Working Paper 31211.
- Aoki, Kosuke. 2001. “Optimal monetary policy responses to relative-price changes.” *Journal of Monetary Economics* 48 (1): 55–80.
- Atalay, Enghin. 2017. “How important are sectoral shocks?” *American Economic Journal: Macroeconomics* 9 (4): 254–280.
- Baqae, 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. [10.1257/aer.20201229](https://doi.org/10.1257/aer.20201229).
- Basu, Susanto. 1995. “Intermediate Goods and Business Cycles: Implications for Productivity and Welfare.” *American Economic Review* 85 (3): 512.
- Benigno, Gianluca, and Christoph Thoenissen. 2008. “Consumption and real exchange rates with incomplete markets and non-traded goods.” *Journal of International Money and Finance* 27 (6): 926–948.
- Benigno, Pierpaolo, and Gauti B. Eggertsson. 2023. “It’s Baaack: The Surge in Inflation in the 2020s and the Return of the Non-Linear Phillips Curve.” April. [10.3386/w31197](https://doi.org/10.3386/w31197), NBER Working Paper 31197.
- Blanchard, Olivier, and Jordi Gali. 2007. “Real wage rigidities and the new Keynesian model.” *Journal of Money Credit and Banking* 39 (1, S): 35–65. [10.1111/j.1538-4616.2007.00015.x](https://doi.org/10.1111/j.1538-4616.2007.00015.x), Conference on Quantitative Evidence on Price Determination, Federal Reserve Board Gemgf, Washington, DC, SEP 29-30, 2005.
- Blanchard, Olivier J., and Ben S. Bernanke. 2023. “What Caused the US Pandemic-Era Inflation?” June. [10.3386/w31417](https://doi.org/10.3386/w31417), NBER Working Paper 31417.
- Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar. 2019. “Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake.” *Review of Economics and Statistics* 101 (1): 60–75.
- Boehm, Christoph E., Andrei A. Levchenko, and Nitya Pandalai-Nayar. 2023. “The Long and Short (Run) of Trade Elasticities.” *American Economic Review* 113 (4): 861–905. [10.1257/aer.20210225](https://doi.org/10.1257/aer.20210225).

- Bouakez, Hafedh, Emanuela Cardia, and Francisco Ruge-Murcia. 2014. “Sectoral price rigidity and aggregate dynamics.” *European Economic Review* 65 1–22.
- Carvalho, Carlos. 2006. “Heterogeneity in price stickiness and the real effects of monetary shocks.” *Frontiers in Macroeconomics* 2 (1): .
- Carvalho, Carlos, and Fernanda Nechio. 2011. “Aggregation and the PPP puzzle in a sticky-price model.” *American Economic Review* 101 (6): 2391–2424.
- Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. 2021. “Supply chain disruptions: Evidence from the great east japan earthquake.” *The Quarterly Journal of Economics* 136 (2): 1255–1321.
- Castro, Nicolás. 2019. “The importance of production networks and sectoral heterogeneity for monetary policy.” Available at SSRN 3499902.
- Comin, Diego A., Robert C. Johnson, and Callum J. Jones. 2023. “Supply Chain Constraints and Inflation.” April. [10.3386/w31179](https://doi.org/10.3386/w31179), NBER Working Paper 31179.
- di Giovanni, Julian, Şebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yıldırım. 2022. “Global Supply Chain Pressures, International Trade, and Inflation.” July. [10.3386/w30240](https://doi.org/10.3386/w30240), NBER Working Paper 30240.
- di Giovanni, Julian, Şebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yıldırım. 2023. “Quantifying the Inflationary Impact of Fiscal Stimulus under Supply Constraints.” *AEA Papers and Proceedings* 113 76–80. [10.1257/pandp.20231028](https://doi.org/10.1257/pandp.20231028).
- Dix-Carneiro, Rafael, João Paulo Pessoa, Ricardo Reyes-Heroles, and Sharon Traiberman. 2023. “Globalization, trade imbalances, and labor market adjustment.” *The Quarterly Journal of Economics* 138 (2): 1109–1171.
- Eggertson, Gauti B., and Don Kohn. 2023. “The Inflation Surge of the 2020s: The Role of Monetary Policy.” May, Mimeo, Brown University and Brookings Institution.
- Erceg, Christopher J, Dale W Henderson, and Andrew T Levin. 2000. “Optimal monetary policy with staggered wage and price contracts.” *Journal of Monetary Economics* 46 (2): 281–313.
- Fernald, John, and Huiyu Li. 2022. “The Impact of COVID on Productivity and Potential Output.” Jackson Hole Economic Symposium Proceedings.
- Ferrante, Francesco, Sebastian Graves, and Matteo Iacoviello. 2023. “The Inflationary Effects of Sectoral Reallocation.” *Journal of Monetary Economics*.
- Fornaro, Luca, and Federica Romei. 2023. “Monetary policy in an unbalanced global economy.”
- Gagliardone, Luca, and Mark Gertler. 2023. “Oil Prices, Monetary Policy and Inflation Surges.” Working Paper 31263, National Bureau of Economic Research.

- Gourinchas, Pierre-Olivier, Şebnem Kalemli-Özcan, Veronika Penciakova, and Nick Sander. 2021. “Fiscal Policy in the Age of COVID: Does it ‘Get in all of the Cracks?’.” 10.3386/w29293, Jackson Hole Symposium Proceedings.
- Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning. 2021. “Monetary Policy in Times of Structural Reallocation.” Jackson Hole Economic Symposium Proceedings.
- Hale, Thomas, Noam Angrist, Rafael Goldszmidt et al. 2021. “A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker).” *Nature Human Behaviour* 5 (4): 529–538. 10.1038/s41562-021-01079-8.
- Höynck, Christian. 2020. “Production networks and the flattening of the Phillips curve.” Mimeo, Universitat Pompeu Fabra.
- Jordá, Óscar, Celeste Liu, Fernanda Nechio, and Fabián Rivera-Reyes. 2022. “Why Is U.S. Inflation Higher than in Other Countries?” *FRBSF Economic Letter* 2022 (07): , <https://EconPapers.repec.org/RePEc:fip:fedfel:93890>.
- Jordá, Óscar, and Fernanda Nechio. 2022. “Inflation and Wage Growth Since the Pandemic.” <https://doi.org/10.24148/wp2022-17>, Federal Reserve Bank of San Francisco Working Paper 2022-17.
- Karabarbounis, Loukas, and Brent Neiman. 2014. “The global decline of the labor share.” *The Quarterly journal of economics* 129 (1): 61–103.
- Klenow, Peter J, and Oleksiy Kryvtsov. 2008. “State-dependent or time-dependent pricing: Does it matter for recent US inflation?” *The Quarterly Journal of Economics* 123 (3): 863–904.
- La’O, Jennifer, and Alireza Tahbaz-Salehi. 2022. “Optimal monetary policy in production networks.” *Econometrica* 90 (3): 1295–1336.
- Lorenzoni, Guido, and Iván Werning. 2023. “Wage price spirals.” *Brookings Papers in Economic Activity*.
- Nakamura, Emi, and Jón Steinsson. 2008. “Five facts about prices: A reevaluation of menu cost models.” *The Quarterly Journal of Economics* 123 (4): 1415–1464.
- Nakamura, Emi, and Jón Steinsson. 2010. “Monetary non-neutrality in a multisector menu cost model.” *The Quarterly journal of economics* 125 (3): 961–1013.
- Nakamura, Emi, and Jón Steinsson. 2013. “Price rigidity: Microeconomic evidence and macroeconomic implications.” *Annual Review of Economics* 5 (1): 133–163.
- Oberfield, Ezra, and Devesh Raval. 2021. “Micro data and macro technology.” *Econometrica* 89 (2): 703–732.

- 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.
- Pasten, Ernesto, Raphael Schoenle, and Michael Weber. 2023. “Sectoral Heterogeneity in Nominal Price Rigidity and the Origin of Aggregate Fluctuations.” *American Economic Journal: Macroeconomics*.
- Peter, Alessandra, and Cian Ruane. 2023. “The aggregate importance of intermediate input substitutability.” Technical report, National Bureau of Economic Research.
- Reyes-Heroles, Ricardo. 2016. “The role of trade costs in the surge of trade imbalances.” *Princeton University, mimeograph*.
- Rubbo, Elisa. 2023a. “Networks, Phillips curves, and monetary policy.” *Econometrica* 91 (4): 1417–1455.
- Rubbo, Elisa. 2023b. “What drives inflation? Lessons from disaggregated price data.” September, Mimeo, Booth School of Business at the University of Chicago.
- Shapiro, Adam H. 2022a. “How Much Do Supply and Demand Drive Inflation?” June, FRBSF Economic Letter.
- Shapiro, Adam H. 2022b. “Decomposing Supply and Demand Driven Inflation.” September, FRBSF Working Paper.
- de Soyres, François, Alexandre Gaillard, Ana Maria Santacreu, and Dylan Moore. 2024. “Supply Disruptions and Fiscal Stimulus: Transmission through Global Value Chains.” *American Economic Association Papers and Proceedings*.
- Woodford, Michael. 2003. *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton University Press.

A Solution

To solve the model, we calibrate consumption and input weights, GDP shares and expenditure shares using the OECD Inter-Country Input-Output (ICIO) Tables. We calibrate the CES functions such that the weights coincide with the input and consumption shares. We normalize all prices, wages and rental rates to 1 at the initial steady state. We calculate all changes in world currency units while keeping track of exchange rate movements of countries relative to the world currency, which enables us to convert price changes to local currency when calculating domestic inflation rates.

Figure A.1. Structure of enhanced input-output matrix Ω

(a) Ω Matrix											(b) Row / Column Indices			
	C	Y	Z	VA	X	CB	L	K	Ric	Fut	Index	Description	Size	Elasticity
C	0	0	0	0	0	Ω^C	0	0	0	0	C	Current Consumption	\mathcal{N}	1
Y	0	0	Ω_Z^Y	Ω_{VA}^Y	0	0	0	0	0	0	Y	Goods / Varieties	$\mathcal{N} \times \mathcal{J}$	θ
Z	0	0	0	0	Ω^Z	0	0	0	0	0	Z	Intermediate Bundle	$\mathcal{N} \times \mathcal{J}$	ε
VA	0	0	0	0	0	0	Ω_L^{VA}	Ω_K^{VA}	0	0	VA	Value-Added	$\mathcal{N} \times \mathcal{J}$	γ
X	0	Ω^X	0	0	0	0	0	0	0	0	X	Country-Sector Bundles	$\mathcal{N} \times \mathcal{J}$	ξ_i
CB	0	Ω^{CB}	0	0	0	0	0	0	0	0	CB	Consumption Bundles	$\mathcal{N} \times \mathcal{J}$	ξ'_i
L	0	0	0	0	0	0	0	0	0	0	L	Sector Specific Labor	$\mathcal{N} \times \mathcal{J}$	
K	0	0	0	0	0	0	0	0	0	0	K	Sector Specific Capital	$\mathcal{N} \times \mathcal{J}$	
Ric	$1 - \beta$	0	0	0	0	0	0	0	0	β	Ric	Ricardian Consumer	\mathcal{N}	1
Fut	0	0	0	0	0	0	0	0	0	0	Fut	Future Consumption	\mathcal{N}	

Note: All sub-matrix definitions are given in the Sections 2.1 and 2.2. Non-zero sub-matrices are colored and light green colored sub-matrices indicate diagonal matrices.

We provide a unified representation of the model by creating an enhanced input-output table, which is depicted in Figure A.1. This generalized input-output matrix integrates households, sector-level outputs, factors and input/consumption bundles that are required for production or used for consumption, with all these entities shown as rows and columns (row and column indices and their sizes are given in Panel A.1b). Each row, i , in this matrix corresponds to a single CES aggregator

with corresponding elasticity of substitution of σ_i and a price P_i . Given the CES assumption, we can then write the price index for each row as:

$$\begin{aligned} P_i^{1-\sigma_i} &= \sum_j \Omega_{ij} P_j^{1-\sigma_i} & \text{if } \sigma_i \neq 1, \\ \log(P_i) &= \sum_j \Omega_{ij} \log(P_j) & \text{if } \sigma_i = 1, \end{aligned} \tag{A.1}$$

where the second equation corresponds to the Cobb-Douglas case.

We write the market-clearing condition for each row entry using information contained in the columns of the Ω matrix presented in [Figure A.1](#). For a given column j , we denote its total output by Y_j . This output is used by other entities as inputs or for consumption. X_{ij} is the amount of j used by row i . The market-clearing condition for each row can be written as:

$$P_j Y_j = \sum_i P_j X_{ij} = \sum_i \frac{P_j X_{ij}}{P_i Y_i} P_i Y_i. \tag{A.2}$$

Using the CES assumption, we then write the optimal input ratio of j in i as a function of relative prices:

$$\frac{P_j X_{ij}}{P_i Y_i} = \left(\frac{P_j}{P_i} \right)^{1-\sigma_i}. \tag{A.3}$$

Dividing both sides of [\(A.2\)](#) by global GDP, we express a sector j 's output as a function of world output, i.e., its global Domar weight, which is currency free. Hence, we can relate the Domar weights to each other:

$$\frac{P_j Y_j}{\text{GDP}_W} \equiv \lambda_j = \sum_i \Omega_{ij} \left(\frac{P_j}{P_i} \right)^{1-\sigma_i} \frac{P_i Y_i}{\text{GDP}_W} = \sum_i \Omega_{ij} \left(\frac{P_j}{P_i} \right)^{1-\sigma_i} \lambda_i. \tag{A.4}$$

The Domar weight equations capture the propagation of the consumption of countries down to the payments to factors of production along the global supply chains. Equations [\(A.1\)](#) and [\(A.4\)](#) solve for the prices (relative to the numéraire) and Domar weights. We assume domestic monetary policy set interest rates at the zero lower bound $(1 + i_n(0)) = 1$. As the intertemporal shifters (ϕ_{ns}) are exogenous, we can use the intertemporal block given by equations [\(9\)](#) and [\(10\)](#), to solve for exchange rates ($\mathcal{E}_n(0)$) and the world interest rate $(1 + i^W(0))$. Finally, we also respect

the downward wage rigidity and labor constraints given in Equations (15), (16) and (17). We use the AMPL/Knitro optimizer to solve for these equations. Since we start by calibrating CES functions with equilibrium prices set to 1, our methodology yields solutions akin to the hat-algebra methodology often used in the trade literature.

B Proofs

Proof of Proposition 1

The rich structure that we introduced in our model can be simplified to capture the first-order effect of shocks on inflation. Here, we will just focus on factors, goods and consumption ignoring the bundling at different levels. The production function in sector ni is given in terms of all other sectors and factors by:

$$Y_{ni} = A_{ni} F_{ni} \left(\{X_{ni,mj}\}_{mj \in \mathcal{S}}, L_{ni}, K_{ni} \right),$$

where F_{ni} is a nested CES function, \mathcal{S} is the set of all country-sector pairs and $X_{ni,mj}$ denotes the amount of output of country-sector mj used by ni . With this, we can write the firm profit maximization problem as:

$$\pi_{ni} = P_{ni} Y_{ni} - \sum_{mj \in \mathcal{S}} P_{mj} X_{ni,mj} - W_{ni} L_{ni} - R_{ni} K_{ni}.$$

Using Shepard's Lemma, the change in prices are related to the price changes of all other sectors and factor price changes with:

$$d \log P_{ni} = -d \log A_{ni} + \sum_{mj \in \mathcal{S}} \frac{P_{mj} X_{ni,mj}}{P_{ni} Y_{ni}} d \log P_{mj} + \frac{W_{ni} L_{ni}}{P_{ni} Y_{ni}} d \log W_{ni} + \frac{R_{ni} K_{ni}}{P_{ni} Y_{ni}} d \log R_{ni}.$$

Recall that:

$$X_{ni,mj} = X_{n,mj} \frac{X_{ni,j}}{X_{n,j}}.$$

At steady state, define the country-sector to country-sector input-output matrix as:

$$\begin{aligned}\Omega_{ni,mj}^{SS} &\equiv \frac{P_{mj}X_{ni,mj}}{P_{ni}Y_{ni}} = \frac{P_{mj}X_{n,mj}}{P_{ni}Y_{ni}} \frac{P_{n,j}X_{ni,j}}{P_{n,j}X_{n,j}} \\ &= \left(\frac{P_{mj}X_{n,mj}}{P_{n,j}X_{n,j}} \right) \left(\frac{P_{n,j}X_{ni,j}}{P_{ni}^Z Z_{ni}} \right) \left(\frac{P_{ni}^Z Z_{ni}}{P_{ni}Y_{ni}} \right) \\ &= \Omega_{n,mj}^X \Omega_{ni,j}^Z \Omega_{ni,Z}^Y.\end{aligned}$$

Similarly, we write the labor and capital shares as:

$$\begin{aligned}\Omega_{ni}^{SF,L} &\equiv \frac{W_{ni}L_{ni}}{P_{ni}Y_{ni}} = \left(\frac{W_{ni}L_{ni}}{P_{ni}^{VA}VA_{ni}} \right) \left(\frac{P_{ni}^{VA}VA_{ni}}{P_{ni}Y_{ni}} \right) = \Omega_{ni,L}^{VA} \Omega_{ni,VA}^Y, \\ \Omega_{ni}^{SF,K} &\equiv \frac{R_{ni}K_{ni}}{P_{ni}Y_{ni}} = \Omega_{ni,K}^{VA} \Omega_{ni,VA}^Y.\end{aligned}$$

Finally, the consumption share of country-sector mj is expressed as:

$$\Omega_{n,mj}^{CS} \equiv \frac{P_{mj}C_{n,mj}}{P_n C_n} = \left(\frac{P_{mj}C_{n,mj}}{P_{n,j}^{CB}C_{n,j}} \right) \left(\frac{P_{n,j}^{CB}C_{n,j}}{P_n C_n} \right) = \Omega_{n,mj}^{CB} \Omega_{n,j}^C.$$

With these definitions, we can write the changes in prices in vector notation with (and combining capital and labor under factors and denoting both their prices with W):

$$d \log P = -d \log A + \Omega^{SS} d \log P + \Omega^{SF} d \log W.$$

We define the Leontief inverse for Ω^{SS} :

$$\Psi^{SS} = [I - \Omega^{SS}]^{-1},$$

we can solve for the price changes in terms of productivity change and factor price changes:

$$d \log P = -\Psi^{SS} d \log A + \Psi^{SS} \Omega^{SF} d \log W.$$

Similarly, the CPI can be written as the weighted average of the good prices with weights $\Omega_{n,mj}^{CS}$.

With this, the CPI can be written as:

$$d \log \text{CPI}_n = \sum_{mj} \Omega_{n,mj}^{CS} d \log P_{mj}^n = d \log \mathcal{E}_n + \Omega_n^{CS} d \log P,$$

where Ω_n^{CS} is the n^{th} row of the Ω^{CS} matrix, P_{mj}^n is the price of good mj in country n 's local currency and \mathcal{E}_n is the exchange rate in country n vis-à-vis the global currency. Combining with the price change equation, we can write the CPI change as:

$$d \log \text{CPI}_n = d \log \mathcal{E}_n - \Omega_n^{CS} \Psi^{SS} d \log A + \Omega_n^{CS} \Psi^{SS} \Omega^{SF} d \log W.$$

Let's define the country-specific Domar weight for the labor:

$$(\Lambda^n)^T \equiv \Omega_n^{CS} \Psi^{SS} \Omega^{SF}$$

as the share of expenditures of country n that ends up in the owners of factor f . Since the factors are where all the payments are accumulated, sum over these Domar weights equal to 1:

$$\sum_f \Lambda_f^n = (\Lambda^n)^T \mathbf{1}_F = 1,$$

where $\mathbf{1}_F$ is a column vector of ones of size F . Similarly, we can define the country-specific sector Domar-weights as:

$$(\lambda_n)^T = \Omega_n^{CS} \Psi^{SS}.$$

Hence, the CPI can be written as:

$$d \log \text{CPI}_n = d \log \mathcal{E}_n - (\lambda_n)^T d \log A + (\Lambda^n)^T d \log W.$$

The Global factor Domar weights are given by:

$$\Lambda_f = \frac{W_f L_f}{E},$$

where E is the total global expenditure. Therefore:

$$d \log W_f = d \log \Lambda_f - d \log L_f + d \log E.$$

We choose $E = 1$ to be our numeraire, hence $d \log E = 0$. With these, we can write the CPI as:

$$\begin{aligned} d \log \text{CPI}_n &= d \log \mathcal{E}_n - (\lambda_n)^T d \log A + (\Lambda^n)^T d \log \Lambda - (\Lambda^n)^T d \log L + \underbrace{(\Lambda^n)^T \mathbf{1}_{\mathcal{F}}}_{=1} d \log E \\ &= d \log \mathcal{E}_n - (\lambda_n)^T d \log A - (\Lambda^n)^T d \log L + (\Lambda^n)^T d \log \Lambda. \end{aligned}$$

□

C Additional Tables

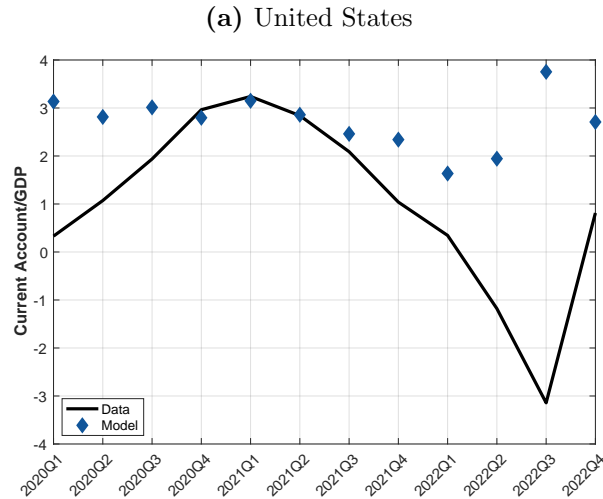
Table C.1. Sector-level Labor Shares

	Euro Area	United States	Russia	China+
Durables	0.61	0.57	0.84	0.44
Non-Durables	0.58	0.49	0.58	0.55
Services	0.54	0.59	0.72	0.68
Energy	0.32	0.15	0.17	0.49

Note: This table shows the share of value-added that accrued to labor. Value added is compensation to employees (labor) plus gross operating surplus (capital). Data for the Euro Area, United States and China+ comes from the Structural Analysis Database (STAN) year 2018. For Russia, we use information from the Socioeconomic Accounts available from the World Input-Output tables.

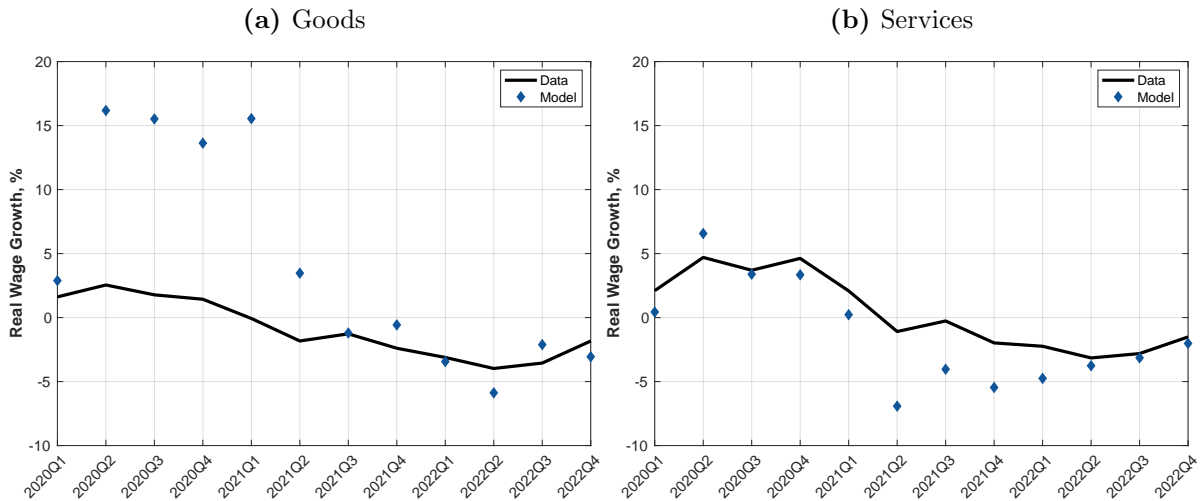
D Additional Figures

Figure D.2. Euro Area Current Account-to-GDP Ratio: Model vs. Data



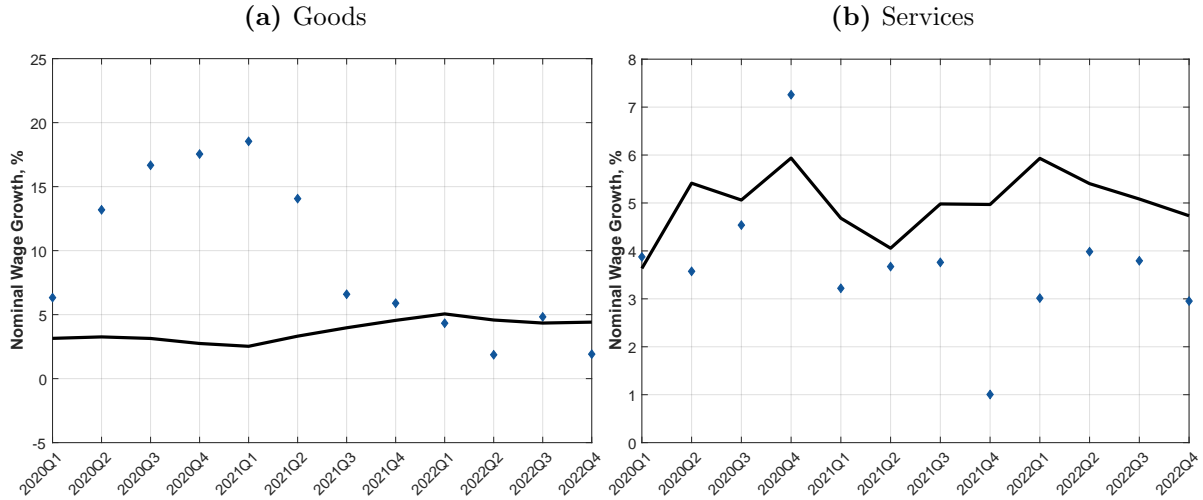
Note: This figure shows the current account-to-GDP ratio implied by the baseline model (blue solid line). We also plot the current account-to-GDP ratio as in the data (black solid line) for comparison.

Figure D.3. Sector-Specific Real Wages Growth: Sectoral wages deflated by aggregate price



Note: This figure shows sector-specific real wage growth. Black lines represent the data, while blue diamond represents the model. We compute real wages by deflating nominal wages in that sector by the aggregate price. All numbers are year-on-year growth, and each panel shows the real wage for a different sector. In the model, we aggregate nominal wage growth across the durables, non-durables, and energy sectors to construct nominal wage growth in the goods sector. We subtract overall inflation from this number to construct real wage growth. We source sector-level nominal wages from the Bureau of Labor Statistics average hourly earnings series with codes: CES0600000003 (goods) and CES0800000003 (services). Aggregate price corresponds to code CPIAUCSL (headline CPI).

Figure D.4. Sector-level Nominal Wage Growth United States



Note: This figure shows nominal wage growth (year on year) implied by the baseline model (blue diamonds) relative to the data (black lines).

E Disaggregating Sectors

In our baseline model, we have four sectors, namely non-durables, durables, services, and energy. The reason behind this choice is the data availability. On the other hand, for the Euro Area and the United States, we have more information at the detailed industry levels. Hence, as a robustness, we use a hybrid version of sectors, where we have 44 sectors for the US and the Euro Area but keep 4 sectors for the rest of the countries. As shown in Table E.2, since each detailed sector maps to a single aggregate sector, we can still use the CES structure we develop in Section 2, albeit with different levels of sectoral bundles present in different countries. In particular, sectoral intermediate and consumption bundles are also at 44 sector levels in the United States and the Euro Area but at the four sector level for the rest.

Figure E.6 shows the result when feeding in all shocks with this more disaggregated structure. The blue diamonds correspond to our earlier results, while the pink diamonds correspond to the results of the disaggregated model. This exercise gauges the role of sectoral heterogeneity in understanding the recent inflationary period. Overall, the disaggregated model does no worse than the aggregated model; if anything, it does better.

Figure D.5. Sector-level Prices United States: Decomposition



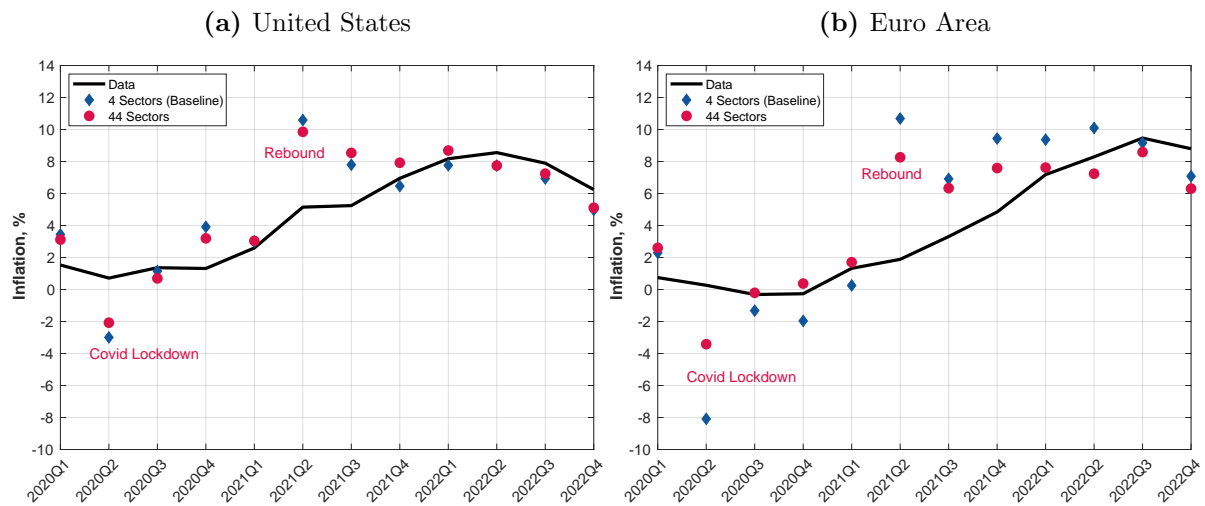
Note: This figure shows annual inflation at the sectoral level.

Table E.2. Aggregate and Detailed Sectors

Detailed	Detailed Sector	Aggregate	Aggregate Sector
1	Agriculture, hunting, forestry	3	Services
2	Fishing and aquaculture	3	Services
3	Mining and quarrying, energy producing products	4	Energy
4	Mining and quarrying, non-energy producing products	2	Non durable
5	Mining support service activities	2	Non durable
6	Food products, beverages and tobacco	2	Non durable
7	Textiles, textile products, leather and footwear	2	Non durable
8	Wood and products of wood and cork	2	Non durable
9	Paper products and printing	2	Non durable
10	Coke and refined petroleum products	4	Energy
11	Chemical and chemical products	2	Non durable
12	Pharmaceuticals, medicinal chemical and botanical products	2	Non durable
13	Rubber and plastics products	2	Non durable
14	Other non-metallic mineral products	2	Non durable
15	Basic metals	2	Non durable
16	Fabricated metal products	2	Non durable
17	Computer, electronic and optical equipment	1	Durable
18	Electrical equipment	1	Durable
19	Machinery and equipment, nec	1	Durable
20	Motor vehicles, trailers and semi-trailers	1	Durable
21	Other transport equipment	1	Durable
22	Manufacturing nec; repair and installation of machinery and equipment	1	Durable
23	Electricity, gas, steam and air conditioning supply	3	Services
24	Water supply; sewerage, waste management and remediation activities	3	Services
25	Construction	3	Services
26	Wholesale and retail trade; repair of motor vehicles	3	Services
27	Land transport and transport via pipelines	3	Services
28	Water transport	3	Services
29	Air transport	3	Services
30	Warehousing and support activities for transportation	3	Services
31	Postal and courier activities	3	Services
32	Accommodation and food service activities	3	Services
33	Publishing, audiovisual and broadcasting activities	3	Services
34	Telecommunications	3	Services
35	IT and other information services	3	Services
36	Financial and insurance activities	3	Services
37	Real estate activities	3	Services
38	Professional, scientific and technical activities	3	Services
39	Administrative and support services	3	Services
40	Public administration and defence; compulsory social security	3	Services
41	Education	3	Services
42	Human health and social work activities	3	Services
43	Arts, entertainment and recreation	3	Services
44	Other service activities	3	Services

Note: This table shows the mapping between the aggregate and detailed sectors. Detailed sectors correspond to the sectors present in ICIO with one difference: We merge the sector "Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use" with the "Other service activities."

Figure E.6. United States and Euro Area Inflation Rates: The Role of Disaggregation



Note: This figure shows annual inflation implied by the aggregate model (blue diamonds) and the disaggregated model (pink dots) relative to the headline CPI inflation in the data (black solid line) when feeding the model with all shocks. Recall that the pink diamonds show implied inflation by the model using the version with 44 sectors for the US and Euro Area. As before, 2020Q2 highlights the Covid lockdown period, while 2021Q2 highlights a “base effect” that exist in macroeconomic time series, as economic activity had a huge rebound relative to the Covid lockdown phase once the economy reopened.