Inflation Dynamics in Production Networks*

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Abstract

This study empirically examines the differences in inflation dynamics between the US and Japan. Using a structural model of sectoral inflation, we quantify the roles of production networks, price stickiness, and structural shocks in driving these variations. Our partial equilibrium framework captures sectoral inflation as a tractable form, enabling us to estimate the model and analytically explore the channels through which pass-through to inflation operates. The model can generate inflation persistence across sectors through production networks, further reinforced by price stickiness within each sector. The full-information Bayesian estimation results reveal that impulse response functions to sectoral shocks are similar between the two countries but that differences in inflation dynamics arise from two factors: the different sources of specific sectoral inflation, particularly in an energy-related sector, and contrasting price-setting behaviors. US firms tend to change prices in the same direction as import price shocks, leading to higher pass-through, whereas Japanese firms are inclined to set prices to absorb import price shocks. Policy experiments based on the estimated model demonstrate that a 10% increase in tariffs results in a 0.6–1.2% rise in US producer price inflation.

JEL Classification: E3

Keywords: Inflation dynamics; production networks; input-output linkages; price stickiness

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1 Introduction

A significant wave of inflation impacted the global economy following the COVID-19 pandemic around 2021. However, the level and variability of inflation differed substantially across countries and their respective underlying causes. Figure 1 compares the inflation rates in the producer price index (PPI) for domestically produced goods and services, the import price index (IPI), and the wage index between the US and Japan. The figure highlights that the US economy experienced substantial increases in PPI inflation, nearly matching the extent of IPI inflation, indicating a high degree of import price pass-through to domestic inflation. In 2022, the PPI rose even further relative to the IPI. In contrast, Japan's inflation dynamics exhibit markedly larger differences between the PPI and the IPI, reflecting a lower degree of import price pass-through to domestic inflation. Consequently, fluctuations in PPI inflation remained relatively modest in Japan. Why do the two economies experience such different inflation dynamics?

The objective of this study is to explore and provide a comprehensive explanation for why the pass-through of underlying shocks to inflation differs between the US and Japan. To this end, we identify and quantify the factors driving these differences by estimating a structural model for sectoral inflation in each country. This analysis allows us to empirically examine several potential explanations, including variations in production network structures, differences in the degree of price stickiness across sectors, and the nature and impact of underlying structural shocks. Addressing these dimensions requires both tractability in modeling sectoral inflation dynamics and compatibility in sectoral structures across the two economies.

More specifically, we construct a partial-equilibrium model for sectoral inflation that incorporates production networks via exogenous input-output (I-O) linkages and price stickiness. A notable contribution here is that the model delivers an equilibrium law of motion for sectoral inflation, expressed as a vector autoregressive moving-average (VARMA) process consisting of a set of state variables and structural shocks. This tractable equilibrium representation enables the estimation of the model with numerous parameters and facilitates analytical exploration of the channels through which inflation pass-through operates. We show that interdependence in production networks generates greater inflation persistence. In our partial-equilibrium setting, sectoral import prices and wages are exogenous and follow AR(1) processes. This partial-equilibrium model, rather than a general equilibrium model, is suitable for our empirical analysis because these exogenous processes for import prices and wages are fully identified from the corresponding sectoral data. Moreover, our partial-equilibrium approach can help mitigate potential issues arising from the system estimation of a general equilibrium model where import prices and wages are endogenized but possibly misspecified.

We estimate the model while explicitly accounting for production networks. Using Bayesian techniques, particularly the Sequential Monte Carlo method, we estimate parameters associated with price stickiness across multiple sectors as well as structural shocks driving sectoral inflation fluctuations, given the I-O linkage parameters. Based on the estimated model, we investigate

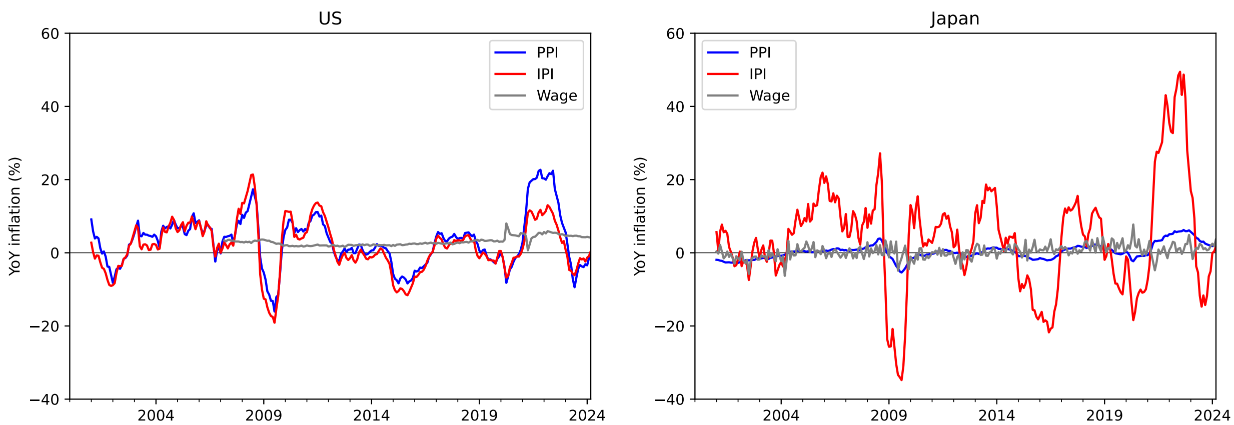


Figure 1: Comparison of Inflation Rates in Producer Prices, Import Prices, and Wages between the US and Japan

Notes: This figure compares the year-over-year inflation rates in the producer price index for domestically produced goods and services (PPI, blue), the import price index (IPI, red), and the wage index (gray) between the US and Japan. See Appendix C.1 for details on the data sources.

differences in impulse responses to various shocks and conduct variance decomposition of shocks for the US and Japanese economies. We also conduct a quantitative assessment of how specific shocks—such as tariff changes proposed by the Trump Administration—propagate through the production network. Our multi-sector framework allows us to simulate increases in tariffs on particular products by adding shocks to import prices in the corresponding sectors.

To ensure compatibility in our cross-country analysis, we construct a new dataset that standardizes sectoral classification into 12 main categories for both the US and Japan. Off-the-shelf sectoral data are not suitable for international comparison because the definition of sectors and product categories varies across the two economies. We assemble monthly time series for producer prices, import prices, and wages that are consistent with the sectoral classification, using more disaggregated data from January 2000 to April 2022. This dataset enables a precise comparison of inflation dynamics between the US and Japan while preserving consistency with highly disaggregated sectoral data.[1]

Our main findings are fourfold. First, according to the equilibrium law of motion for sectoral inflation, interconnections within production networks generate cross-sectoral inflation persistence, where inflation in one sector depends on the inflation rates of other sectors from the preceding period. Moreover, an increase in price stickiness in one sector amplifies cross-sectoral inflation persistence in other sectors.

Second, the estimated model reveals that impulse response functions (IRFs) of aggregate inflation to productivity and wage shocks are surprisingly similar between the US and Japan. Although I-O linkages and estimated parameters, such as price stickiness and shock persistence, differ across the two economies, these differences do not account for the variation in the pass-through of these

[1] We plan to make these data available to other researchers through our companion website.

shocks to inflation. In contrast, the IRFs to import price shocks differ between the two countries, highlighting a larger propagation of these shocks to aggregate inflation in Japan compared to the US. However, this result contrasts with our motivating observation (Figure 1) that Japan experienced milder changes in PPI inflation than the US.

Third, two key factors can account for the observed difference in inflation dynamics between the US and Japan. One is the difference in the sources of sectoral inflation in the two countries. In the US, fluctuations in energy prices—such as oil and natural gas—are largely driven by productivity shocks, which act as domestic cost factors, because the US not only imports but also produces these resources domestically. In contrast, energy price changes in Japan are predominantly driven by import price shocks, as nearly 100% of Japan's natural resources are imported. As a result, even if IRFs are conditionally similar, differences in the underlying shocks lead to divergent inflation dynamics between the two countries.

Another key factor is the difference in price-setting behavior between the US and Japan. A historical decomposition of both aggregate and sectoral inflation exhibits distinct patterns. In the US, the contributions of productivity shocks and import price shocks generally move in the same direction. In Japan, these shocks often contribute in the opposite direction. This contrast suggests that US firms tend to pass import price shocks onto consumers, sometimes even exceeding full pass-through, whereas Japanese firms are more inclined to adjust their prices to absorb import price shocks.

Finally, our quantitative assessment of the tariff increases announced by President Trump indicates a sizable impact on US inflation. In particular, the estimated model suggests that a 10% increase in tariffs leads to a 0.6–1.2% rise in the US PPI inflation rate, depending on the sectors subject to the additional tariffs.

Existing studies on inflation dynamics under production networks fall into two categories: either theoretical studies without estimation (e.g., Rubbo, 2023; Afrouzi and Bhattarai, 2023) or empirics with the estimation of reduced-form or general equilibrium models (e.g., Ahn, Park, and Park, 2017; Smets, Tielens, and Hove, 2018; Chin and Lin, 2023).

On a theoretical front, this study is closely related to Rubbo (2023) and Afrouzi and Bhattarai (2023).[2] Rubbo (2023) examines optimal monetary policy in an environment with production networks and introduces the concept of a divine coincidence price index as a policy benchmark. In a similar spirit, Aoki (2001), La'O and Tahbaz-Salehi (2022), and Qiu, Wang, Xu, and Zanetti (2025) explore optimal monetary policy in multi-sector settings under sticky prices or incomplete information. Afrouzi and Bhattarai (2023) analytically derive an equilibrium representation for inflation and GDP in a multi-sector New Keynesian model, offering sufficient statistics for them. Compared to these studies, this paper makes a novel contribution by deriving a tractable equilibrium

[2] Seminal theoretical studies on the effects of production networks on the aggregate economy include Hulten (1978), Long and Plosser (1983), Foerster, Sarte, and Watson (2011), Sudo (2012), Acemoglu, Akcigit, and Kerr (2016), Baqaee and Farhi (2019, 2020), and Rojas-Bernal (2023). In the context of price stickiness and aggregate inflation dynamics, important contributions have been made by Basu (1995), Carvalho (2006), and Nakamura and Steinsson (2010). For a comprehensive survey on these topics, see Carvalho and Tahbaz-Salehi (2019).

solution for sectoral inflation, represented as a VARMA process. While Afrouzi and Bhattarai (2023) claim their sufficient statistics approach provides a closed-form solution for inflation and GDP, their framework still relies on integrals over past and future variables. Our partial-equilibrium framework delivers a simpler equilibrium representation, in contrast to the general-equilibrium frameworks employed in those studies.

Several theoretical studies provide insights into the quantitative significance of production networks in shaping inflation dynamics. For instance, Pasten, Schoenle, and Weber (2020) develop and simulate a DSGE model with 341 sectors, relying on calibration to explore mechanisms of the propagation of inflation across sectors. Their subsequent work, Pastén, Schoenle, and Weber (2024), employs a similar methodology. Similarly, Hasui and Kobayashi (2023) quantify the effects of cost-push shocks within production networks, given calibrated parameters. di Giovanni, Şebnem Kalemli-Özcan, Silva, and Yıldırım (2023) and Amiti, Heise, Karahan, and Şahin (2024) examine the causes of the post-COVID-19 inflation surge. While their motivation aligns with ours and they approach the issue from various angles, a key difference is that we estimate the model parameters from data, rather than relying on calibration.

Conventional empirical studies on inflation in multi-sector settings typically employ reduced-form estimation methods, such as VAR models or panel data approaches. Notable examples include Ahn, Park, and Park (2017), Forbes, Hjortsoe, and Nenova (2020), and Chin and Lin (2023). For Japan, relevant studies include Shioji and Uchino (2011) and Nakamura, Nakano, Osada, and Yamamoto (2024). Additionally, global linkages in inflation spillovers have been analyzed by Auer, Levchenko, and Sauré (2019). In a general equilibrium framework, Bouakez, Cardia, and Ruge-Murcia (2009, 2014) estimate two types of multi-sector models with 6 and 30 sectors, respectively, using the simulated method of moments. Their approach involves estimating 60 parameters from 86 moments, primarily related to variances and autocovariances. While they employ the simulated method of moments for estimation, we utilize likelihood-based Bayesian techniques. Smets, Tielens, and Hove (2018) conduct a Bayesian estimation of a general equilibrium model with seven sectors. Meanwhile, Ruge-Murcia and Wolman (2022) estimate a 15-sector model using maximum likelihood estimation, although their framework does not explicitly incorporate I-O linkages.

The remainder of this paper is organized as follows. Section 2 lays out our analytical framework. Section 3 describes how we construct our datasets for both the US and Japan and explains our estimation methods. Section 4 presents empirical findings. Finally, Section 5 concludes.

2 The Model

In this section, we develop a structural model of sectoral inflation incorporating production networks. This model is built upon a partial equilibrium framework of monopolistic firms producing differentiated intermediate goods. Each firm uses a diverse array of intermediate goods and imported goods from various sectors, and labor as inputs, and sets its own price in the face of Rotemberg-type price adjustment costs. We treat the sectoral I-O linkages, import prices, and wages as exogenously given, which enables us to derive an equilibrium law of motion for sectoral and aggregate inflation in a tractable form. Appendix A provides the complete set of equilibrium conditions along with their derivation.

2.1 Setup

The model includes N intermediate-goods sectors, each of which is indexed by i. Within each sector i, a continuum of firms, indexed by $f \in [0,1]$, produces each intermediate good Y_{ift} using N domestically-produced intermediate goods, M imported goods ($M \leq N$), and labor.

Sectoral output Y_{it} is aggregated as

$$Y_{it} = \left(\int_0^1 Y_{ift}^{\frac{\sigma_i - 1}{\sigma_i}} df \right)^{\frac{\sigma_i}{\sigma_i - 1}},$$

where σ_i denotes the elasticity of substitution among differentiated goods within sector i. Aggregate output is given by

$$Y_t = \left(\sum_i^N \left(\frac{A_i}{N} \right)^{\frac{1}{\theta}} Y_{it}^{\frac{\theta - 1}{\theta}} \right)^{\frac{\theta}{\theta - 1}},$$

where A_i is a parameter associated with a weight for sector i, and θ measures the elasticity of substitution across sectors. We normalize $\{A_i\}_{i=1}^N$ so that $\sum_i^N (A_i/N) = 1$. Subject to these aggregators, the optimal allocation of Y_{ift} and Y_{it} leads to the demand curve for each individual good:

$$Y_{ift} = (A_i/N)\,(P_{it}/P_t)^{-\theta}\,(P_{ift}/P_{it})^{-\sigma_i}\,Y_t, \tag{1}$$

where sectoral and aggregate price indices are given by:

$$P_{it} = \left(\int_0^1 P_{ift}^{1-\sigma_i} df \right)^{\frac{1}{1-\sigma_i}}, \tag{2}$$

$$P_t = \left(\sum_i^N \frac{A_i}{N} P_{it}^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{3}$$

respectively.

In the presence of Rotemberg-type price adjustment costs, each firm f in sector i maximizes its value:

$$V_{ift} = \mathbb{E}_t \left[\sum_{k=0}^{\infty} \Lambda_{t,t+k} \left\{ \frac{P_{ift+k}}{P_{t+k}} - RMC_{ift+k} - \frac{\kappa_i}{2} \left(\frac{P_{ift+k}}{P_{ift+k-1}} - 1 \right)^2 \right\} Y_{ift+k} \right],$$

where RMC_{ift} represents firm-specific real marginal cost, subject to the downward-sloping demand curve (1). For simplicity, we assume zero trend inflation to focus on fluctuations around the trend.[3] Log-linearizing the first-order condition with respect to reset price P_{ift} under the symmetric

[3] While our analysis could be extended to incorporate non-zero trend inflation, it would require that trend inflation be common across sectors.

equilibrium (dropping subscript f) yields the sector-level Phillips curve of the following form:

$$\pi_{it} = \frac{\sigma_i}{\kappa_i}\widetilde{RMC}_{it} + \beta \mathbb{E}_t \pi_{it+1}, \tag{4}$$

where $\pi_{it} \equiv P_{it}/P_{it-1} - 1$ and $\widetilde{RMC}_{it} \equiv RMC_{it} - (\sigma_i - 1)p_{it}/\sigma_i$ with $p_{it} \equiv P_{it}/P_t$ being the relative price.

At the sectoral level, the production function takes the following Cobb–Douglas form:

$$Y_{it} = e^{\varepsilon_{it}} \left(\prod_{j=1}^{N} Y_{ijt}^{\omega_{ij}}\right) \cdot \left(\prod_{m=1}^{M} Y_{imt}^{\omega_{im}}\right) \cdot L_{it}^{\omega_{iw}}, \tag{5}$$

where Y_{imt} denotes imported input from sector m, L_{it} is labor input to sector i, and ε_{it} is a productivity shock in sector i.[4] Parameters ω_{ij}, ω_{im}, and ω_{iw} represent weights for each input, satisfying constant returns to scale: $\Sigma_j \omega_{ij} + \Sigma_m \omega_{im} + \omega_{iw} = 1$. These weights are obtained from the I-O tables that we describe in Section 3.1. Then, cost minimization yields the expression for real marginal cost:

$$RMC_{it} = \prod_{j=1}^{N} \left(\frac{P_{jt}}{\omega_{ij} P_t}\right)^{\omega_{ij}} \cdot \prod_{m=1}^{M} \left(\frac{P_{mt}^*}{\omega_{im} P_t}\right)^{\omega_{im}} \cdot \left(\frac{W_{it}}{\omega_{iw} P_t}\right)^{\omega_{iw}} \cdot e^{-\varepsilon_{it}},$$

where RMC_{it} is real marginal cost in sector i, P_{mt}^* is import price in sector m, and W_{it} is wage in sector i.

The sector-specific productivity shocks ε_{it}, import prices P_{mt}^*, and wages W_{it} are exogenous and follow the stochastic AR(1) processes:

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \mu_{it}, \qquad \mu_{it} \sim \text{i.i.d. } N(0, \sigma_i^2), \tag{6}$$

$$\widehat{P}_{mt}^* = \rho_m^* \widehat{P}_{mt-1}^* + \mu_{mt}^*, \qquad \mu_{mt}^* \sim \text{i.i.d. } N(0, \sigma_m^{*2}), \tag{7}$$

$$\widehat{W}_{it} = \rho_i^w \widehat{W}_{it-1} + \mu_{it}^w, \qquad \mu_{it}^w \sim \text{i.i.d. } N(0, \sigma_i^{w2}), \tag{8}$$

where hatted variables represent log deviations from their steady state or trend levels, and ρ_i, ρ_m^*, and ρ_i^w are the persistence parameters. For model estimation, the disturbances μ_{it}, μ_{mt}^*, and μ_{it}^w are assumed to be mutually and serially uncorrelated.

Underlying common global factors, such as exchange rates and oil prices, are likely to cause these shocks to be correlated with others. Indeed, as shown in Section 4.6, the smoothed estimates of these shocks can be correlated *ex post*, given the data used for estimation and the estimated model parameters. However, incorporating such correlations into the model is quite challenging, as it requires properly identifying both global and sector-specific shocks by imposing additional cross-equation restrictions, which are somewhat judgmental and potentially subject to misspecification

[4] In this production function, sector i goods are used to produce sector i goods, implying that that firms in sector i produce output using inputs aggregated at the sector level. Therefore, the sector-level input aggregation is exogenous to each individual firm.

issues. Therefore, we adopt an agnostic approach to estimate the model with only mild restrictions.

As shown in the following subsection, assuming the exogenous AR(1) processes for import prices P^*_{mt} and wages W_{it} enables us to derive an equilibrium law of motion for sectoral and aggregate inflation in a tractable form. Moreover, this assumption is suitable for our empirical analysis because these exogenous processes for import prices and wages are fully pinned down by the corresponding sectoral data. This identification strategy can help mitigate potential issues arising from the system estimation of a general equilibrium model where import prices and wages are determined endogenously but possibly misspecified.

Nonetheless, our approach and estimation results should be interpreted with caution, particularly because of the partial equilibrium nature of the framework. Aggregate factors, such as monetary policy, may play a key role in explaining differences in inflation dynamics between the US and Japan. That said, monetary policy in Japan was constrained by the effective lower bound for an extended period, limiting its influence and potentially amplifying inflation volatility. Interestingly, the patterns observed in Figure 1 appear inconsistent with this narrative. While this observation does not justify disregarding general equilibrium considerations altogether, as incorporated in Bouakez, Cardia, and Ruge-Murcia (2009, 2014), Smets, Tielens, and Hove (2018), and Ruge-Murcia and Wolman (2022), we adopt a partial-equilibrium framework for the reasons outlined above.

2.2 Inflation Dynamics

Let $\pi^*_{mt} \equiv \widehat{P}^*_{mt} - \widehat{P}^*_{mt-1}$ and $\pi^w_{it} \equiv \widehat{W}_{it} - \widehat{W}_{it-1}$. Then, given the definition of vectors and matrices summarized in Table 1, we can derive the following equilibrium law of motion for sectoral inflation.

Proposition 1 *An N by 1 vector of sectoral inflation, $\mathbf{\Pi}_t$, is given by*

$$\mathbf{\Pi}_t = -\mathbf{G}\left(\mathbf{e}_t - \mathbf{e}_{t-1}\right) + \mathbf{G}^*\mathbf{\Pi}^*_t + \mathbf{G_w}\mathbf{\Pi}^w_t + \mathbf{G_L}\mathbf{\Pi}_{t-1} \tag{9}$$

where coefficient matrices $\mathbf{G_L}$, $\mathbf{G}$, $\mathbf{G}^*$, and $\mathbf{G_w}$ are determined by

$$(1+\beta)\mathbf{G_L} = \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G_L} + \mathbf{I} \tag{10}$$

and

$$\mathbf{G} = -\beta\mathbf{G}(\mathbf{I}-\mathbf{P}) + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G} + \mathbf{K} \tag{11}$$

$$\mathbf{G}^* = -\beta\mathbf{G}^*(\mathbf{I}-\mathbf{P}^*) + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G}^* + \mathbf{K}\Omega^* \tag{12}$$

$$\mathbf{G_w} = -\beta(\mathbf{I}-\mathbf{P_w})\mathbf{G_w} + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G_w} + \mathbf{K\Omega_w}. \tag{13}$$

Appendix A contains the proof for this proposition.

According to equation (9), sectoral inflation dynamics is governed by a tractable VARMA process, which consists of the minimum state variables: sectoral productivity shocks in the previous

Table 1: Definition of Vectors and Matrices

	Dimension	Element	Attribute
$\mathbf{\Pi}_t$	$N \times 1$	i-th element: π_{it}	Observables
$\mathbf{\Pi}_t^*$	$M \times 1$	m-th element: π_{mt}^*	Observables
$\mathbf{\Pi}_t^w$	$N \times 1$	i-th element: π_{it}^w	Observables
$\mathbf{e}_t$	$N \times 1$	i-th element: ε_{it}	Unobservables
$\mathbf{G}$	$N \times N$	Element (i,j): Γ_{ij}	Coefficient matrix
$\mathbf{G}^*$	$N \times M$	Element (i,m): Γ_{im}^*	Coefficient matrix
$\mathbf{G}_w$	$N \times N$	Element (i,j): Γ_{ij}^w	Coefficient matrix
$\mathbf{G}_L$	$N \times N$	Element (i,j): Γ_{ij}^L	Coefficient matrix
$\mathbf{K}$	Diagonal $N \times N$	Element (i,i): $(\sigma_i - 1)/\kappa_i$	Estimated
$\mathbf{P}$	Diagonal $N \times N$	Element (i,i): ρ_j	Estimated
$\mathbf{P}^*$	Diagonal $M \times M$	Element (m,m): ρ_m^*	Estimated
$\mathbf{P}_w$	Diagonal $N \times N$	Element (i,i): ρ_i^w	Estimated
$\mathbf{\Omega}$	$N \times N$	Element (i,j): $\omega_{ii} - 1$ for $j = i$; ω_{ij} for $j \neq i$	Set from I-O tables
$\mathbf{\Omega}^*$	$N \times M$	Element (i,m): ω_{im}	Set from I-O tables
$\mathbf{\Omega}_w$	Diagonal $N \times N$	Element (i,i): ω_{iw}	Set from I-O tables

and current periods, import price shocks, wage shocks, and inflation in the previous period. Although the coefficient matrix $\mathbf{G_L}$ is not available in closed form due to its quadratic nature, the three other coefficient matrices $\mathbf{G}$, $\mathbf{G}^*$, and $\mathbf{G_w}$ can readily be obtained in a linear form once $\mathbf{G_L}$ is determined.

Our equilibrium representation is useful for estimation purposes. It is straightforward to rewrite the VARMA representation (9) into a state-space form, so that we can evaluate the likelihood function using the Kalman filter because of its linear structure and the normality of shocks. This enables us to estimate model parameters such as price stickiness $\mathbf{K}$, persistence $\mathbf{P}$, $\mathbf{P}^*$, and $\mathbf{P}_w$, and the standard deviation of shocks, given the known I-O linkages represented by $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$.

In the model, the pass-through of underlying shocks to inflation is explicitly defined by the coefficient matrices $\mathbf{G}$, $\mathbf{G}^*$, and $\mathbf{G_w}$, which represent the pass-through of productivity, import price, and wage shocks, respectively. While the concept of pass-through is often used ambiguously, this model offers a precise definition as the response of inflation to these structural shocks. Moreover, the model allows us to quantify the degree of pass-through relative to the benchmark of 100% pass-through. Our model inherently predicts a pass-through below 100% due to two key factors: price stickiness ($\kappa_i > 0$) and I-O linkages ($\omega_{ij} < 1$).

Inflation Persistence The coefficient matrix $\mathbf{G_L}$ captures the degree of inflation persistence. From equation (10), $\mathbf{G_L}$ can be determined as a fixed point of the following equation:

$$\mathbf{G_L} = ((1+\beta)\mathbf{I} - \mathbf{K\Omega})^{-1} \left(\mathbf{I} + \beta \mathbf{G_L}^2\right).$$

When production networks are interconnected (i.e., $\omega_{ij} > 0$), $\mathbf{G_L}$ becomes non-diagonal. That is, inflation persistence in each sector is influenced by that in other sectors. Note that the diagonal elements of $\mathbf{\Omega}$ are negative because $\omega_{ii} - 1 < 0$. Thus, as price becomes flexible (i.e., κ_i decreases), the components of $\mathbf{K}$, i.e., $(\sigma_i - 1)/\kappa_i$, increase, and thereby the eigenvalues of $\mathbf{G_L}$ decrease toward zero, implying a decrease in inflation persistence.[5]

Special Case of Two Sectors (N = 2) In a special case of two sectors, we can obtain the following analytical property for $\mathbf{G_L}$. Appendix B provides the proofs for the following lemmas.

Lemma 1 *Suppose two sectors $N = 2$ and denote $\mathbf{G_L} \equiv \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}$. Then:*

(i) an increase in ω_{12} from zero induces a positive g_{12} and increases g_{11}.

(ii) an increase in κ_2 if combined with $\omega_{12} > 0$ increases g_{22} and g_{12}, while it decreases g_{11}.

This lemma implies the following: (i) Interconnected production networks, particularly in the upstream stage characterized by $\omega_{12} > 0$ (i.e. sector 1 uses goods produced in sector 2), make inflation in sector 1 dependent on inflation in sector 2 ($g_{12} > 0$). Additionally, they amplify the dependence of inflation in sector 1 on its own sector (g_{11}). (ii) An increase in price stickiness in sector 2 (κ_2) leads to a direct increase in its own inflation persistence (g_{22}) and, through a pass-through effect, an increase in cross-sector inflation persistence (g_{12}). However, inflation persistence in sector 1 (g_{11}) of its own decreases, driven by a reduction in cross-sector inflation persistence (g_{21}).

The degree of inflation persistence is more clearly given by the eigenvalues of $\mathbf{G_L}$. Denoting the eigenvalues as λ_1 and λ_2, we have the following lemma.

Lemma 2 *If the non-diagonal elements of $\mathbf{G_L}$, both g_{12} and g_{21}, are zero, then $\lambda_1 = g_{11}$ and $\lambda_2 = g_{12}$. Suppose $g_{11} \geq g_{12} \geq 0$. Then, a small increase in g_{12} and g_{21} from zero (given g_{11} and g_{22}) increases λ_1 from g_{11}, while decreasing λ_2 from g_{22}.*

This lemma suggests that the two eigenvalues can be isolated from each other by the non-diagonal elements of $\mathbf{G_L}$. This property has significant implications for aggregate inflation dynamics. Specifically, aggregate inflation persistence is predominantly determined by the sector with the highest price stickiness, as argued by Aoki (2001) and Carvalho (2006).

2.3 Aggregate Inflation

From the sequences of sectoral inflation $\mathbf{\Pi}_t$, we can characterize aggregate inflation dynamics. Aggregate inflation π_t is given by

$$\pi_t = \mathbf{A}\mathbf{\Pi}_t, \tag{14}$$

[5]While we derive the equilibrium representation (9) for sectoral inflation $\mathbf{\Pi}_t \equiv \mathbf{P}_t - \mathbf{P}_{t-1}$, we could also obtain one for the corresponding sectoral price levels $\mathbf{P}_t$ as a solution to the sector-level Phillips curves given by equation (4). In that case, $\mathbf{G_L}$ would capture price-level persistence rather than inflation persistence. Furthermore, estimating the equilibrium law of motion (9) for sectoral inflation might encounter issues related to over-differencing. Over-differencing could lead to a loss of information in the time series data and, consequently, biased parameter estimates—especially when the original system contains cointegration relationships. However, our model avoids these issues because all the model variables are expressed as deviations from their steady states or trend levels. Therefore, using inflation rates instead of price levels for estimation does not cause any biases due to over-differencing.

where $\mathbf{A}$ is a 1 by N vector, with each element being a weight for each sector. In the subsequent analysis, we mainly use the total output shares reported in Table 2 as the aggregation weights.[6]

Combining this expression with Equation (9), the equilibrium law of motion for aggregate inflation is expressed as

$$\pi_t = -\mathbf{AG}\left(\mathbf{e}_t - \mathbf{e}_{t-1}\right) + \mathbf{AG}^*\mathbf{\Pi}_t^* + \mathbf{AG}_\mathbf{w}\mathbf{\Pi}_t^w + \mathbf{AG}_\mathbf{L}\mathbf{\Pi}_{t-1}. \tag{15}$$

We focus on the coefficient matrix regarding inflation persistence, represented by $\mathbf{AG_L}$. Suppose that $\mathbf{G_L}$ has full rank (rank $= N$). Let $\mathbf{P}$ and $\mathbf{\Lambda}$ denote the matrix of unit eigenvectors and the diagonal matrix of eigenvalues (λ_i), respectively, for $\mathbf{G_L}$, such that $\mathbf{PG_L} = \mathbf{\Lambda P}$. Define $\mathbf{W} \equiv \mathbf{AP}^{-1}$, where $\mathbf{W}$ is a $1 \times N$ vector representing weights in terms of eigenvectors. Then, we can write $\mathbf{AG_L}$ $= (\mathbf{WP})(\mathbf{P}^{-1}\mathbf{\Lambda P}) = \mathbf{W\Lambda P}$. A special case arises when $\mathbf{A}$ corresponds to one of the eigenvectors for $\mathbf{G_L}$ (i.e., one of the rows of $\mathbf{P}$). In this case, $\mathbf{AG_L} = \lambda\mathbf{A}$, where λ is the eigenvalue corresponding to $\mathbf{A}$, indicating that inflation persistence is determined solely by the eigenvalue. But, in general, $\mathbf{AG_L} \neq \lambda\mathbf{A}$.

Aggregate inflation in our model is comparable to Rubbo (2023)'s *divine coincidence index*—the aggregate inflation measure weighted by sectoral sales shares and price rigidities. While the definition of our aggregate inflation, given by equation (14), relies solely on sectoral sales shares ($\mathbf{A}$), its equilibrium law of motion (15) is influenced by price rigidities across sectors as well as I-O linkages, similar to the divine coincidence framework. A distinct feature of our analysis is that we derive the equilibrium law of motion for aggregate inflation as a tractable VARMA process, whereas Rubbo (2023) does not provide an equivalent for the divine coincidence index, which is only incorporated within the New Keynesian Phillips curve.[7]

3 Empirical Strategy

3.1 Data

For our empirical analysis, we construct I-O tables and monthly time-series data on domestic prices, import prices, and wages based on the same sectoral classification between the US and Japan. Although the official statistics of the two countries employ different sectoral classifications, we harmonize them to enable meaningful comparison. The sectoral classification for 15 sectors is shown in Table 2. Note that, for expositional purposes, we primarily focus on 12 sectors (excluding Government and two other minor sectors) in the following analysis. This is because the remaining three sectors do not have contributions to other sectors as intermediate inputs.[8] In this subsection,

[6] For details on the aggregation of sectoral inflation and possible alternative weights, see Appendix C.7.

[7] In a static version of the model in Rubbo (2023), firms that cannot reoptimize prices under Calvo-type price stickiness set their prices at steady-state levels rather than at those in the previous period. The same assumption is made by Qiu et al. (2025), who extend her analysis to an open economy setting.

[8] The US dataset includes two relatively minor sectors: Scrap, Used and Secondhand Goods and Noncomparable Imports and Rest-of-the-World Adjustment, the latter of which is labeled as "Others." No data on these sectors are available for Japan.

Table 2: Harmonized Sector Classification

		US		Japan	
	Sector	Share	Price data	Share	Price data
01	Agriculture, Forestry, Fishing, and Hunting	0.015	D/M/W	0.013	D/M/–
02	Mining	0.019	D/M/W	0.001	D/M/W
03	Utilities	0.020	D/–/W	0.028	D/–/W
04	Construction	0.040	D/–/W	0.056	–/–/W
05	Durable Goods	0.088	D/M/W	0.185	D/M/W
06	Nondurable Goods	0.103	D/M/W	0.125	D/M/W
07	Commerce	0.100	D/–/W	0.100	D/–/W
08	Transportation and Warehousing	0.035	D/–/W	0.052	D/–/W
09	Information	0.039	D/–/W	0.049	D/–/W
10	Finance and Insurance	0.073	D/–/W	0.034	D/–/W
11	Real Estate and Rental and Leasing	0.103	D/–/W	0.076	D/–/W
12	Services	0.272	D/–/W	0.239	D/–/W
13	Government	0.092	D/–/–	0.042	–/–/–
14	Scrap, Used and Secondhand Goods	< 0.001	–/–/–	–	–/–/–
15	Others	< 0.001	–/–/–	–	–/–/–

Notes: This table reports the 15 harmonized sectors in the US and Japan, along with their relative shares of total output in each economy. The columns labeled "Price data" indicate the availability of data for three types of price indices for each sector: domestic prices (D), import prices (M), and wages (W). The hyphen (–) indicates that the corresponding price data is not available.

we briefly outline the data construction process, with detailed explanations provided in Appendix C.

To construct the I-O tables, first, we compile the I-O matrix at its most detailed level, consisting of approximately 400 commodities for the US and 500 commodities for Japan. The domestic I-O matrix for the US is obtained by subtracting the I-O matrix for imported goods from the total I-O matrix. The total I-O matrix for Japan is decomposed using the ratio of gross output to the total supply of each product. Second, we aggregate the detailed I-O matrix into sectoral levels by summing the corresponding commodity-level data. The I-O tables used in this study cover the year 2012 for the US and 2011 for Japan.

We construct the monthly domestic and import price indices P_{it} and P^*_{mt} at the sectoral level using the Producer Price Index (PPI) and Industry Import Index for the US and the Corporate Goods Price Index (CGPI), Services Producer Price Index, and Wholesale Services Price Index for Japan. Price indices are initially constructed for the most detailed classifications in the I-O matrix and then aggregated to the 12 sectoral levels using weights derived from the demand for each intermediate commodity.

The monthly sectoral wage indices W_{it} are obtained from the Current Employment Statistics for the US and the Monthly Labour Survey for Japan. Wages are defined as the average hourly earnings of all employees, calculated as total cash earnings divided by total hours worked per capita.

Table 3: Cost Shares of Domestic, Imported Commodities, and Labor by Sector

	US			Japan		
Sector	Domestic	Import	Labor	Domestic	Import	Labor
Agriculture, Forestry, Fishing, and Hunting	0.785	0.062	0.153	0.749	0.068	0.183
Mining	0.667	0.091	0.242	0.715	0.028	0.257
Utilities	0.651	0.065	0.284	0.533	0.349	0.118
Construction	0.505	0.047	0.449	0.567	0.036	0.397
Durable Goods	0.599	0.152	0.249	0.734	0.080	0.186
Nondurable Goods	0.680	0.207	0.113	0.618	0.229	0.153
Commerce	0.544	0.021	0.435	0.425	0.013	0.562
Transportation and Warehousing	0.599	0.058	0.343	0.586	0.040	0.374
Information	0.666	0.057	0.277	0.651	0.019	0.330
Finance and Insurance	0.559	0.058	0.383	0.509	0.016	0.475
Real Estate and Rental and Leasing	0.837	0.020	0.143	0.763	0.010	0.227
Services	0.421	0.027	0.552	0.445	0.032	0.523
Government	0.359	0.038	0.603	0.443	0.019	0.538
Scrap, Used and Secondhand Goods	0.544	0.083	0.373	–	–	–
Others	0.386	0.037	0.577	–	–	–

Note: This table presents the shares of intermediate inputs from domestically produced and imported commodities, and employee compensation in the total cost for each sector.

The earliest observation period in these indices is January 2000, and the most recent observation period is July 2023. All the indices are seasonally adjusted.

Table 3 presents a summary of the I-O tables for the US and Japan. The table highlights notable differences in production networks between the two countries. For instance, in the utilities sector, output in Japan relies heavily on imports (34.9%) compared to the US (6.5%). This discrepancy reflects Japan's dependence on imported energy resources, whereas the US primarily produces its own energy. In contrast, the production of durable goods in Japan is more reliant on domestic inputs, with 73.4% of goods sourced domestically, compared to 59.9% in the US.

3.2 Estimation Methods

The model is estimated with Bayesian methods using the monthly time series described in the previous subsection. The set of observables contains the inflation rates of domestic price indices P_{it}, import price indices P^*_{mt}, and wage indices W_{it} in each sector, but not all the sectoral series are available in our dataset. All the inflation series are in percentage terms and demeaned. Thus, depending on the availability of the data, the observation equations that relate the data to model variables in each country are given by

$$\text{US:} \begin{bmatrix} 100\Delta \log P_{1t} \\ \vdots \\ 100\Delta \log P_{13t} \\ 100\Delta \log P^*_{1t} \\ 100\Delta \log P^*_{2t} \\ 100\Delta \log P^*_{5t} \\ 100\Delta \log P^*_{6t} \\ 100\Delta \log W_{1t} \\ \vdots \\ 100\Delta \log W_{12t} \end{bmatrix} = \begin{bmatrix} \pi_{1t} \\ \vdots \\ \pi_{13t} \\ \pi^*_{1t} \\ \pi^*_{2t} \\ \pi^*_{5t} \\ \pi^*_{6t} \\ \pi^w_{1t} \\ \vdots \\ \pi^w_{12t} \end{bmatrix}; \qquad \text{Japan:} \begin{bmatrix} 100\Delta \log P_{1t} \\ \vdots \\ 100\Delta \log P_{3t} \\ 100\Delta \log P_{5t} \\ \vdots \\ 100\Delta \log P_{12t} \\ 100\Delta \log P^*_{1t} \\ 100\Delta \log P^*_{2t} \\ 100\Delta \log P^*_{5t} \\ 100\Delta \log P^*_{6t} \\ 100\Delta \log W_{2t} \\ \vdots \\ 100\Delta \log W_{12t} \end{bmatrix} = \begin{bmatrix} \pi_{1t} \\ \vdots \\ \pi_{3t} \\ \pi_{5t} \\ \vdots \\ \pi_{12t} \\ \pi^*_{1t} \\ \pi^*_{2t} \\ \pi^*_{5t} \\ \pi^*_{6t} \\ \pi^w_{2t} \\ \vdots \\ \pi^w_{12t} \end{bmatrix}.$$

Combining these observation equations and the equilibrium law of motion for sectoral inflation (9), we evaluate the likelihood functions using the Kalman filter.

Because we need to estimate a large number of parameters, the Random-Walk Metropolis-Hastings algorithm—one of the most commonly used algorithms in Bayesian estimation—can become stuck in a local mode and fail to explore the full posterior distribution of the model's parameters. To address this issue, we adopt a generic Sequential Monte Carlo (SMC) algorithm with likelihood tempering, as described in Herbst and Schorfheide (2014, 2015), to approximate the posterior distribution. The details of the algorithm are provided in Appendix D. Based on particles from the final importance sampling in the algorithm, we make inferences about parameters and approximate the marginal data densities.

3.3 Fixed Parameters and Priors

To avoid identification issues, we fix several parameters in the model. We set I-O linkage parameters, which constitute $\boldsymbol{\Omega}$, $\boldsymbol{\Omega}^*$, and $\boldsymbol{\Omega}_w$, from the I-O tables in 2012 for the US and in 2011 for Japan. Preliminary investigation of the I-O tables for the US and Japan indicates that there are no imported inputs from several sectors: Construction, Commerce, and Real Estate and Rental and Leasing in the US; and Construction, Real Estate and Rental and Leasing, and Government in Japan. For these sectors, we exclude their import price shocks from the model, by setting $\rho^*_m = \sigma^*_m = 0$.

The subjective discount factor β is fixed at $0.98^{1/12}$, which corresponds to the steady-state real interest rate of approximately 2% annually under the log-utility function. The elasticity of substitution among differentiated goods in each sector σ_i is fixed at 5, implying that the steady-state markup is 1.25. These fixed parameter values and the priors presented below are common across the two countries.

All other parameters in the model are estimated, with their prior distributions presented in Table 4. The prior mean of the price stickiness parameter κ_i is set at 25, with a standard deviation

Table 4: Prior Distributions of Parameters

Parameter	Distribution	Para(1)	Para(2)
κ_i	Gamma	25.00	4.000
ρ_i^ϵ	Beta	0.500	0.150
ρ_m^*	Beta	0.500	0.150
ρ_i^w	Beta	0.500	0.150
σ_i^ϵ	Inverse Gamma	2.000	4.000
σ_m^*	Inverse Gamma	2.000	4.000
σ_i^w	Inverse Gamma	2.000	4.000

Note: Para(1) and Para(2) denote the mean and standard deviation (S.D.) for the Gamma and Beta distributions, and ν and s for the Inverse Gamma distribution of the form $p(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-\nu s^2/2\sigma^2}$.

of 4. Given the fixed value of the elasticity of substitution among differentiated goods within each sector, $\sigma_i = 5$, this prior mean implies a slope of 0.2 for the sectoral Phillips curve in terms of real marginal costs given by equation (4). This prior is deliberately chosen to be relatively diffuse, allowing the data to shape the posterior distribution of these parameters.

The priors for the persistence parameters ρ_i^ϵ, ρ_m^*, and ρ_i^w, corresponding to sectoral productivity, import price, and wage shocks, respectively, are specified with a mean of 0.5 and a standard deviation of 0.15. Regarding the standard deviations of the shocks σ_i^ϵ, σ_m^*, and σ_i^w, inverse Gamma priors are imposed with a mean of 2 and a standard deviation of 4.

4 Estimation Results

4.1 Parameter Estimates

Figures 2 and 3 graphically illustrate the posterior mean estimates of parameters, along with their 90% credible intervals, for the US and Japan. For the purpose of comparison, each panel plots the combination of estimated parameters for the same sector in the two countries, so that the deviation from the 45-degree line indicates the difference in each parameter estimate between the US and Japan. The actual numbers of the posterior mean estimates and credible intervals, as well as the marginal data density, for each country are reported in Table E.1 of Appendix E.1.

A notable finding on the price stickiness parameters κ_i is that the US estimates exhibit more heterogeneity and dispersion across sectors than Japan's estimates, particularly in the Agriculture, Mining, and Utilities sectors. The mean estimates in the US range from 3.4 to 40.7, whereas those in Japan range from 19.3 to 39.3. This greater heterogeneity in the US contrasts with the findings of Ueda (2024), who shows that the dispersion of price stickiness across sectors is lower in the US than in Japan. However, our results are consistent with his findings that prices in the Nondurable Goods sector are stickier in the US than in Japan, while those in the Services sector are more flexible in the US than in Japan.

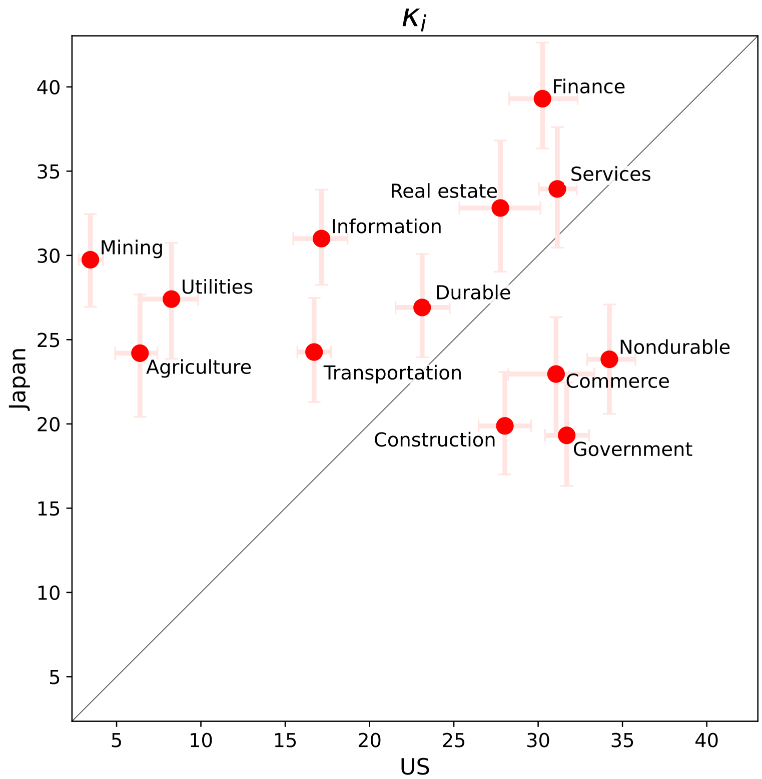


Figure 2: Posterior Estimates of Price Stickiness in the US and Japan

Note: The figure plots the combination of the posterior mean estimates of the price stickiness parameters, along with their 90% credible intervals (shaded lines), for each sector in the US and Japan.

On average, the price stickiness parameters appear lower in the US than in Japan; the simple averages of each mean estimate for the US and Japan are 22.7 and 27.4, respectively. However, averaging these mean estimates based on the total output weights—used in the aggregation of sectoral inflation—gives 27.8 for the US and 28.0 for Japan, which are very close to each other. Thus, the aggregate implication of price stickiness is similar between the two countries, despite the differences at the sectoral level.

We confirm that the correlation of the price stickiness parameters κ_i between the US and Japan is statistically insignificant, reflecting the deviation of most of the plots from the 45-degree line in Figure 2. In Appendix E.2, we also examine the consistency of our price stickiness estimates κ_i with micro-level evidence presented in Bils and Klenow (2004) and Ueda (2024). As is consistent with theory, our estimates of κ_i are negatively correlated with the frequency of price changes in the corresponding CPI items for both countries. However, the correlations are statistically insignificant.

On the persistence parameters of sectoral shocks, the estimates for productivity shocks ρ_i^{ϵ} are more heterogeneous in Japan than in the US. The simple averages across sectors are higher in the US than in Japan. However, as do the price stickiness parameters, aggregating the mean estimates using the total output weights gives almost the same averages: approximately 0.74 for both countries.

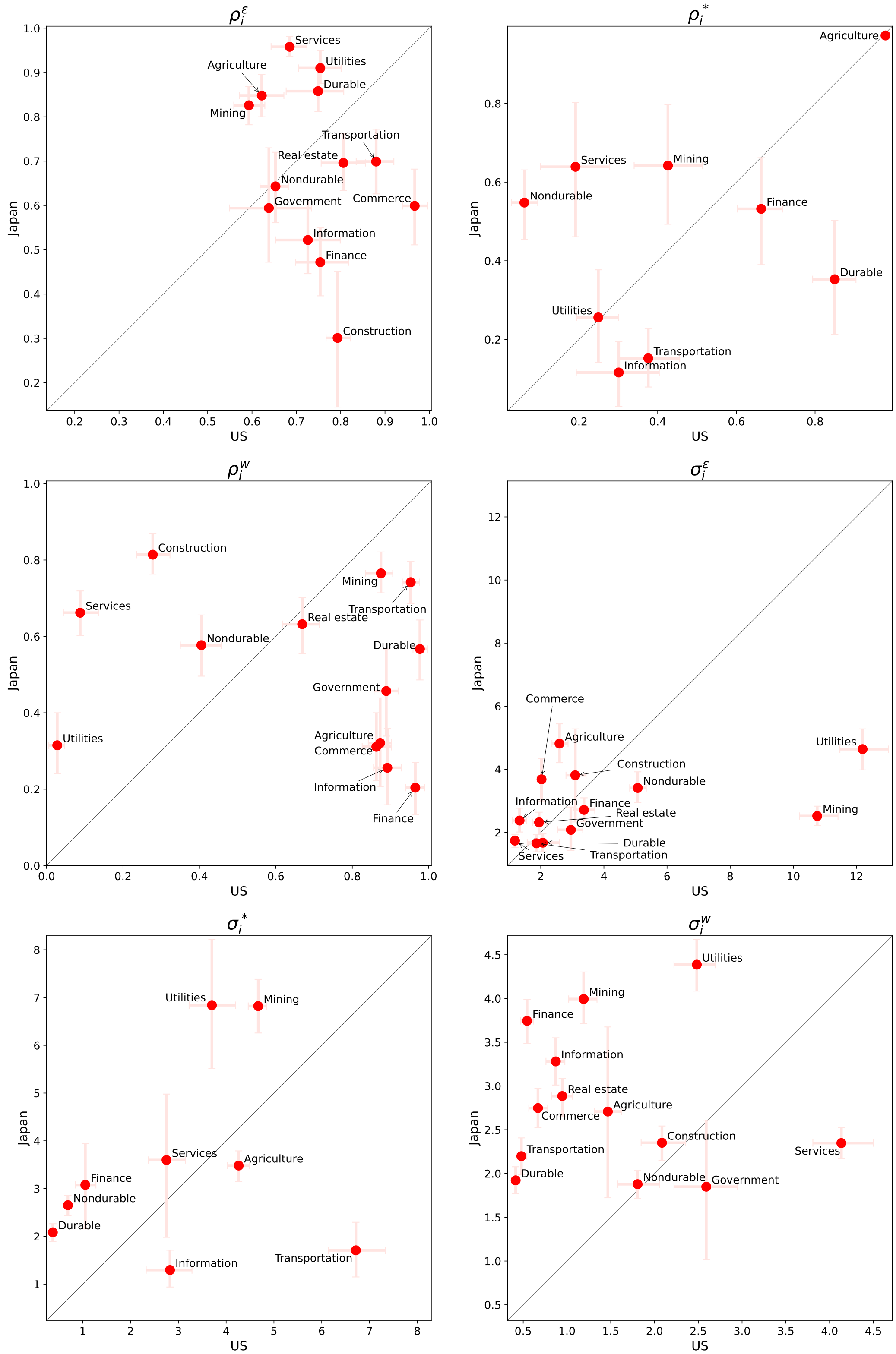


Figure 3: Posterior Estimates of Persistence and Standard Deviation Parameters in the US and Japan

Note: The figure plots the combination of the posterior mean estimates of the persistence and standard deviation of the productivity, import-price, and wage shocks, along with their 90% credible intervals (shaded lines), for each sector in the US and Japan.

The estimates for the persistence of import price shocks ρ_m^* exhibit large heterogeneity across sectors in both countries, but their averages are not significantly different: 0.49 for the US and 0.45 for Japan. In contrast, the estimates for the persistence of wage shocks ρ_i^w are mostly higher in the US than in Japan, averaging 0.63 and 0.51, respectively. The lower persistence of wage shocks in Japan is attributed to the characteristics of Japan's wage index data, which, as illustrated in Figure 1, are quite volatile. In addition to the general high volatility of Japan's labor market data, its wage indices particularly exhibit idiosyncratic fluctuations due to the biannual bonuses paid to regular employees, which vary based on firms' performance. As for the heterogeneity in wage shock persistence, the US estimates are more dispersed across sectors than Japan's estimates, ranging from 0.03 to 0.97 for the US and from 0.20 to 0.81 for Japan.

The standard deviations of sectoral shocks on productivity σ_i^ϵ, import price σ_m^*, and wage σ_i^w, are also highly heterogeneous between the two countries and across sectors. The simple averages of the mean estimates for the US and Japan are 3.8 and 2.9 for productivity shocks, 3.2 and 3.5 for import price shocks, and 1.6 and 2.8 for wage shocks, respectively. Thus, the estimates for productivity shocks are larger in the US, whereas those for import price and wage shocks are larger in Japan. Similarly to the persistence parameters addressed above, the dispersion of the estimates across sectors is more pronounced in the US than in Japan.

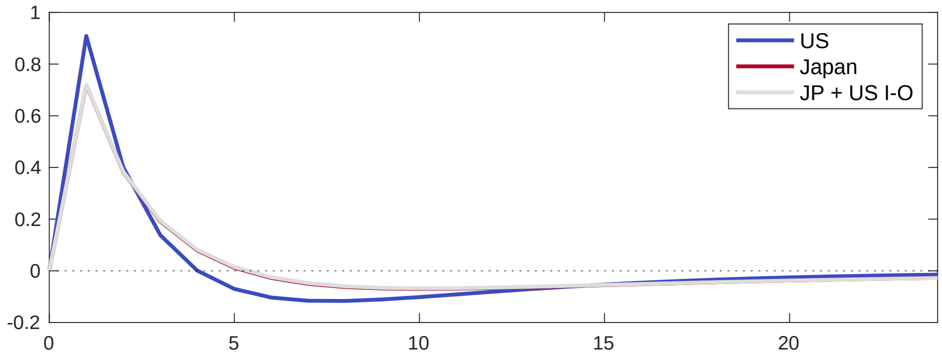
4.2 Impulse Response Functions and the Role of Input-Output Linkages

In this subsection, we analyze the IRFs of aggregate and sectoral inflation to the three types of shocks in the model: productivity shocks, import price shocks, and wage shocks, given the posterior mean estimates of parameters for the US and Japan. We also conduct a counterfactual analysis to investigate to what extent differences in I-O linkages between the two countries cause variations in the propagation of the shocks by imposing the US I-O structure on the model estimated for the Japanese economy.[9]

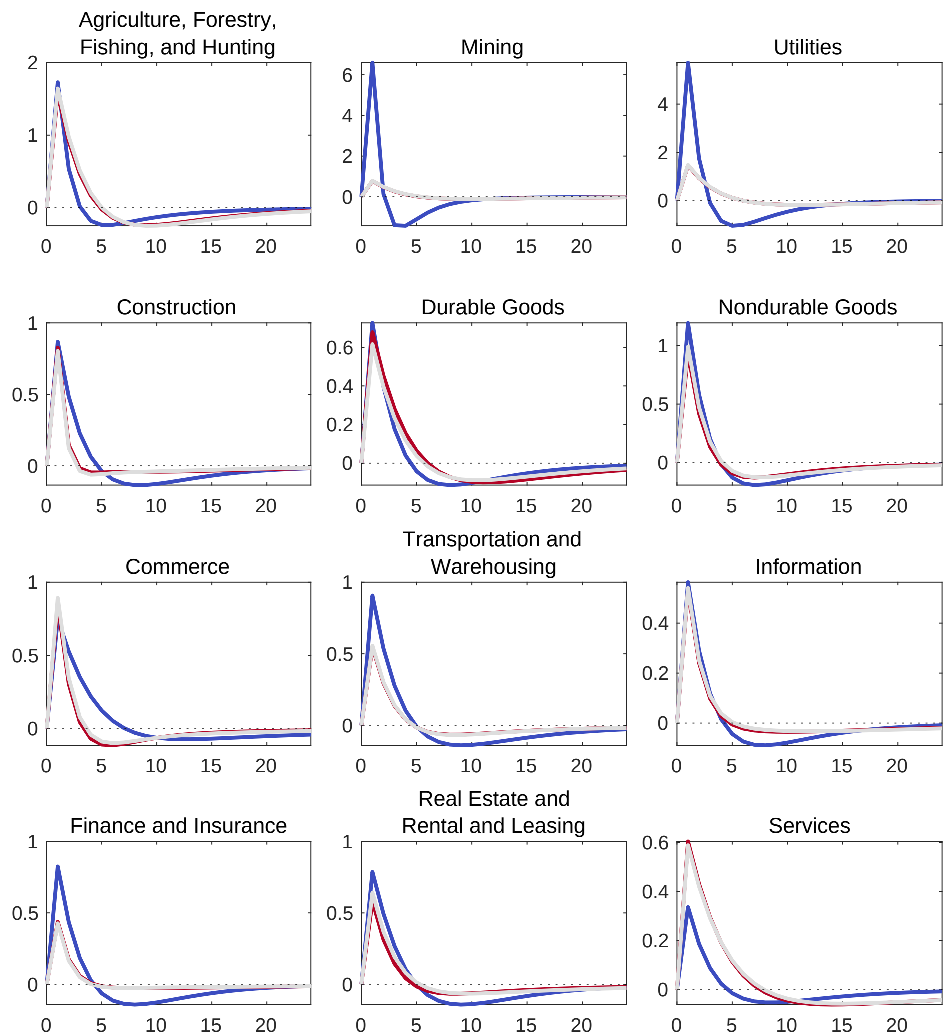
Figure 4 compares the responses of aggregate and sectoral inflation to the one-standard-deviation negative productivity shocks (i.e., positive cost-push shocks) to all the sectors in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines). To derive the responses of aggregate inflation, we aggregate sectoral inflation rates using the total output shares reported in Table 2. The results on aggregate responses are robust to different aggregation methods, as demonstrated in Appendix E.3.

As shown in the top panel, the responses of aggregate inflation to the productivity shocks in the US and Japan are quite similar. The productivity shocks have a relatively smaller impact initially, but have slightly more persistent effects in Japan than in the US. The counterfactual responses, based on the parameter estimates for Japan but under the US I-O structure, are almost identical to the actual responses in Japan (i.e., the gray line overlaps with the red one). This means that differences in the production network structure do not account for the observed differences in the

[9]The number of sectors is slightly different in the US and Japan. When we impose the US production network structure, we exclude Sectors 14 and 15 from the model and normalize the sum of sectoral shares to unity.



(a) Responses of Aggregate Inflation



(b) Sectoral Responses

Figure 4: Responses to Productivity Shocks

Notes: The figure shows the responses of aggregate and sectoral inflation to the one-standard-deviation negative productivity shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

aggregate inflation dynamics in terms of the responses to productivity shocks.

The rest of the panels in Figure 4 display the sectoral responses to the productivity shocks.[10] The responses of sectoral inflation rates are significantly different in the US and Japan for some sectors, such as the Mining, Utilities, Transportation and Warehousing, Finance and Insurance, and Services sectors. For the other sectors, however, the responses are quantitatively close to each other in the two economies. Those sectors that exhibit large discrepancies between the US and Japan have small total output shares, as shown in Table 2. Consequently, the aggregate responses are largely similar across the two countries. The counterfactual sectoral responses remain almost unchanged compared to the actual responses for the Japanese economy. At the sectoral level, variations in the production network structure do not result in significant differences in the propagation of sectoral productivity shocks.

Figure 5 compares the responses of aggregate and sectoral inflation to the one-standard-deviation import price shocks to all the import sectors in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines).

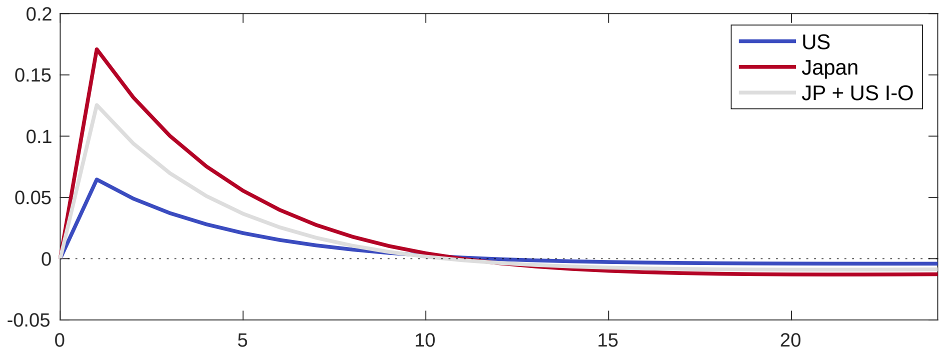
According to the top panel, there is a noticeable difference in the responses of aggregate inflation between the US and Japan. The initial impact is much larger in Japan than in the US, although the persistence is similar in both economies. The difference in the initial impact is mainly due to the estimated size of the shocks that are larger in Japan than in the US, as shown in Figure 3. However, Japan's counterfactual responses based on the US I-O linkages are somewhat subdued, suggesting that Japan's I-O linkage structure contributes to enhancing the propagation of import price shocks.

The lower panels in Figure 5 display the sectoral responses to the import price shocks. As most of the estimated standard deviations for the import price shocks are larger in Japan, almost all the sectoral responses are more pronounced in Japan than in the US. The counterfactual responses with the US production network structure are suppressed in most of the sectors compared to the ones with the Japanese structure, as is consistent with the result on aggregate inflation. In particular, the counterfactual response of inflation in the Utilities sector in Japan almost coincides with its US counterpart. Thus, the difference in this sector's response between the two countries is solely due to Japan's distinct I-O structure, which has a higher dependence on imported goods compared to the US.

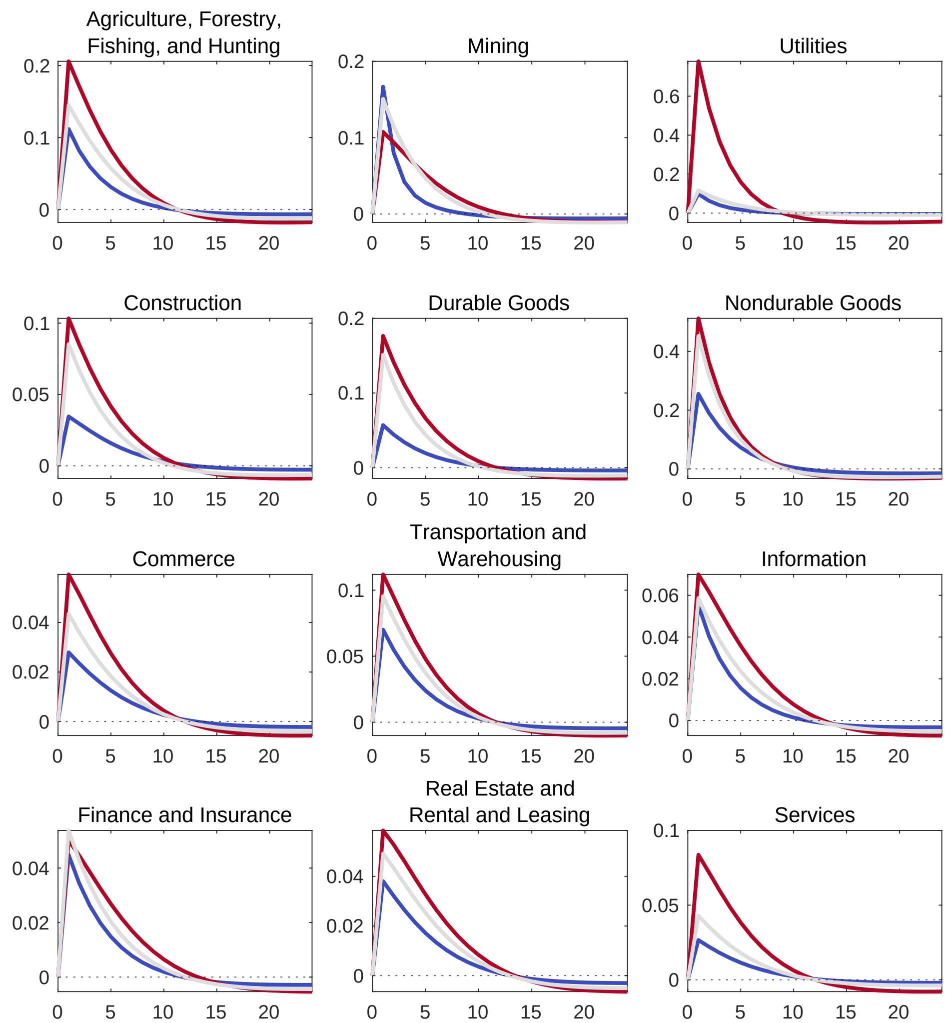
Figure 6 compares the responses of aggregate and sectoral inflation to the one-standard-deviation wage shocks to all the sectors in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines).

The top panel demonstrates that, unlike the import price shocks, the responses of aggregate inflation to the wage shocks in the US and Japan are quantitatively similar. The counterfactual

[10] For ease of presentation, we do not present sector 13 (for the US, sectors 14 and 15 as well). The same applies to the following IRFs.



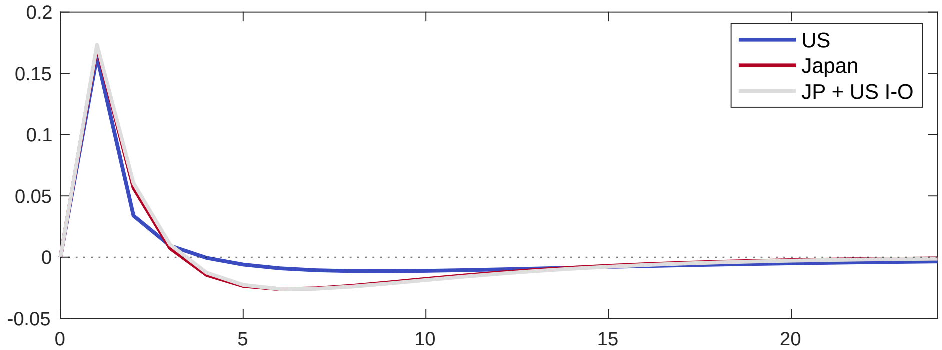
(a) Responses of Aggregate Inflation



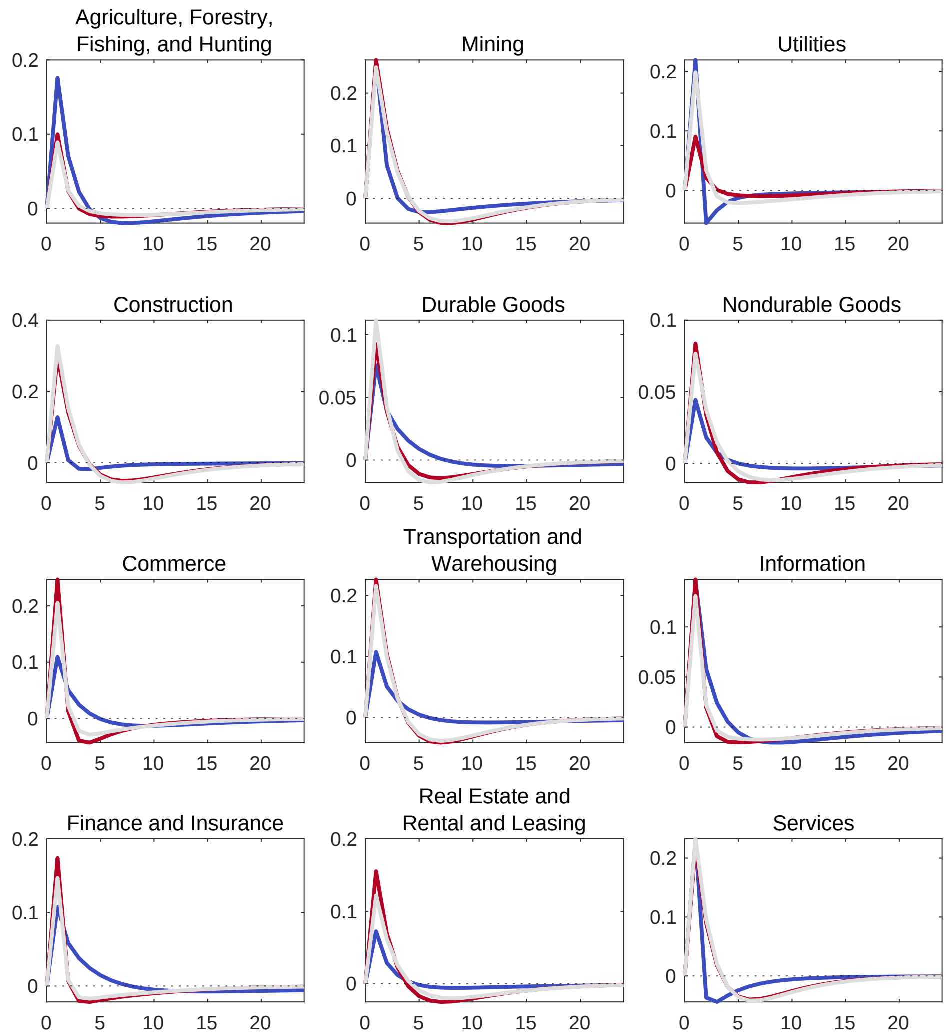
(b) Sectoral Responses

Figure 5: Responses to Import Price Shocks

Notes: The figure shows the responses of aggregate and sectoral inflation to the one-standard-deviation import price shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.



(a) Responses of Aggregate Inflation



(b) Sectoral Responses

Figure 6: Responses to Wage Shocks

Notes: The figure shows the responses of aggregate and sectoral inflation to the one-standard-deviation wage shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

responses, based on the parameter estimates for Japan but under the US I-O structure, are almost identical to the actual responses in Japan.

The remaining panels in Figure 6 display the sectoral responses to the wage shocks, highlighting heterogeneity both across sectors and between the two economies. Wage shocks are more important in some sectors in the US than those in Japan (and vice versa). However, such heterogeneity does not account for the almost identical aggregate responses, which we observe in the top panel of the same figure. The counterfactual responses with the US production network structure are similar to the actual responses with the Japanese structure, except for the Utilities sector.

There are three takeaways from the exercises above. First, differences in domestic production structure (either the I-O linkages or wage shares) do not account for differences in aggregate inflation dynamics between the US and Japan. Second, differences in production network structure regarding import goods play an important role in differentiating aggregate inflation dynamics. In particular, both the estimated size of import price shocks and reliance on imported intermediate goods create sizable differences in the propagation of import price shocks. Third, although the responses to import price shocks differ between the US and Japan, this disparity does not account for our motivating observation (Figure 1) that Japan experienced milder changes in PPI inflation compared to the US.

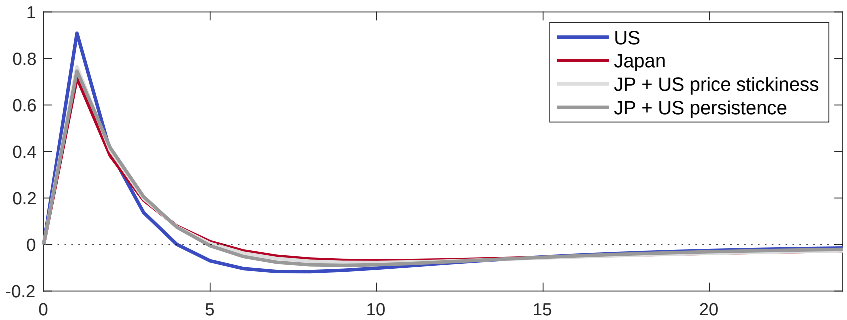
4.3 Counterfactual Impulse Response Functions: The Role of Structural Parameters

In this subsection, we analyze the counterfactual responses of aggregate inflation, based on the estimated model for the Japanese economy with a subset of parameters being replaced with the US estimates. We consider two cases. One is to replace all the price-stickiness parameters in Japan with the US estimates,[11] while keeping the rest of the parameters unchanged. The other is to replace all the persistence parameters in Japan with their US counterparts.[12] Each panel in Figure 7 presents the aggregate responses to the one-standard-deviation shocks about productivity, import prices, and wages in all the sectors, respectively.

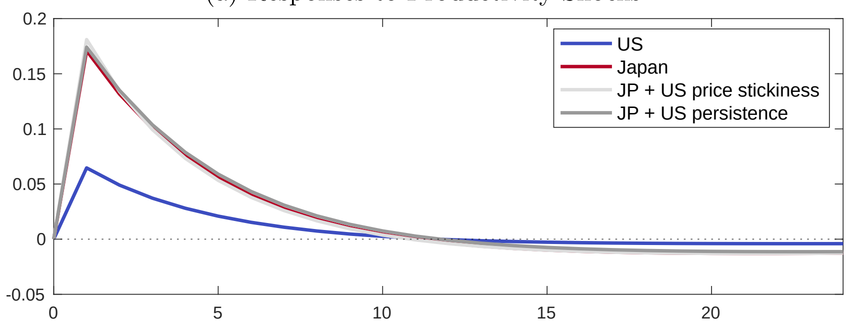
Similar to the counterfactual responses under the US I-O linkages, differences in the price stickiness parameters between the US and Japan do not make significant differences in the *aggregate* inflation responses. This is consistent with the finding in Section 4.1 that the weighted averages of the estimated price stickiness parameters are very close to each other in the US and Japan. The same applies to differences in the shock persistence parameters. The only exception is the responses to the wage shocks. As shown in Figure 3, the estimated persistence of wage shocks is generally higher in the US than in Japan. This difference contributes to more pronounced counterfactual responses of aggregate inflation to wage shocks in Japan. Although they do not make significant

[11] We also considered 100% pass-through scenarios with κ's being zero. Under such scenarios, initial responses become five to eleven times larger than the actual responses.

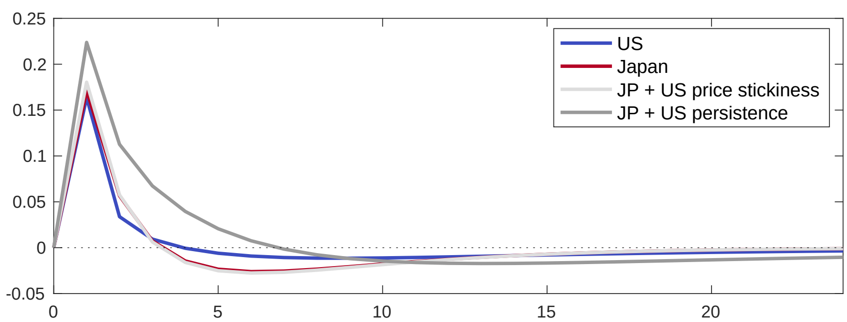
[12] In practice, we cannot replace all Japanese persistence parameters with the US ones. Because there is no US estimate for the persistence parameter for imported goods in the Commerce sector (i.e., ρ_7^*), we keep the Japanese estimate for this parameer.



(a) Responses to Productivity Shocks



(b) Responses to Import Price Shocks



(c) Responses to Wage Shocks

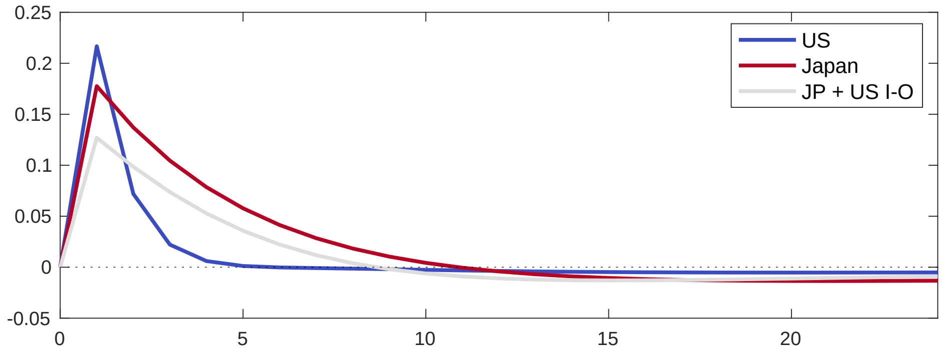
Figure 7: Counterfactural Responses of Aggregate Inflation

Notes: The figure shows the responses of aggregate inflation to the one-standard-deviation shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US κ_i's (light gray lines) and those with the US ρ_i's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

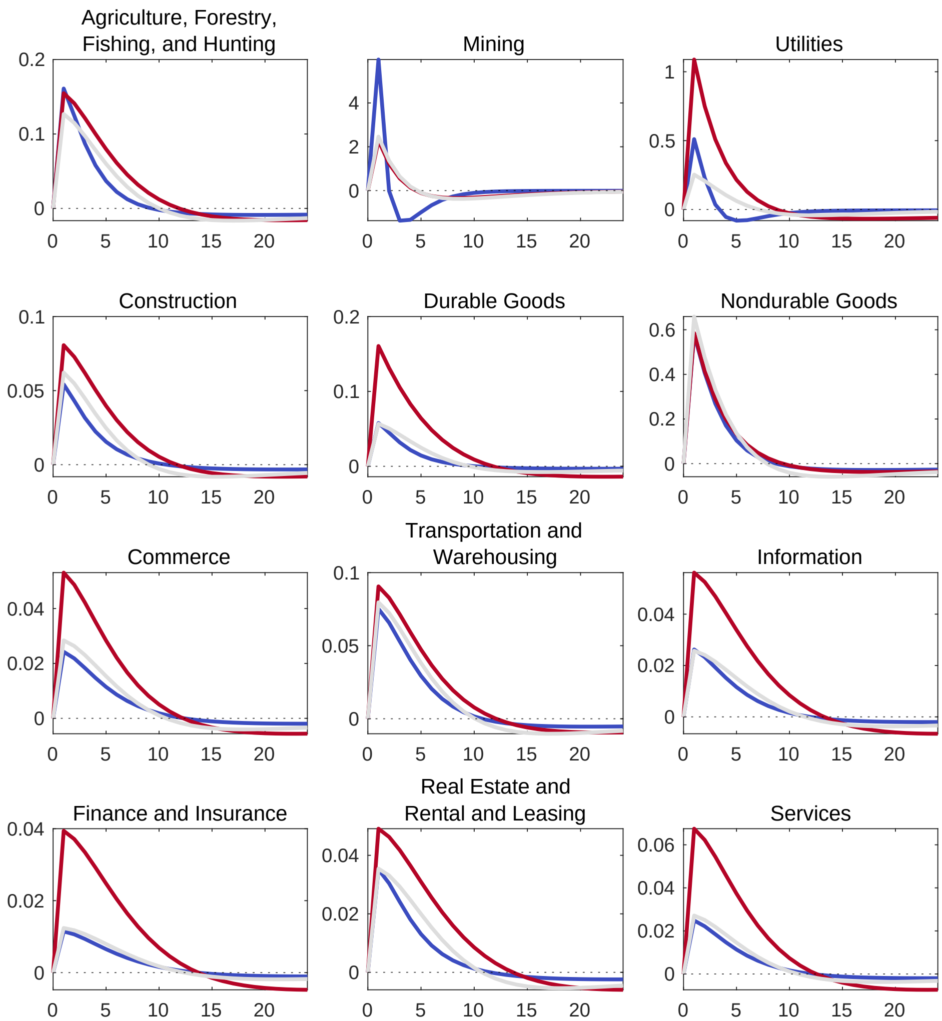
differences in the aggregate dynamics, counterfactual responses at the sectoral level exhibit some heterogeneity. Detailed results are presented in Appendix E.4.

4.4 Impulse Response Functions to a Common Energy Price Shock

The impulse response analyses presented above are based on country-specific shocks affecting all sectors, meaning that we have examined the impacts of estimated one-standard-deviation shocks about productivity, import prices, and wages in all sectors, respectively. In this subsection, we shift



(a) Responses of Aggregate Inflation



(b) Sectoral Responses

Figure 8: Responses to a Common Energy Price Shock

Notes: The figure shows the responses of aggregate and sectoral inflation to the 10% decrease in the Mining sector's productivity shock as well as the 10% increase in the Mining sector's import price shock for the US (blue lines) and Japan (red lines), together with the counterfactual responses of the Japanese economy with the US I-O linkages (light gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

our focus to a sector-specific shock that is globally common across the US and Japan. We analyze how, and to what extent, the pass-through of such a common shock to inflation differs between the two countries.

In particular, we consider an energy price shock as a representative common global shock. Specifically, we define it as a 10% negative productivity shock in the Mining sector, combined with a 10% increase in the import price of the Mining sector's commodities. This definition reflects the fact that the Mining sector includes energy production, such as crude oil and natural gas. In other words, this shock simultaneously raises both the marginal cost of domestic mining production and the import price of its related commodities by the same magnitude. As a result, the common energy price shock leads to price increases not only in the Mining sector itself but also in other sectors—such as the Utility sector—that depend heavily on fossil fuel imports.

Figure 8 compares the responses of aggregate and sectoral inflation to the common energy price shock in the US (blue lines) and Japan (red lines), as well as the counterfactual responses of the Japanese economy with the US I-O linkages (light gray lines). The top panel of Figure 8 shows that the initial responses of aggregate inflation are similar in the US and Japan, with both reaching approximately 0.2%. One notable difference between the two countries is that the energy price shock has more persistent effects in Japan, which can be attributed to its larger estimates of the persistence parameters for both productivity and import price shocks, as illustrated in Figure 3. When Japan's I-O linkages are replaced with those of the US, the initial response decreases by 5 basis points. This result suggests that, between the smaller share of energy-related imports and the larger share of domestic energy-related production in the US, the former effect dominates the latter. As a result, replacing Japan's I-O linkages with those of the US leads to the smaller overall impact of the energy price shock.

The lower panels of Figure 8 display the sectoral responses to the common energy price shock. Japan's sectoral inflation rates are substantially higher in almost all sectors than their US counterparts due to the greater reliance of Japanese industries on imported natural resources. An exception is the US Mining sector, where the sectoral inflation exhibits a significantly larger increase upon impact. This is due to the much lower estimate of the price stickiness parameter κ_i in the US Mining sector, as shown in Figure 2. According to the sector-level Phillips curve (4), the pass-through of real marginal cost to sectoral inflation is inversely related to κ_i. Thus, the effects of the energy price shock on prices are more pronounced in the US Mining sector, where firms adjust prices more flexibly.

4.5 Variance Decomposition

Given the aforementioned similarity of IRFs between the US and Japan, what explains the difference in inflation dynamics observed in Figure 1? We argue that there are two key reasons, each presented in the present and the following subsections, respectively.

The first reason is that the drivers of inflation variability differ between the two countries. Table 5 summarizes the forecast error variance decomposition of aggregate inflation in the US and

Japan, respectively, at various forecast horizons: one month, quarter, year, and infinity, given the posterior mean estimates of each model's parameters. In aggregating sectoral inflation, we use weights for total output, as in the preceding analyses. The decomposition of aggregate inflation based on alternative weights is presented in Appendix E.5.

In both countries, the volatility of aggregate inflation is mainly driven by sectoral productivity shocks, accounting for more than 90% in the US and more than 70% in Japan, at all forecast horizons. However, the second most important driver of aggregate inflation differs between the two countries. In the US, wage shocks are the second most important driver, accounting for 6.8–7.9% of the variance of aggregate inflation. In contrast, import price shocks are the second most important in Japan, accounting for 17.0–21.9% of aggregate inflation. Given the larger estimates of the standard deviation of wage shocks in the US and the similarity of the estimated persistence and the standard deviation of the import price shocks across the two countries, as addressed in Section 4.1, this difference in the contribution of the associated shocks is mainly due to the differences in the I-O linkages, rather than the differences in the nature of sectoral shocks, between the US and Japan.

The contribution of import price shocks is quite small in the US, ranging from 1.4–2.5%. On the other hand, the contribution of wage shocks is small in Japan, ranging from 3.9–5.5%. Taking account of the relatively large estimates of the standard deviation of wage shocks in Japan, the latter result suggests that Japan's I-O linkages give rise to the limited pass-through of wage shocks to aggregate inflation.

At the sectoral level, productivity shocks to the Mining, Utilities, and Nondurable Goods sectors explain more than half of the variance of aggregate inflation in the US. Wage shocks to the Services sector also play a non-negligible role in explaining more than 5% of the volatility in aggregate inflation. Regarding Japan, productivity shocks to the Durable Goods, Nondurable Goods, and Services sectors explain nearly 60% of the variance of aggregate inflation. In addition, the contribution of import shocks to the Mining sector amounts to 16–21% in Japan, depending on the forecast horizons.

The variance decomposition of inflation in the Mining sector differs between the US and Japan, primarily due to differences in their production network structures. Table 6 presents the shares of domestically produced and imported commodities in the total intermediate demand for each sector in the two countries. In the US, the Mining sector comprises both domestically produced and imported commodities, whereas in Japan, it is almost entirely composed of imported commodities. The Mining sector is a typical energy-related sector. In the US, fluctuations in energy prices—such as those of oil and natural gas—are influenced by both domestic cost factors and import prices, as the US not only imports but also produces these resources domestically. In contrast, energy price changes in Japan are predominantly driven by import price shocks, given that nearly 100% of Japan's natural resources are imported. This difference in the I-O linkages results in a larger contribution of import price shocks to the variance of the Mining sector's inflation in Japan than in the US.

Table 5: Variance Decomposition of Aggregate Inflation

Forecast horizons	1 month		1 quarter		1 year		∞	
Country	US	Japan	US	Japan	US	Japan	US	Japan
Sum of productivity shocks	0.906	0.775	0.905	0.751	0.907	0.742	0.907	0.743
Sum of import price shocks	0.014	0.170	0.023	0.207	0.025	0.217	0.025	0.219
Sum of wage shocks	0.079	0.055	0.072	0.041	0.068	0.041	0.068	0.039
Productivity shock								
Agriculture, etc.	0.006	0.009	0.005	0.009	0.005	0.009	0.005	0.009
Mining	0.243	0.000	0.203	0.000	0.200	0.000	0.195	0.000
Utilities	0.222	0.041	0.210	0.046	0.210	0.045	0.208	0.047
Construction	0.013	0.016	0.014	0.011	0.014	0.010	0.014	0.009
Durable Goods	0.032	0.141	0.034	0.138	0.034	0.133	0.034	0.134
Nondurable Goods	0.134	0.159	0.135	0.121	0.137	0.119	0.136	0.113
Commerce	0.067	0.082	0.099	0.057	0.100	0.057	0.106	0.054
Transportation; Warehousing	0.013	0.007	0.015	0.006	0.015	0.006	0.016	0.006
Information	0.003	0.005	0.003	0.004	0.003	0.004	0.003	0.003
Finance and Insurance	0.059	0.002	0.069	0.002	0.069	0.002	0.070	0.002
Real Estate; Rental and Leasing	0.038	0.013	0.044	0.010	0.043	0.010	0.044	0.010
Services	0.055	0.294	0.056	0.345	0.056	0.346	0.056	0.354
Government	0.021	0.004	0.019	0.003	0.019	0.003	0.019	0.002
Scrap; Used and Secondhands	0.000	-	0.000	-	0.000	-	0.000	-
Others	0.000	-	0.000	-	0.000	-	0.000	-
Import price shock								
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001
Mining	0.013	0.160	0.020	0.196	0.022	0.206	0.023	0.207
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durable Goods	0.000	0.002	0.000	0.002	0.000	0.002	0.000	0.002
Nondurable Goods	0.000	0.007	0.000	0.009	0.000	0.009	0.000	0.009
Commerce	-	0.000	-	0.000	-	0.000	-	0.000
Transportation; Warehousing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Information	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Services	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Government	0.000	-	0.000	-	0.000	-	0.000	-
Scrap; Used and Secondhands	0.000	-	0.000	-	0.000	-	0.000	-
Others	0.001	-	0.001	-	0.001	-	0.001	-
Wage shock								
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mining	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Construction	0.000	0.003	0.000	0.002	0.000	0.002	0.000	0.002
Durable Goods	0.000	0.002	0.000	0.002	0.000	0.002	0.000	0.001
Nondurable Goods	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Commerce	0.001	0.008	0.001	0.005	0.001	0.005	0.001	0.005
Transportation; Warehousing	0.000	0.002	0.000	0.002	0.000	0.001	0.000	0.001
Information	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.001	0.001	0.001	0.000	0.001	0.000	0.001	0.000
Real Estate; Rental and Leasing	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
Services	0.064	0.036	0.054	0.028	0.050	0.027	0.049	0.026
Government	0.013	0.001	0.015	0.000	0.015	0.000	0.015	0.000
Scrap; Used and Secondhands	0.000	-	0.000	-	0.000	-	0.000	-
Others	0.000	-	0.000	-	0.000	-	0.000	-

Note: The table presents the forecast error variance decomposition of aggregate inflation in the US and Japan, based on the posterior mean estimates of each model's parameters.

Table 6: Sectoral Shares of Domestically Produced and Imported Commodities

	US		Japan	
Sector	Domestic	Import	Domestic	Import
Agriculture, Forestry, Fishing, and Hunting	0.913	0.087	0.794	0.206
Mining	0.519	0.481	0.032	0.968
Utilities	0.996	0.004	>0.999	<0.001
Construction	1.000	0.000	1.000	0.000
Durable Goods	0.700	0.300	0.905	0.095
Nondurable Goods	0.843	0.157	0.848	0.152
Commerce	1.000	0.000	0.985	0.015
Transportation and Warehousing	0.978	0.022	0.957	0.043
Information	0.988	0.012	0.977	0.023
Finance and Insurance	0.953	0.047	0.967	0.033
Real Estate and Rental and Leasing	1.000	0.000	1.000	0.000
Services	0.977	0.023	0.981	0.019
Government	0.996	0.004	0/0	0/0
Scrap, Used and Secondhand Goods	0.828	0.172	–	–
Others	0.000	1.000	–	–

Notes: This table presents the shares of domestically produced and imported commodities in the total intermediate demand for each sector. The value of 0/0 indicates that the total intermediate demand is zero, making the result undefined.

While we consider country-specific shocks to be the drivers of inflation dynamics in the US and Japan, these shocks also contain an underlying common global shock—such as an energy price shock—that affects both countries. However, our analysis in the previous subsection suggests that, even if we were able to isolate such a common global shock in our analysis, its distinct propagation alone would not fully account for the differences in inflation dynamics between the two countries. As shown in Figure 8, the responses of aggregate inflation to an energy price shock are similar in both the US and Japan.

4.6 Historical Decomposition

The second reason for the difference in inflation dynamics between the US and Japan lies in their contrasting price-setting behaviors, as illustrated by the following historical decomposition.

Figure 9 compares the historical decomposition of aggregate inflation in the US over the period 2008–2022 with that in Japan over the period 2000–2020, highlighting the contribution of sectoral shocks stemming from productivity, import prices, and wages, based on the posterior mean estimates of the parameters in each model. Each contribution in the figure shows the sum of contributions of associated sectoral shocks. In aggregating sectoral inflation, we use weights for total output, as employed in the preceding analyses. Alternative weights for aggregate inflation are considered in Appendix E.6.

While both economies experience fluctuations in aggregate inflation driven by a combination

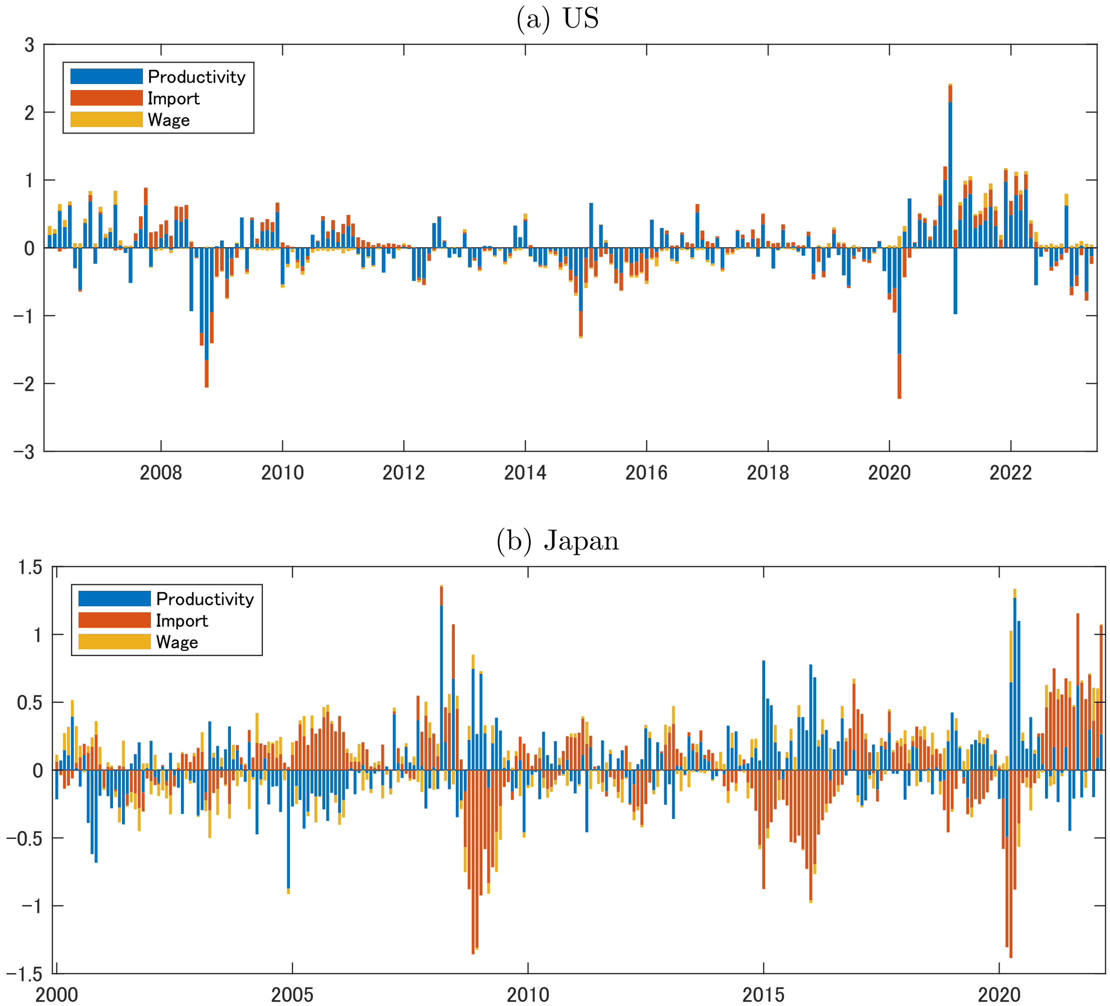


Figure 9: Historical Decomposition of Aggregate Inflation: US and Japan

Notes: The figure shows the historical decomposition of aggregate inflation in the US and Japan, based on the posterior mean estimates of the models' parameters. Each contribution is the sum of contributions of corresponding sectoral shocks.

of productivity, import price, and wage shocks, productivity shocks play a dominant role in contributing to inflation variability in both the US and Japan. Moreover, import price shocks are the second most important factor in explaining inflation dynamics for both countries. This point seems inconsistent with the results of variance decomposition in the US, which indicate that wage shocks are more significant than import price shocks. However, in the historical decomposition, this may occur because the effects of wage shocks in different sectors offset each other in each period, leading to a seemingly diminished role in aggregate terms.[13]

[13] Regarding the contribution of productivity and import price shocks, the results may appear different between the variance and historical decomposition. The historical decomposition suggests a smaller role for productivity shocks and a greater role for import price shocks compared to the variance decomposition. This difference primarily arises from whether shocks are assumed to be correlated. While variance decomposition assumes shocks are orthogonal, as specified in the model, historical decomposition relies on smoothed estimates of shocks, which may be correlated *ex*

A key distinction between the two countries lies in the interaction between productivity and import price shocks. In the US, productivity shocks and import price shocks generally contribute in the same direction to aggregate inflation. This alignment suggests that periods of negative productivity shocks, which raise production costs and cause inflationary pressures, are often accompanied by positive import price shocks that exert similar effects on inflation, such as rising commodity prices during the period 2021–2022. Conversely, positive productivity shocks coincide with declining import prices, amplifying disinflationary pressures.

In Japan, however, domestic productivity shocks and import price shocks tend to contribute in the opposite direction to each other. Positive import price shocks drive inflation upward, such as rising import prices due to the Japanese yen's depreciation during the period 2005–2006. However, Japanese firms did not raise their prices in response to positive import price shocks. Such pricing behavior is identified as positive domestic productivity shocks in our model, which reduce production costs (or, given production costs, which are interpreted as lowering their markups) and offset the inflationary pressures. Increases in productivity align with the findings in Ueda, Watanabe, and Watanabe (2019), who document firms' efforts to improve product quality and expand product variety under Japan's deflationary environment.[14]

The pricing behavior of Japanese firms appears to have shifted in the most recent period. The figure shows that since 2021, when import price shocks exerted upward pressure on aggregate inflation, the offsetting effect of domestic productivity shocks has significantly diminished. Additionally, wage shocks have positively contributed to the heightened inflation since 2022. Consequently, aggregate inflation was elevated substantially.

This divergence between the two economies reflects structural differences in production networks, as illustrated by Tables 3 and 6. The US may experience a closer alignment between domestic productivity and global price dynamics, possibly due to greater integration with global supply chains. In contrast, Japan's economy appears to decouple the effects of domestic productivity changes from external price movements, resulting in opposing contributions. These dynamics underscore the complex interplay of domestic and external factors in shaping inflation dynamics in each country.

Moreover, the distinct patterns of historical decomposition in the US and Japan can be explained by how shocks are identified in the estimated model. In our empirical framework, both import price and wage shocks are directly pinned down from the corresponding sectoral data. Given these shocks, domestic productivity shocks are then identified as the residuals of the equilibrium law of motion for observed sectoral inflation. When the contributions of identified positive import price and wage shocks are not large enough to fully account for heightened domestic inflation, productivity shocks are identified as negative, thereby contributing positively to domestic inflation. This is often the case in the US. On the other hand, when the contributions of positive import price and

post. For instance, if the estimates of import price shocks are positively correlated across sectors, their contribution in the historical decomposition is likely to increase.

[14] Conversely, declining import prices that reduce inflationary pressures are tempered by negative productivity shocks that increase production costs and contribute to mitigating deflationary pressures.

wage shocks exceed the actual increase in domestic inflation, productivity shocks are identified as positive, playing an offsetting role in domestic inflation. The latter case is typically observed in Japan, particularly during periods before 2000.

Figure 10 presents the historical decomposition of each sectoral inflation in the US. As in the decomposition of aggregate inflation, productivity shocks are the primary driver of inflation dynamics in all sectors. However, the contribution of the other two shocks is highly heterogeneous across sectors. Substantial contributions of import price shocks are found in the sectors of Agriculture, etc.; Durable Goods; Nondurable Goods; Transportation and Warehousing; Information; Real Estate, Rental, and Leasing; and Services. Wage shocks play a significant role in labor-intensive sectors, such as Agriculture, etc.; Information; Finance and Insurance; Services; and Government sectors.

The historical decomposition of sectoral inflation in Japan is shown in Figure 11. The patterns of the contribution of shocks to sectoral inflation dynamics in Japan are similar to those in the US, with productivity shocks being the primary driver of inflation in all sectors, followed by import price shocks in most sectors. A remarkable difference between the two countries is that, in Japan, import price shocks are more prevalent and tend to contribute to sectoral inflation in the opposite direction to productivity shocks, as observed in the historical decomposition of aggregate inflation. The contribution of wage shocks is more pronounced in Japan than in the US, particularly in the sectors of Mining; Commerce; Transportation and Warehousing; Information; and Finance and Insurance.

A comparison of historical decompositions between the US and Japan at the sectoral level reveals that import price shocks contribute more significantly in Japan than in the US, particularly in energy-related sectors such as Mining and Utilities. This finding aligns with the results of the variance decomposition of sectoral inflation. In the US, energy prices are shaped by both domestic and import cost factors, whereas in Japan, they are mostly driven by import price shocks due to the near-total reliance on imported natural resources. The historical decomposition of sectoral inflation highlights the importance of accounting for sectoral heterogeneity and production network structures in the analysis of inflation dynamics.

4.7 Policy Experiments: Effects of Tariff Increases

In January 2025, US President Donald Trump announced a series of substantial tariff increases on a broad array of imported goods, including automobiles and steel, from major trading partners such as Canada, Mexico, and China. These policy measures, intended to promote domestic industries and address trade imbalances, have profound implications for inflation dynamics by altering input costs and overall price levels. Our estimated model provides a rigorous quantitative assessment of the inflationary effects of these tariffs, explicitly accounting for the role of production networks in transmitting cost pressures across sectors.[15]

[15] Our partial equilibrium framework does not account for the general equilibrium effects of tariff increases on aggregate inflation—for example, a potential decline in demand for goods and services due to higher prices, which

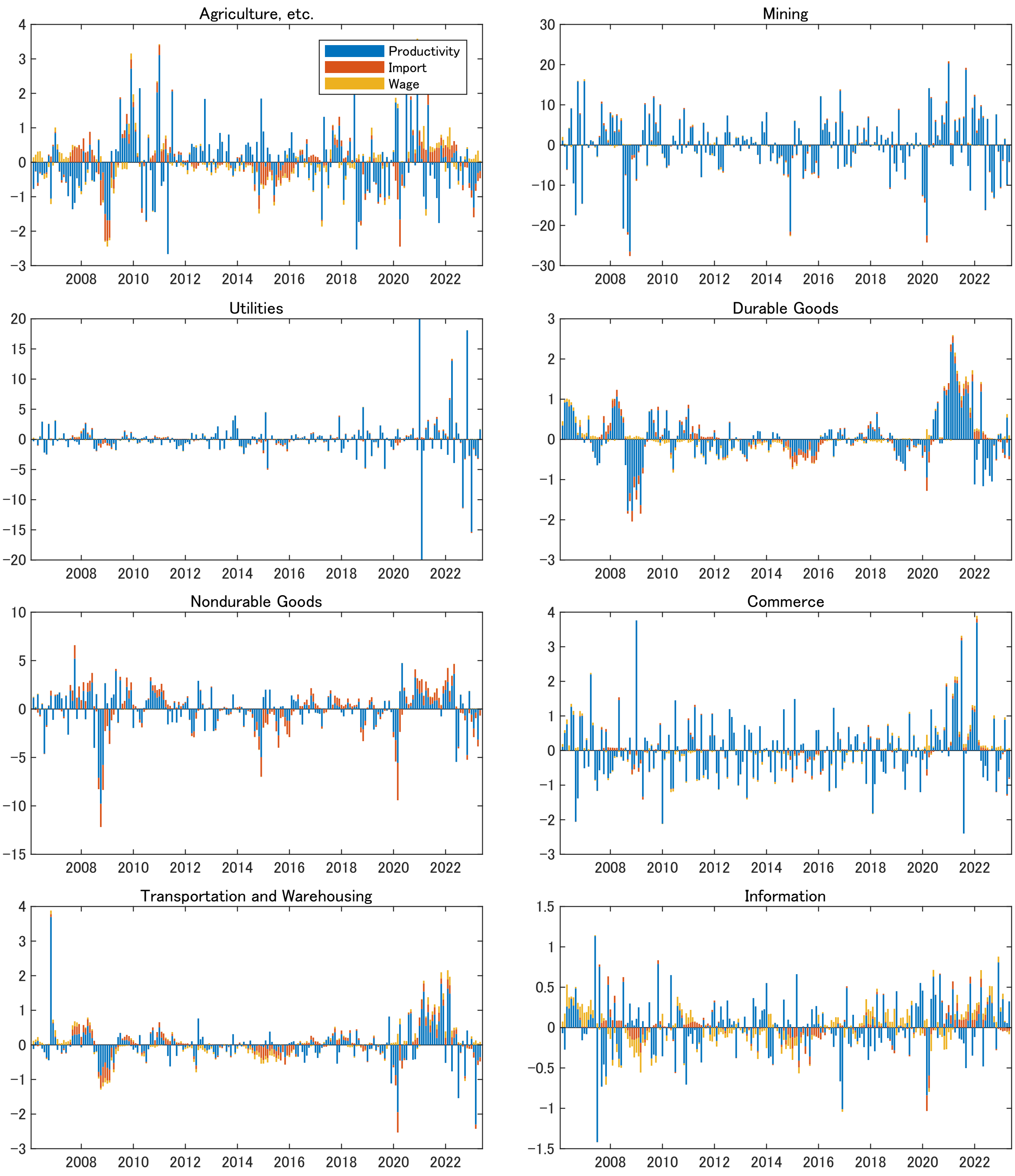


Figure 10: Historical Decomposition of Sectoral Inflation: US

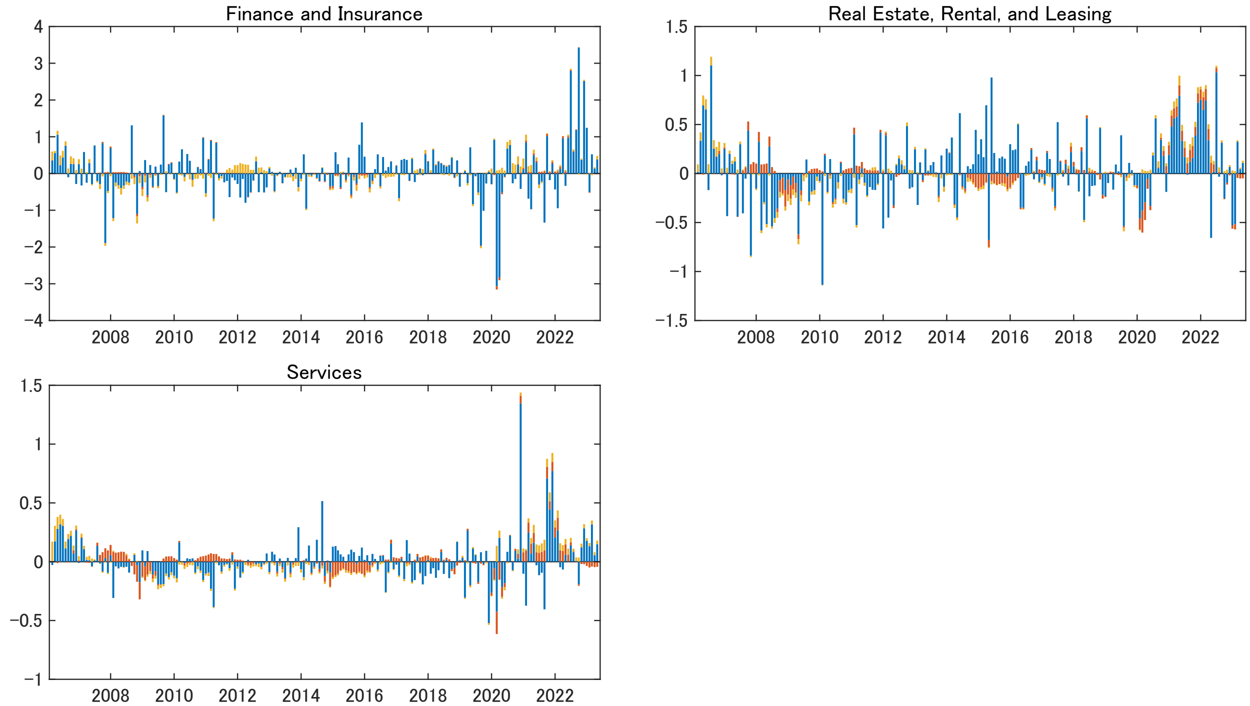


Figure 10: Historical Decomposition of Sectoral Inflation: US (Continued)

Notes: The figure shows the historical decomposition of sectoral inflation in the US, based on the posterior mean estimates of the model's parameters. Each contribution is the sum of contributions of corresponding sectoral shocks.

We analyze three distinct tariff scenarios, each imposing a 10% increase in US import prices through a shock to μ^*_{mt}, but differing in the sectors subject to the additional tariffs. The first scenario is the most comprehensive, applying tariff increases to all imported goods. The second scenario restricts the tariffs to the Durable and Nondurable Goods sectors, while the third limits them to the Mining and Durable Goods sectors. The tariff shock is transitory and follows an AR(1) process with a half-life of four years, corresponding to the tenure of a US president ($\rho^*_m = 0.9857$).

Figure 12 presents the IRFs to the imposed tariff shocks, illustrating their inflationary effects at both the aggregate and sectoral levels. When a uniform 10% tariff increase is applied across all imports, the aggregate inflation rate reaches a peak of approximately 0.3% per month, translating into a cumulative year-on-year inflation increase of 1.2%. Sectoral inflation dynamics reveal that the Mining, Durable Goods, and Nondurable Goods sectors experience the most pronounced inflation surges, reflecting their higher dependence on imported inputs. As the tariff scope narrows, the inflationary impact becomes more contained, with the aggregate inflation response diminishing by nearly half, highlighting the role of sectoral exposure and production linkages in determining the economy-wide price effects of trade policy changes.

would dampen inflationary pressures.

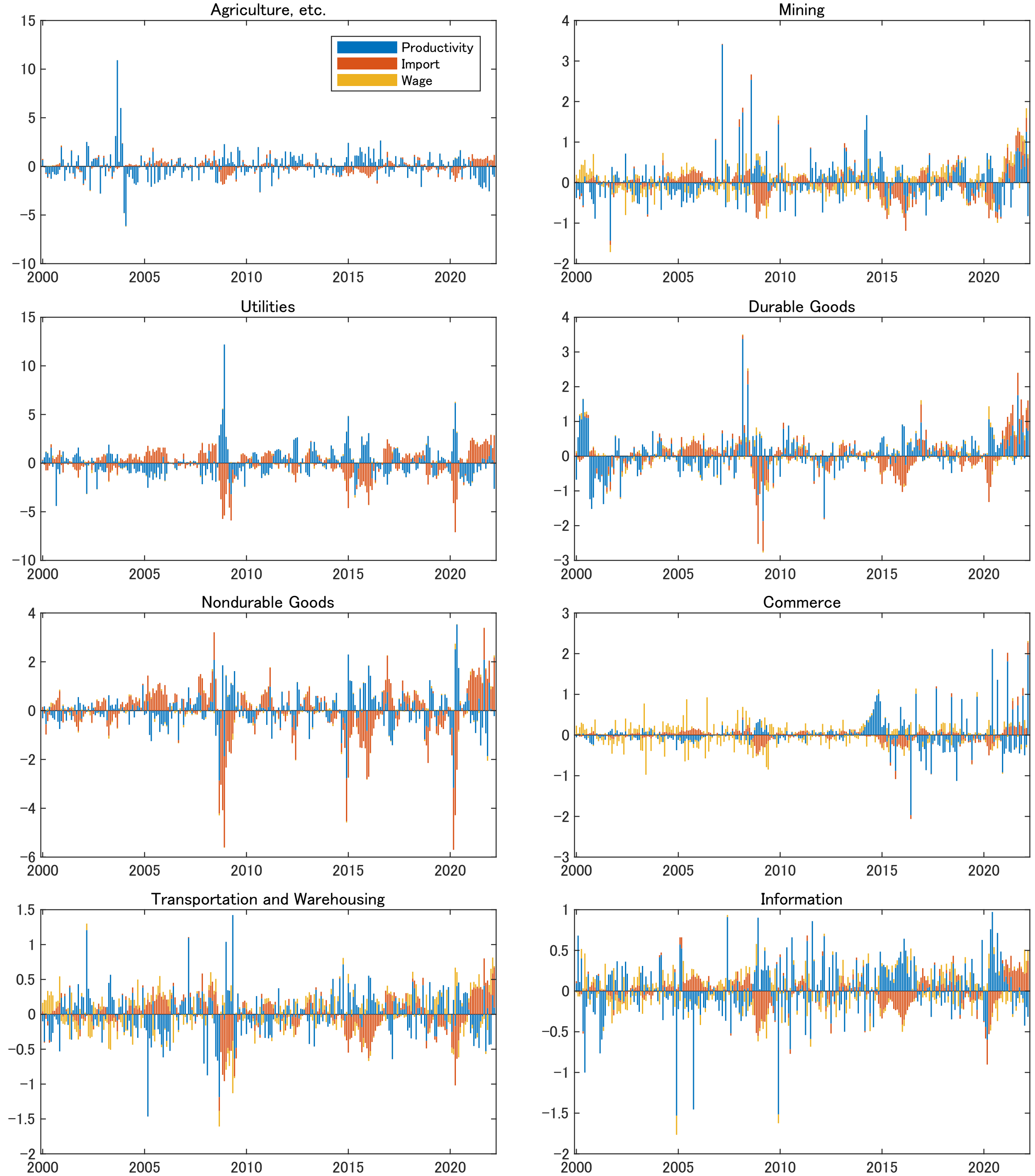


Figure 11: Historical Decomposition of Sectoral Inflation: Japan

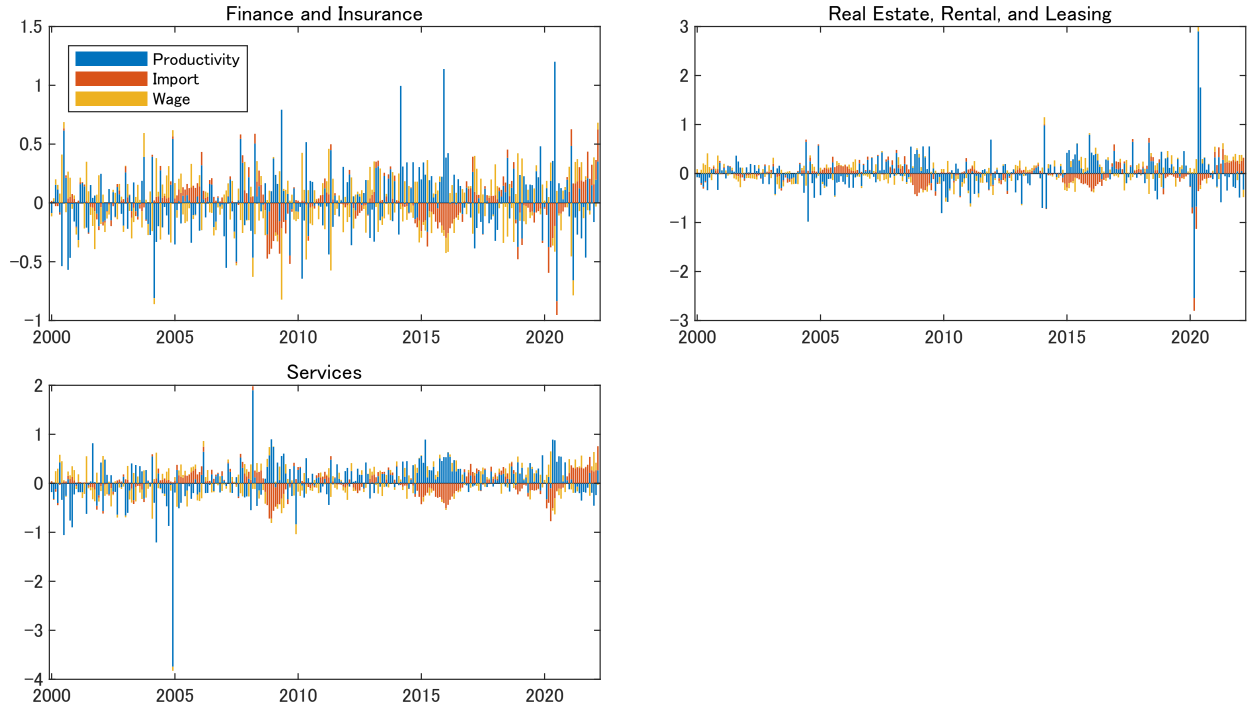


Figure 11: Historical Decomposition of Sectoral Inflation: Japan (Continued)

Notes: The figure shows the historical decomposition of sectoral inflation in Japan, based on the posterior mean estimates of the model's parameters. Each contribution is the sum of contributions of corresponding sectoral shocks.

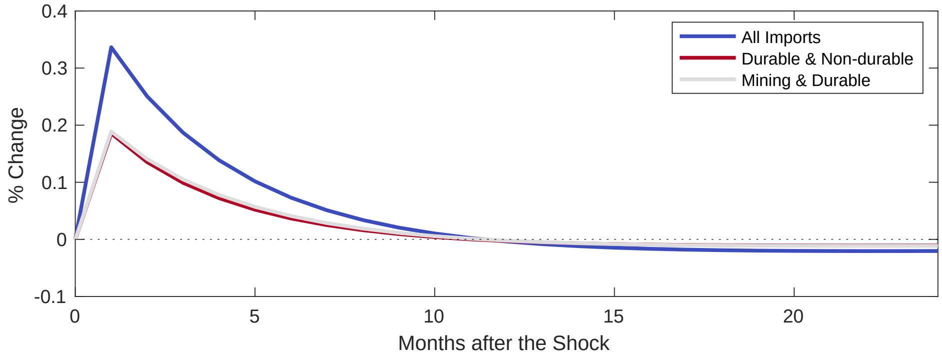
5 Conclusion

This paper has developed and estimated a structural model of sectoral inflation incorporating production networks to analyze inflation dynamics in the US and Japan. Overall, this study underscores the importance of considering sectoral heterogeneity and production network structures when analyzing inflation dynamics.

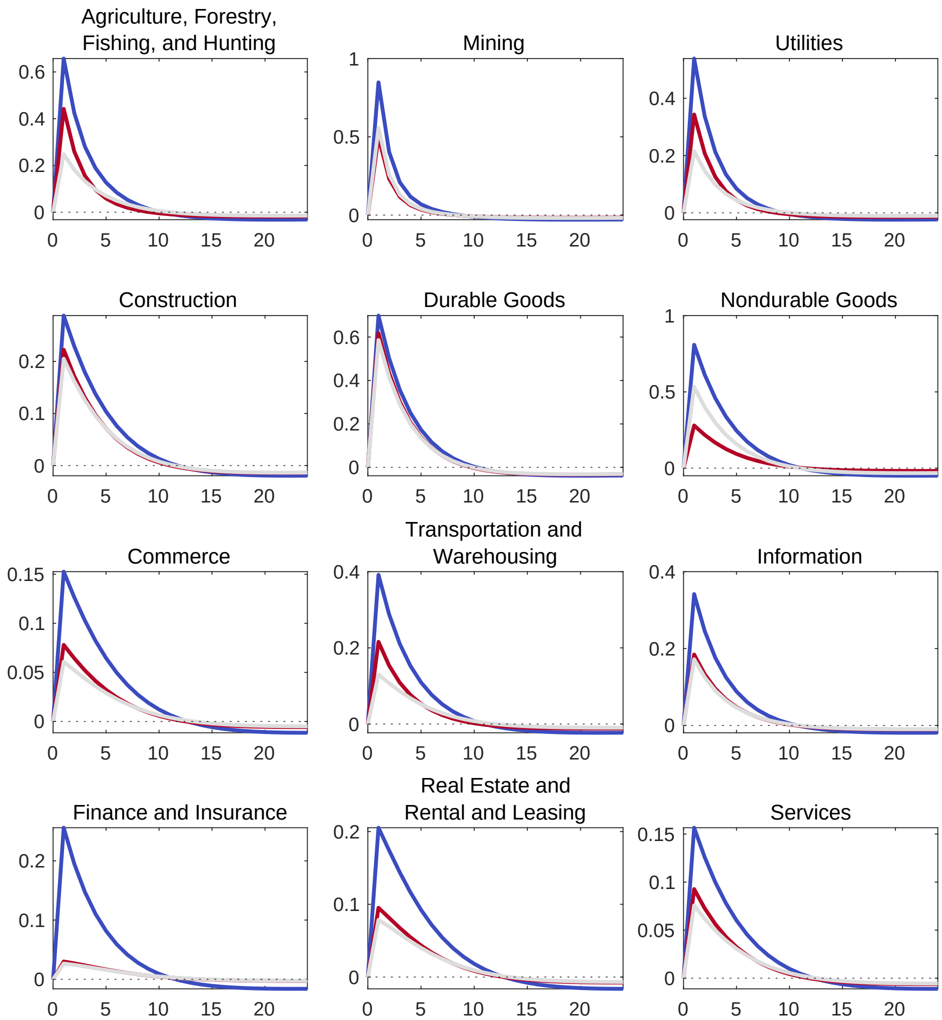
Future research could extend this framework first to incorporate changes in I-O linkages over time and explore the general equilibrium effects of sectoral shocks on the aggregate economy.

Second, the differences in inflation levels between the US and Japan warrant further investigation. In this study, we treat trend inflation as given and focus solely on deviations from it. However, since trend inflation is likely both a driver and a consequence of sectoral inflation dynamics, incorporating trend inflation into the analysis represents an important direction for future research.

Finally, further investigation into consumer price indices is necessary. This study limits its analysis to producer price indices. Examining the pass-through from producer price indices (business-to-business) to consumer price indices (business-to-consumer) requires careful consideration of market structures, particularly those involving retailers.



(a) Responses of Aggregate Inflation



(b) Sectoral Responses

Figure 12: Responses to Tariff Increases

Notes: The figure shows the responses of aggregate and sectoral inflation to the 10% import price shocks to all sectors (blue lines), the Durable and Nondurable Goods sectors (red lines), and the Mining and Durable Goods sectors (light gray lines), respectively. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

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Appendix to "Inflation Dynamics in Production Networks"

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A Derivation of the Model

In the presence of Rotemberg-type price adjustment costs, each firm f in sector i maximizes its value:

$$V_{ift} = \mathbb{E}_t \left[\sum_{k=0}^{\infty} \Lambda_{t,t+k} \left\{ \frac{P_{ift+k}}{P_{t+k}} - RMC_{ift+k} - \frac{\kappa_i}{2} \left(\frac{P_{ift+k}}{P_{ift+k-1}} - 1 \right)^2 \right\} Y_{ift+k} \right],$$

subject to the demand curve:

$$Y_{ift} = (A_i/N) \left(P_{it}/P_t\right)^{-\theta} \left(P_{ift}/P_{it}\right)^{-\sigma_i} Y_t,$$

where RMC_{ift} represents firm-specific real marginal cost.

The first-order condition with respect to P_{ift} yields the optimal reset price:

$$\begin{aligned} 0 = &\left\{ \frac{1}{P_t} - \kappa_i \left(\frac{P_{ift}}{P_{ift-1}} - 1 \right) \frac{1}{P_{ift-1}} \right\} Y_{ift} \\ &+ \left\{ \frac{P_{ift}}{P_t} - RMC_{ift} - \frac{\kappa_i}{2} \left(\frac{P_{ift}}{P_{ift-1}} - 1 \right)^2 \right\} (-\sigma_i) \frac{Y_{ift}}{P_{ift}} \\ &+ \mathbb{E}_t \left[\Lambda_{t,t+1} \kappa_i \left(\frac{P_{ift+1}}{P_{ift}} - 1 \right) \frac{P_{ift+1} Y_{ift+1}}{P_{ift}^2} \right]. \end{aligned}$$

Under the symmetric equilibrium (dropping subscript f), we obtain

$$\begin{aligned} 0 = &\left\{ p_{it} - \kappa_i \pi_{it} \left(1 + \pi_{it}\right) \right\} - \sigma_i \left\{ p_{it} - RMC_{it} - \frac{\kappa_i}{2} \pi_{it}^2 \right\} \\ &+ \mathbb{E}_t \left[\Lambda_{t,t+1} \kappa_i \pi_{it+1} \left(1 + \pi_{t+1}\right) \frac{Y_{it+1}}{Y_{it}} \right], \end{aligned}$$

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where $\pi_{it} \equiv P_{it}/P_{it-1} - 1$ and $p_{it} \equiv P_{it}/P_t$. Log-linearization yields

$$\begin{aligned}\pi_{it} &= \frac{\sigma_i}{\kappa_i}\left\{RMC_{it} - (\sigma_i - 1)p_{it}/\sigma_i\right\} + \beta\mathbb{E}_t\pi_{it+1} \\ &= \frac{\sigma_i}{\kappa_i}\widetilde{RMC}_{it} + \beta\mathbb{E}_t\pi_{it+1},\end{aligned} \tag{A.1}$$

where $\widetilde{RMC}_{it} \equiv RMC_{it} - (\sigma_i - 1)p_{it}/\sigma_i$.

Production technology is given by the following Cobb–Douglas function:

$$Y_{it} = e^{\varepsilon_{it}}\left(\prod_{j=1}^{N} Y_{ijt}^{\omega_{ij}}\right)\cdot\left(\prod_{m=1}^{M} Y_{imt}^{\omega_{im}}\right)\cdot L_{it}^{\omega_{iw}}, \tag{A.2}$$

Then, the cost minimization yields

$$RMC_{it} = \prod_{j=1}^{N}\left(\frac{P_{jt}}{\omega_{ij}P_t}\right)^{\omega_{ij}}\cdot\prod_{m=1}^{M}\left(\frac{P_{mt}^*}{\omega_{im}P_t}\right)^{\omega_{im}}\cdot\left(\frac{W_{it}}{\omega_{iw}P_t}\right)^{\omega_{iw}}\cdot e^{-\varepsilon_{it}}.$$

Assuming $P_i = P$ for all i at the steady state, log-linearization yields

$$\widetilde{RMC}_{it} = \frac{\sigma_i - 1}{\sigma_i}\left(\sum_{j=1}^{N}\omega_{ij}\widehat{p}_{jt} + \sum_{m=1}^{M}\omega_{im}\widehat{p}_{mt}^* + \omega_{iw}\widehat{w}_{it} - \varepsilon_{it} - \widehat{p}_{it}\right), \tag{A.3}$$

where $\widehat{x}_t$ represents the log-linearization of x_t. This equation can be written as

$$\widetilde{RMC}_{it} - \widetilde{RMC}_{it-1} = \frac{\sigma_i - 1}{\sigma_i}\left(\sum_{j=1}^{N}\omega_{ij}\pi_{jt} + \sum_{m=1}^{M}\omega_{im}\pi_{mt}^* + \omega_{iw}\pi_{it}^w - (\varepsilon_{it} - \varepsilon_{it-1}) - \pi_{it}\right),$$

$$\widetilde{RMC}_{it} = \widetilde{RMC}_{it-1} + \sum_{j=1}^{N}\omega_{ij}^*\pi_{jt} + \sum_{m=1}^{M}\omega_{im}^*\pi_{mt}^* + \omega_{iw}^*\pi_{it}^w - (\varepsilon_{it} - \varepsilon_{it-1}), \tag{A.4}$$

where $\widehat{p}_{it} - \widehat{p}_{it-1} = \pi_{it} - \pi_t$ and, for a concise expression, we re-define $\varepsilon_{it} \equiv \frac{\sigma-1}{\sigma}\varepsilon_{it}$ for simplicity and

$$\omega_{ii}^* \equiv \frac{\sigma_i - 1}{\sigma_i}(\omega_{ii} - 1), \tag{A.5}$$

$$\omega_{ij}^* \equiv \frac{\sigma_i - 1}{\sigma_i}\omega_{ij}, \qquad (j \neq i) \tag{A.6}$$

$$\omega_{im}^* \equiv \frac{\sigma_i - 1}{\sigma_i}\omega_{im}, \tag{A.7}$$

$$\omega_{iw}^* \equiv \frac{\sigma_i - 1}{\sigma_i}\omega_{iw}. \tag{A.8}$$

Further, we assume the following AR(1) processes:

$$\widehat{P}^*_{mt} = \rho^*_m \widehat{P}^*_{mt-1} + \mu^*_{mt}, \tag{A.9}$$

$$\widehat{W}_{it} = \rho^w_i \widehat{W}_{it-1} + \mu^w_{it}, \tag{A.10}$$

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \mu_{it}, \tag{A.11}$$

where μ_{it}, μ^*_{mt}, and μ^w_{it} are assumed to be mutually and serially uncorrelated with mean zero.

Then, the equilibrium law of motion for inflation in sector i is of the form:

$$\pi_{it} = -\sum_{j=1}^{N} \Gamma_{ij}\left(\varepsilon_{jt} - \varepsilon_{it-1}\right) + \sum_{m=1}^{M} \Gamma^*_{im}\pi^*_{mt} + \sum_{j=1}^{N} \Gamma^w_{ij}\pi^w_{jt} + \sum_{j=1}^{N} \Gamma^L_{ij}\pi_{jt-1}. \tag{A.12}$$

To determine the coefficient matrices Γ_{ij}, Γ^*_{im}, Γ^w_{ij}, and Γ^L_{ij}, substitute equation (A.3) and one-period-ahead expectation of equation (A.12) into equation (A.1):

$$\begin{aligned}
\pi_{it} &= \frac{\sigma_i}{\kappa_i}\widetilde{RMC}_{it} + \beta\mathbb{E}_t\pi_{it+1} \\
&= \frac{\sigma_i}{\kappa_i}\left(\widetilde{RMC}_{it-1} + \sum_{j=1}^{N}\omega^*_{ij}\pi_{jt} + \sum_{m=1}^{M}\omega^*_{im}\pi^*_{mt} + \omega^*_{iw}\pi^w_{it} - (\varepsilon_{it} - \varepsilon_{it-1})\right) \\
&\quad + \beta\mathbb{E}_t\left[\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt+1} - \varepsilon_{jt}\right) + \sum_{m=1}^{M}\Gamma^*_{im}\left(\widehat{P}^*_{mt+1} - \widehat{P}^*_{mt}\right) + \sum_{j=1}^{N}\Gamma^w_{ij}\left(\widehat{W}_{jt+1} - \widehat{W}_{jt}\right) + \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt}\right] \\
&= \pi_{it-1} - \beta\mathbb{E}_{t-1}\left[\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt} - \varepsilon_{jt-1}\right) + \sum_{m=1}^{M}\Gamma^*_{im}\pi^*_{mt} + \sum_{j=1}^{N}\Gamma^w_{ij}\pi^w_{jt} + \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt-1}\right] \\
&\quad + \frac{\sigma_i}{\kappa_i}\left(\sum_{j=1}^{N}\omega^*_{ij}\pi_{jt} + \sum_{m=1}^{M}\omega^*_{im}\pi^*_{mt} + \omega^*_{iw}\pi^w_{it} - (\varepsilon_{it} - \varepsilon_{it-1})\right) \\
&\quad + \beta\mathbb{E}_t\left[\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt+1} - \varepsilon_{jt}\right) + \sum_{m=1}^{M}\Gamma^*_{im}\left(\widehat{P}^*_{mt+1} - \widehat{P}^*_{mt}\right) + \sum_{j=1}^{N}\Gamma^w_{ij}\left(\widehat{W}_{jt+1} - \widehat{W}_{jt}\right) + \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt}\right] \\
&= \pi_{it-1} + \beta\left(\sum_{j=1}^{N}(1-\rho_j)\Gamma_{ij}\varepsilon_{jt-1} + \sum_{m=1}^{M}(1-\rho^*_m)\Gamma^*_{im}\widehat{P}^*_{mt-1} + (1-\rho^w_i)\sum_{j=1}^{N}\Gamma^w_{ij}\widehat{W}_{jt-1} - \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt-1}\right) \\
&\quad + \frac{\sigma_i}{\kappa_i}\left(\sum_{j=1}^{N}\omega^*_{ij}\pi_{jt} + \sum_{m=1}^{M}\omega^*_{im}\pi^*_{mt} + \omega^*_{iw}\pi^w_{it} - (\varepsilon_{it} - \varepsilon_{it-1})\right) \\
&\quad - \beta\left(\sum_{j=1}^{N}(1-\rho_j)\Gamma_{ij}\varepsilon_{jt} + \sum_{m=1}^{M}(1-\rho^*_m)\Gamma^*_{im}\widehat{P}^*_{mt} + (1-\rho^w_i)\sum_{j=1}^{N}\Gamma^w_{ij}\widehat{W}_{jt} - \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt}\right) \\
&= \pi_{it-1} - \beta\left(\sum_{j=1}^{N}(1-\rho_j)\Gamma_{ij}(\varepsilon_{jt} - \varepsilon_{jt-1}) + \sum_{m=1}^{M}(1-\rho^*_m)\Gamma^*_{im}\pi^*_{mt} + (1-\rho_w)\sum_{j=1}^{N}\Gamma^w_{ij}\pi^w_{jt} - \sum_{j=1}^{N}\Gamma^L_{ij}(\pi_{jt} - \pi_{jt-1})\right)
\end{aligned}$$

$$+\frac{\sigma_i}{\kappa_i}\left(\sum_{j=1}^{N}\omega_{ij}^{*}\pi_{jt}+\sum_{m=1}^{M}\omega_{im}^{*}\pi_{mt}^{*}+\omega_{iw}^{*}\pi_{it}^{w}-(\varepsilon_{it}-\varepsilon_{it-1})\right).$$

which can be written as

$$\begin{aligned}
&\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt}-\varepsilon_{it-1}\right)+\sum_{m=1}^{M}\Gamma_{im}^{*}\pi_{mt}^{*}+\sum_{j=1}^{N}\Gamma_{ij}^{w}\pi_{jt}^{w}+\sum_{j=1}^{N}\Gamma_{ij}^{L}\pi_{jt-1}\\
&=\pi_{it-1}\\
&\quad-\beta\left(\sum_{j=1}^{N}(1-\rho_j)\Gamma_{ij}(\varepsilon_{jt}-\varepsilon_{jt-1})+\sum_{m=1}^{M}(1-\rho_m^{*})\Gamma_{im}^{*}\pi_{mt}^{*}+(1-\rho_i^{w})\sum_{j=1}^{N}\Gamma_{ij}^{w}\pi_{jt}^{w}+\sum_{j=1}^{N}\Gamma_{ij}^{L}\pi_{jt-1}\right)\\
&\quad+\sum_{j=1}^{N}\left(\beta\Gamma_{ij}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{ij}^{*}\right)\left\{\sum_{l=1}^{N}\Gamma_{jl}\left(\varepsilon_{lt}-\varepsilon_{lt-1}\right)+\sum_{m=1}^{M}\Gamma_{jm}^{*}\pi_{mt}^{*}+\sum_{l=1}^{N}\Gamma_{jl}^{w}\pi_{lt}^{w}+\sum_{l=1}^{N}\Gamma_{jl}^{L}\pi_{lt-1}\right\}\\
&\quad+\frac{\sigma_i}{\kappa_i}\left(\sum_{m=1}^{M}\omega_{im}^{*}\pi_{mt}^{*}+\omega_{iw}^{*}\pi_{it}^{w}-(\varepsilon_{it}-\varepsilon_{it-1})\right).
\end{aligned}$$

Equating the coefficients of $\varepsilon_{jt}-\varepsilon_{it-1}$, π_{mt}^{*}, π_{jt}^{w}, and π_{jt-1} on both sides of the equation, for $j=i$ and $j\neq i$, yields

$$\Gamma_{ii}=-\beta(1-\rho_i)\Gamma_{ii}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{li}+\frac{\sigma_i}{\kappa_i}\tag{A.13}$$

$$\Gamma_{ij}=-\beta(1-\rho_j)\Gamma_{ij}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{lj}\qquad(j\neq i)\tag{A.14}$$

$$\Gamma_{im}^{*}=-\beta(1-\rho_m^{*})\Gamma_{im}^{*}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{lm}^{*}+\frac{\sigma_i}{\kappa_i}\omega_{im}^{*}\tag{A.15}$$

$$\Gamma_{ii}^{w}=-\beta(1-\rho_i^{w})\Gamma_{ii}^{w}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{li}^{w}+\frac{\sigma_i}{\kappa_i}\omega_{iw}^{*}\tag{A.16}$$

$$\Gamma_{ij}^{w}=-\beta(1-\rho_i^{w})\Gamma_{ij}^{w}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{lj}^{w}\qquad(j\neq i)\tag{A.17}$$

$$\Gamma_{ii}^{L}=1-\beta\Gamma_{ii}^{L}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{li}^{L}\tag{A.18}$$

$$\Gamma_{ij}^{L}=-\beta\Gamma_{ij}^{L}+\sum_{l=1}^{N}\left(\beta\Gamma_{il}^{L}+\frac{\sigma_i}{\kappa_i}\omega_{il}^{*}\right)\Gamma_{lj}^{L}\qquad(j\neq i).\tag{A.19}$$

We define the following vectors and matrices:

- $\mathbf{\Pi}_t$: the N by 1 vector, where i-th element is π_{it};
- $\mathbf{\Pi}_t^{*}$: the M by 1 vector, where m-th element is π_{mt}^{*};

- $\mathbf{\Pi}_t^w$: the N by 1 vector, where i-th element is π_{it}^w;
- $\mathbf{e}_t$: the N by 1 vector, where i-th element is ε_{it};
- $\mathbf{G}$: the N by N matrix, where element (i,j) is Γ_{ij};
- $\mathbf{G}^*$: the N by M matrix, where element (i,m) is Γ_{im}^*;
- $\mathbf{G_w}$: the N by N matrix, where element (i,j) is Γ_{ij}^w;
- $\mathbf{G_L}$: the N by N matrix, where element (i,j) is Γ_{ij}^L;
- $\mathbf{P}$: the diagonal N by N matrix, where element (i,i) equals ρ_j;
- $\mathbf{P}^*$: the diagonal M by M matrix, where element (m,m) equals ρ_m^*;
- $\mathbf{P_w}$: the diagonal N by N matrix, where element (i,i) equals ρ_i^w;
- $\mathbf{K}$: the diagonal N by N matrix, where element (i,i) equals $(\sigma_i - 1)/\kappa_i$
- $\mathbf{\Omega}$: the N by N matrix, where element (i,j) equals $\omega_{ii} - 1$ for $j = i$ and ω_{ij} for $j \neq i$;
- $\mathbf{\Omega}^*$: the N by M matrix, where element (i,m) equals ω_{im};
- $\mathbf{\Omega_w}$: the diagonal N by N matrix, where element (i,i) equals ω_{iw};

Then, by stacking equation (A.12) for all i, the equilibrium law of motions for sectoral inflation in all sectors are written in the matrix form:

$$\mathbf{\Pi}_t = -\mathbf{G}\left(\mathbf{e}_t - \mathbf{e}_{t-1}\right) + \mathbf{G}^*\mathbf{\Pi}_t^* + \mathbf{G_w}\mathbf{\Pi}_t^w + \mathbf{G_L}\mathbf{\Pi}_{t-1}, \tag{A.20}$$

where coefficients are given by

$$(1+\beta)\mathbf{G_L} = \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G_L} + \mathbf{I}, \tag{A.21}$$

$$\begin{aligned}
\mathbf{G} &= -\beta\mathbf{G}(\mathbf{I} - \mathbf{P}) + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G} + \mathbf{K}, \\
\mathbf{G}^* &= -\beta\mathbf{G}^*(\mathbf{I} - \mathbf{P}^*) + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G}^* + \mathbf{K}\Omega^*, \\
\mathbf{G_w} &= -\beta(\mathbf{I} - \mathbf{P_w})\mathbf{G_w} + \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\mathbf{G_w} + \mathbf{K\Omega_w}.
\end{aligned}$$

The last three equations can be rewritten as

$$\begin{aligned}
\left((1+\beta)\mathbf{I} - \left(\beta\mathbf{G_L} + \mathbf{K\Omega}\right)\right)\mathbf{G} &= \mathbf{K} + \beta\mathbf{GP} \\
\mathbf{G_L}^{-1}\mathbf{G} &= \mathbf{K} + \beta\mathbf{GP} \\
\mathbf{G} &= \mathbf{G_L}\left(\mathbf{K} + \beta\mathbf{GP}\right) \\
vec(\mathbf{G}) &= vec(\mathbf{G_L K}) + \beta vec(\mathbf{G_L GP})
\end{aligned}$$

$$
\begin{aligned}
&= vec(\mathbf{G_L K}) + \beta \left(\mathbf{P}' \otimes \mathbf{G_L}\right) vec(\mathbf{G}) \\
vec(\mathbf{G}) &= \left(\mathbf{I} - \beta \left(\mathbf{P}' \otimes \mathbf{G_L}\right)\right)^{-1} vec(\mathbf{G_L K}),
\end{aligned} \tag{A.22}
$$

$$
\begin{aligned}
\left((1+\beta)\mathbf{I} - (\beta \mathbf{G_L} + \mathbf{K\Omega})\right) \mathbf{G}^* &= \mathbf{K\Omega}^* + \beta \mathbf{G}^* \mathbf{P}^* \\
\mathbf{G_L}^{-1} \mathbf{G}^* &= \mathbf{K}\Omega^* + \beta \mathbf{G}^* \mathbf{P}^* \\
\mathbf{G}^* &= \mathbf{G_L} \left(\mathbf{K\Omega}^* + \beta \mathbf{G}^* \mathbf{P}^*\right) \\
vec(\mathbf{G}^*) &= \left(\mathbf{I} - \beta \left(\mathbf{P}^{*\prime} \otimes \mathbf{G_L}\right)\right)^{-1} vec(\mathbf{G_L K \Omega}^*),
\end{aligned} \tag{A.23}
$$

$$
\begin{aligned}
\mathbf{G_w} &= \left(-\beta \mathbf{P_w} + (1+\beta)\mathbf{I} - \beta \mathbf{G_L} - \mathbf{K\Omega}\right)^{-1} \mathbf{K\Omega_w} \\
&= \left(-\beta \mathbf{P_w} + \mathbf{G_L}^{-1}\right)^{-1} \mathbf{K\Omega_w}.
\end{aligned} \tag{A.24}
$$

Thus, once we solve for $\mathbf{G_L}$ from equation (A.21) numerically, we can calculate $\mathbf{G}$, $\mathbf{G}^*$, and $\mathbf{G_w}$ from equations (A.22)–(A.24), respectively.

B Special Case of Two Sectors

We investigate the effects of I-O linkages and price stickiness on inflation dynamics in a special case where the number of sectors is two ($N = 2$).

Denoting $\mathbf{G_L} \equiv \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}$, we can write equation (10) as

$$
(1+\beta)\mathbf{G_L} = \left(\beta \mathbf{G_L} + \mathbf{K\Omega}\right) \mathbf{G_L} + \mathbf{I},
$$

$$
(1+\beta)\begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} = \left(\beta \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} + \begin{pmatrix} \frac{\sigma_1-1}{\kappa_1} & 0 \\ 0 & \frac{\sigma_2-1}{\kappa_2} \end{pmatrix} \begin{pmatrix} \omega_{11}-1 & \omega_{12} \\ \omega_{21} & \omega_{22}-1 \end{pmatrix}\right) \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix},
$$

which yields the solution given by

$$
\begin{aligned}
g_{11} &= \frac{1+\beta+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11}) - \sqrt{\left\{1+\beta+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11})\right\}^2 - 4\beta\left\{1+\left(\beta g_{12}+\frac{\sigma_1-1}{\kappa_1}\omega_{12}\right) g_{21}\right\}}}{2\beta} \\
g_{12} &= \frac{\frac{\sigma_1-1}{\kappa_1}\omega_{12}}{1+\beta-\beta g_{11}-\beta g_{22}+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11})} g_{22} \\
g_{21} &= \frac{\frac{\sigma_2-1}{\kappa_2}\omega_{21}}{1+\beta-\beta g_{11}-\beta g_{22}+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22})} g_{11} \\
g_{22} &= \frac{1+\beta+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22}) - \sqrt{\left\{1+\beta+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22})\right\}^2 - 4\beta\left\{1+\left(\beta g_{21}+\frac{\sigma_2-1}{\kappa_2}\omega_{21}\right) g_{12}\right\}}}{2\beta}.
\end{aligned} \tag{B.1}
$$

This solution indicates the following:

- g_{11} in $\mathbf{G_L}$ decreases with σ_1 and increases with κ_1 and ω_{11} (unless g_{21} is too large). Further, it increases with g_{12}, g_{21}, and ω_{12}.

- g_{12} in $\mathbf{G_L}$ is proportional to $\omega_{12}g_{22}$. It is zero when $\omega_{12}g_{22} = 0$.

In other words, a positive ω_{12}

- induces a positive g_{12} in $\mathbf{G_L}$ (dependence on the past inflation rate in the other sector),

- increases g_{11} in $\mathbf{G_L}$ (given ω_{11}).

Next, consider how price stickiness κ_2 in the other sector influences inflation dynamics. The above solution shows that both g_{11} and g_{12} in $\mathbf{G_L}$ are independent of κ_2, except for the channel through g_{21} and g_{22}. Thus, an increase in κ_2

- increases g_{22} (direct effect),

- increases g_{12} (given a positive ω_{12};secondary effect through the other sector $g_{22} \rightarrow$ sector 1),

- decreases g_{11} (given a positive ω_{12} and ω_{21}; third effect through sector 1 $\rightarrow$ the other sector $g_{21} \rightarrow$ sector 1 with κ_1).

The eigenvalues of $\mathbf{G_L}$ characterize the degree of inflation persistence. They are given by the solutions of

$$\lambda^2 - (g_{11} + g_{22})\lambda + (g_{11}g_{22} - g_{12}g_{21}) = 0$$

$$\begin{aligned}\lambda &= \frac{g_{11} + g_{22} \pm \sqrt{(g_{11} + g_{22})^2 - 4(g_{11}g_{12} - g_{12}g_{21})}}{2} \\ &= \frac{g_{11} + g_{22} \pm \sqrt{(g_{11} - g_{22})^2 + 4g_{12}g_{21}}}{2}\end{aligned}$$

If non-diagonal elements g_{12} and g_{21} are zero, λ becomes g_{11} or g_{12}. Suppose $g_{11} \geq g_{12} \geq 0$. Positive g_{12} and g_{21} (given g_{11} and g_{22}) increase one λ slightly from g_{11}, while decreasing the other λ slightly from g_{22}. That is, the eigenvalues diverge, which contributes to an increase in aggregate inflation persistence.

Numerical illulstgration Figure B.1 numerically illustrates how the parameters ω_{12}, ω_{21}, κ_1, and κ_2 influence the components in the coefficient matrices on past inflation $\mathbf{G_L}$ and productivity shocks $\mathbf{G}$, when $N = 2$, $\beta = 0.96$, $\rho = 0.85$, $\sigma = 10$, $\kappa = 10$, $\omega_{11} = \omega_{22} = 0.4$, $\omega_{12} = \omega_{21} = 0.2$, $\omega_m = 0.2$, and $\omega_w = 0.2$ (i.e., $\omega_{ii} + \omega_{i-i} + \omega_m + \omega_w = 1$). In each figure, we change parameter values for both ω_{12} and ω_{21}, only ω_{12}, only ω_{21}, both κ_1 and κ_2, and only κ_2, each of which is displayed in the horizontal axis.

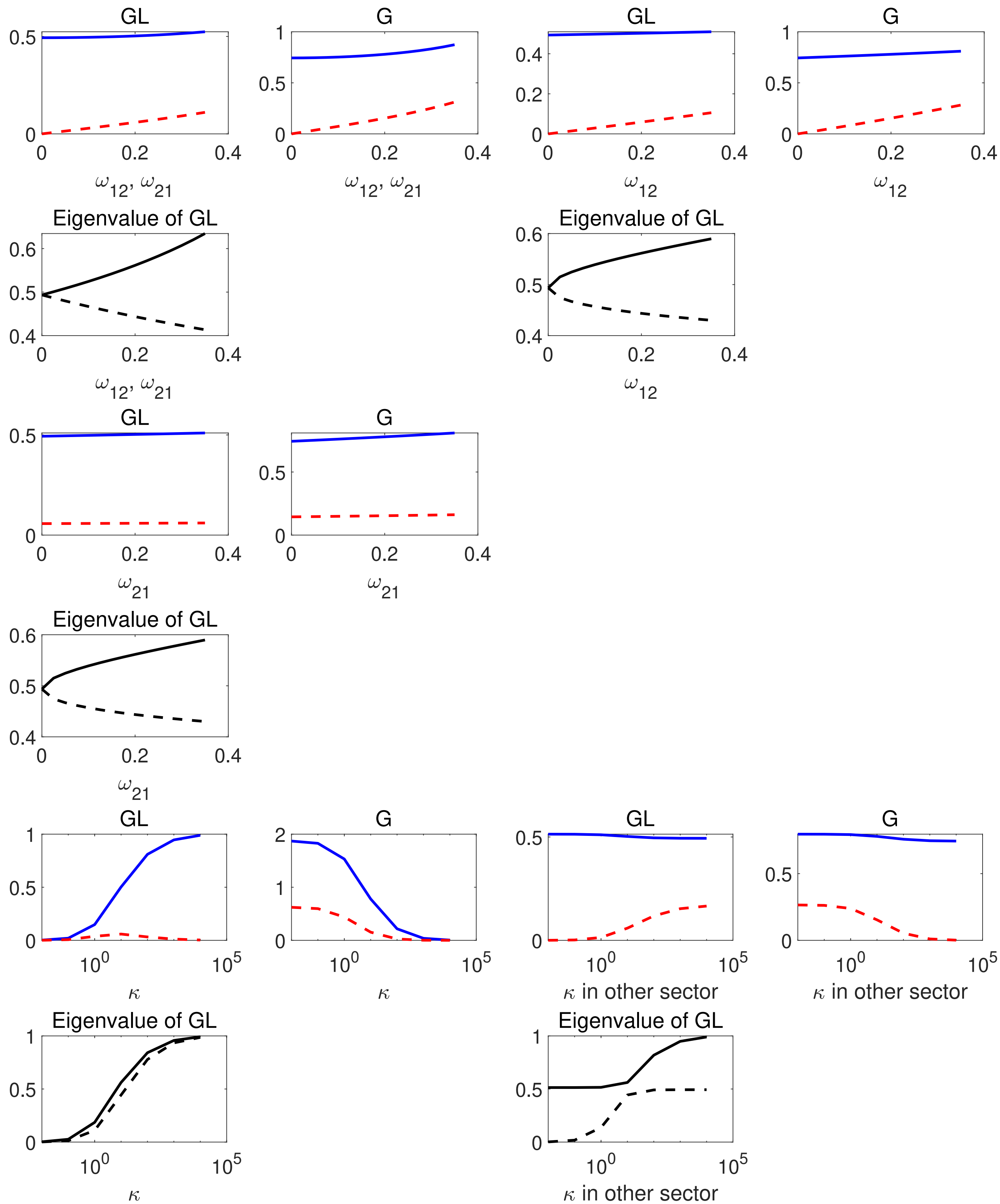


Figure B.1: Effects of ω_{12}, ω_{21}, κ_1, and κ_2 on $\mathbf{G_L}$ and $\mathbf{G}$

Note: The blue and red dashed lines represent g_{11} and g_{12}, respectively, in $\mathbf{G_L}$ or $\mathbf{G}$.

C Data Appendix

This section provides a detailed explanation of how the data used for our empirical analyses are constructed from datasets for the US and Japan.

After Section C.1 explains the sources of the data used for Figure 1 in the main text, Sections C.2 and C.3 describe the methodology to build data on commodity-based I-O matrices and compensation of employees. These data provide the basis for the calculation of $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$ for both the US and Japan. The input-output linkages in these data correspond to the transpose of matrices $\mathbf{\Omega}$ and $\mathbf{\Omega}^*$. In Sections C.4 and C.5, we construct sectoral domestic price indices, import price indices, and wage indices for both countries. These indices are used as observables for model estimation. Section C.6 introduces a sector classification system that allows for a direct comparison between the US and Japan. Then, we describe the procedure for aggregating the I-O tables, sectoral compensation of employees, and price indices according to this classification system. Finally, in Section C.7, the matrices and vectors for the empirical analyses are derived using the constructed data.

C.1 Sources of the data shown in Figure 1

In the main text, Figure 1 plots the time series of the inflation rates on the PPI, IPI, and wage index for the US and Japan.

For the US, the data sources are straightforward. The PPI, IPI, and wage index correspond to the "Producer Price Index for All Commodities", "Import Price Index for BEA End Use, All Commodities", and "Average Hourly Earnings of All Employees, Total Private, Seasonally Adjusted" in the Current Employment Statistics, respectively.

For Japan, there is no direct counterpart to the US PPI in official statistics, as the Corporate Goods Price Index for Japan focuses solely on goods-producing sectors. To incorporate prices in services sectors, we construct Japan's PPI as a weighted average of three price indices: "Producer Price Index Excluding Consumption Tax, All Commodities," "Services Producer Price Index Excluding Consumption Tax, All Items," and "Wholesale Services Price Index Excluding Consumption Tax, Wholesale Trade," using weights for the total output of the corresponding sectors from the I-O table. The IPI corresponds to the "Import Price Index (Japanese yen basis), All Commodities." The wage index is defined as the wage per hour worked, derived from the ratio of "Total Cash Earnings" to "Total of Hours Actually Worked" in the seasonally adjusted data from the Monthly Labour Survey.

C.2 Constructing the Commodity-based I-O Matrix for the US

In this subsection, we describe how we use the "Make" and "Use" tables to construct the commodity-by-commodity I-O matrix and commodity-based value-added matrix for the US. Specifically, we use the 2012 "Make" and "Use" tables after redefinitions published by the Bureau of Economic Analysis (BEA).

In the US, the "Make" and "Use" tables serve as the core of the I-O Accounts. In these tables, each sector is classified based on two distinct criteria: commodity and industry. While a commodity shows a group of similar products, an industry is a group of establishments with similar production processes.

The "Make" table is a matrix of industry-by-commodity. For each row, each column shows the value of each commodity produced by the industry in that row. We refer to this matrix as make matrix hereafter. The "Use" table consists of three components: intermediate portion, final-use portion, and value-added portion. The intermediate portion is a matrix of commodity-by-industry. Given a column, each row shows the value of each commodity used by the intermediate sector in that column. We refer to this matrix as use matrix hereafter. The final-use portion is a matrix representing the value of commodities consumed or invested by final users, as indicated in each column. The value-added portion is a matrix displaying value-added components for each intermediate industry, such as compensation of employees.

The BEA employs the BEA Industry Code to classify both industries and commodities. In the 2012 data, the most disaggregated level of classification, known as the "detail" level, consists of 405 sectors for both commodities and industries. Among these, 401 classifications are common to both categories.

The use and make matrices are asymmetric in the sense that different classifications are used for the rows and columns. To construct a commodity-by-commodity I-O matrix, we combine these two matrices according to the manual provided by the BEA.[1,2] Let $\mathbf{V} = (v_{ij})_{1 \leq i,j \leq N}$ be the industry-by-commodity make matrix that gives for each cell v_{ij} the value of commodity j produced by industry i. And let $\mathbf{U} = (u_{ij})_{1 \leq i,j \leq N}$ be the use matrix that gives for each cell u_{ij} the value of commodity i used by industry j. The basic relations between the matrices $\mathbf{V}$ and $\mathbf{U}$ are expressed by the following equations.

$$\mathbf{q} = \mathbf{U}\mathbf{i}_N + \mathbf{e}, \tag{C.1}$$
$$= \mathbf{V}^\top \mathbf{i}_N,$$
$$\mathbf{g} = \mathbf{V}\mathbf{i}_N, \tag{C.2}$$

where $\mathbf{i}_N$ is the $N \times 1$ vector of ones and $\mathbf{e}$ is an $N \times 1$ vector representing the "Total Final Uses" for each commodity. And $\mathbf{q}$ and $\mathbf{g}$ are $N \times 1$ vectors, referred to as the "Total Commodity Output" and the "Total Industry Output", respectively. Then, we define the following matrices.

$$\mathbf{B} = \mathbf{U} \times \mathrm{diag}(\mathbf{g})^{-1}, \tag{C.3}$$

[1] Similarly, it is also possible to construct industry-by-industry I-O table. However, in order to create an I-O table that is comparable to Japanese data, this study adopts the commodity-by-commodity I-O table.

[2] See U.S. Bureau of Economic Analysis, "Mathematical Derivation of the Total Requirements Tables for Input-Output Analysis," February 2017. Moreover, see Karen J. Horowitz and Mark A. Planting, "Concepts and Methods of the Input-Output Accounts," U.S. Bureau of Economic Analysis, April 2009.

$$\mathbf{D} = \mathbf{V} \times \mathrm{diag}(\mathbf{q})^{-1}, \tag{C.4}$$

where $\mathrm{diag}(\mathbf{g})$ is the diagonal matrix of vector $\mathbf{g}$ and $\mathrm{diag}(\mathbf{q})$ is the diagonal matrix of vector $\mathbf{q}$. The matrices $\mathbf{B}$ and $\mathbf{D}$ are referred to as the direct input matrix and the market share matrix, respectively. Using equations (C.2)–(C.4), equation (C.1) can be rewritten as follows.

$$\mathbf{q} = \mathbf{BDq} + \mathbf{e}. \tag{C.5}$$

In the above equation, the matrix $\mathbf{A} \equiv \mathbf{BD}$ is referred to as the commodity-by-commodity direct requirement. Thus, the commodity-by-commodity I-O matrix is given by

$$\mathbf{X} \equiv \mathbf{A} \times \mathrm{diag}(\mathbf{q}). \tag{C.6}$$

C.2.1 Decomposing the I-O Matrix into the Domestic and Import Sectors

In this study, we make a clear distinction between domestically produced and imported goods and services used as intermediate inputs by domestic sectors.

We decompose the matrix $\mathbf{U}$ into domestic and import sectors, using the "Import" table published by the BEA. The "Import" table is a commodity-by-industry matrix, where each column represents the value of each imported commodity used by the sector in the column. Denoting the import matrix as $\mathbf{U}^*$, the matrix $\mathbf{U}^d$, where each column represents the value of domestically produced commodities used by that column sector, is given by:

$$\mathbf{U}^d = \mathbf{U} - \mathbf{U}^*. \tag{C.7}$$

We use the decomposed matrices $\mathbf{U}^d$ and $\mathbf{U}^*$ instead of $\mathbf{U}$ when calculating $\mathbf{X}$ in equation (C.6). This allows us to obtain the commodity-by-commodity I-O matrix for both domestic and import sectors.

C.2.2 Constructing the Compensation of Employees for each Sector

This subsection describes how we construct data on the commodity-based compensation of employees required to create $\mathbf{\Omega}_w$ by converting the industry-based value-added portion in the "Use" table into a commodity-based matrix. The value-added portion is a $3 \times N$ matrix representing the three value-added components for each industry: "Compensation of employees," "Taxes on production and imports, less subsidies," and "Gross operating surplus."

Let $\mathbf{Y}$ and $\mathbf{Z}$ be $3 \times N$ matrices representing the value-added portion based on industry and commodity, respectively. Using these value-added matrices, the two total output vectors, $\mathbf{q}$ and $\mathbf{g}$, can be expressed as follows:

$$\mathbf{g}^\top = \mathbf{y}^\top + \mathbf{i}_N^\top \mathbf{B} \times \mathrm{diag}(\mathbf{g}), \tag{C.8}$$

$$\mathbf{q}^\top = \mathbf{z}^\top + \mathbf{i}_N^\top \mathbf{A} \times \mathrm{diag}(\mathbf{q}), \tag{C.9}$$

where $\mathbf{y} = \mathbf{Y}^\top \mathbf{i}_3$ and $\mathbf{z} = \mathbf{Z}^\top \mathbf{i}_3$. Postmultiplying equation (C.9) by $\mathbf{V}^{-1} \times \mathrm{diag}(\mathbf{g})$, we have

$$\mathbf{g}^\top = \mathbf{z}^\top \mathbf{V}^{-1} \times \mathrm{diag}(\mathbf{g}) + \mathbf{i}_N^\top \mathbf{B} \times \mathrm{diag}(\mathbf{g}). \tag{C.10}$$

Then, the commodity-based value-added matrix $\mathbf{Z}$ is given by

$$\mathbf{Z} = \mathbf{Y} \times \mathrm{diag}(\mathbf{g})^{-1} \mathbf{V}. \tag{C.11}$$

We can obtain the data on commodity-based compensation of employees as a $1 \times N$ vector from the matrix $\mathbf{Z}$.

C.3 Constructing the Commodity-based I-O Matrix for Japan

This subsection explains the methodology for constructing Japan's I-O matrices and data on the compensation of employees. The data used in this subsection are sourced from the 2011 I-O tables published by the Ministry of Internal Affairs and Communications. Specifically, we use the "Transactions Valued at Producers' Prices" at the "Basic Sector Classification" level.

The Japanese I-O Accounts do not follow the framework based on the "Make" and "Use" tables. Instead, a table called "Transactions Valued at Producers' Prices," consisting of three portions—intermediate portion, final-use portion, and value-added portion—serves as the core data for this statistic. The intermediate portion of this table is similar to the commodity-by-commodity I-O matrix in the US. Given a column, each row shows the value of each commodity used by the sector corresponding to that column. Given a row, each column shows the value of the commodity in that row demanded by each intermediate sector. Sectors in each column are referred to as supply sectors, and sectors in each row are referred to as demand sectors. The demand sectors are classified either by activity or by commodity. The term "activity" refers to a classification based on "units of production activity," which are categorized according to the similarity of input structures or production technologies across production activities.[3] For sectors where a single activity corresponds to a single commodity, classifications are based on commodities even for the demand sectors.

In the 2011 data, the number of sectors at the highest level of disaggregation, known as the "Basic Sector Classification," is 518 for supply sectors and 397 for demand sectors. In this study, we use a 517×396 matrix as the commodity-by-commodity I-O matrix, excluding the "Activities not elsewhere classified." This matrix is then aggregated into a square matrix in which commodities and activities correspond one-to-one, as explained in Section C.6.

[3]For example, the commodity "Electricity" is classified into multiple activities, such as "Electricity (nuclear power)" or "Electricity (thermal power)", based on differences in production activities. On the other hand, commodities like "Gasoline" and "Jet fuel oils," which have significantly different prices and uses, are classified under the single activity "petroleum products" due to similarities in their production activities.

C.3.1 Decomposing the I-O Matrix into the Domestic and Import Sectors

Similar to the US, the values in Japan's I-O table reflect the amounts for both domestic and imported commodities. However, no publicly available data in Japan corresponds to the US "Import" table, except for certain aggregated tables. The I-O table at the "Basic Sector Classification" level provides only the values of "Total imports," denoted by $m_i \geq 0$, for each supply sector $i \in [1, 2, ..., N_r = 517]$.[4]

We assume that the import ratio of supply sector i is the same across all demand sectors $j \in [1, 2, ..., N_c = 396]$, and is represented as

$$c_i = \frac{m_i}{m_i + D_i}, \tag{C.12}$$

where D_i represents the "Domestic production" for commodity i.

Under this assumption, the I-O matrix at the "Basic Sector Classification" level, denoted as $\mathbf{X}_{N_r \times N_c} = (x_{ij})_{1 \leq i \leq N_r, 1 \leq j \leq N_c}$, can be decomposed into the domestic I-O matrix $\mathbf{X}^d$ and the import matrix $\mathbf{X}^*$.

$$\mathbf{X}_{N_r \times N_c} = \{\mathbf{I}_{N_r} - \mathrm{diag}(\mathbf{c})\} \mathbf{X}_{N_r \times N_c} + \mathrm{diag}(\mathbf{c}) \mathbf{X}_{N_r \times N_c}, \tag{C.13}$$

$$\equiv \mathbf{X}^d + \mathbf{X}^*, \tag{C.14}$$

where $\mathbf{I}_{N_r}$ represents the identity matrix of size N_r and $\mathrm{diag}(\mathbf{c})$ is the diagonal matrix of vector $\mathbf{c} = (c_1, ..., c_{N_r})$.

C.3.2 Constructing the Compensation of Employees for each Demand Sector

Now, we construct the data on the sectoral compensation of employees for Japan, which is required to create $\mathbf{\Omega}_w$. In the value-added portion of the Japanese data, there are eleven sectors that are more detailed than those in the US.

We define the compensation of employees for each demand sector j as the sum of the three value-added sectors, as follows:

$$\begin{aligned} \text{Compensation of employees}_j \equiv\ & \text{Wages and salaries}_j \\ & + \text{Contribution of employers to social insurance}_j \\ & + \text{Other payments and allowances}_j. \end{aligned}$$

[4] In the I-O tables, the values of "Total imports" are generally reported as the values obtained by multiplying the amounts of import by -1, that is, as $-m_i$.

C.4 Constructing the Price and Wage Indices for the US

This subsection describes the methodology for constructing three types of monthly price indices—domestic prices, import prices, and wages—by US I-O sectors. These price indices are used to calculate the corresponding inflation rates, which are treated as observables for model estimation. All price data used to construct these indices are sourced from the Bureau of Labor Statistics (BLS). Specifically, domestic price indices are derived from the "Industry Data" and "Discontinued Industry Data (NAICS-basis)" in the Producer Price Index, while import price indices are based on the "Industry Import Index" data from the International Price Index. Wage price indices are derived from the Current Employment Statistics National.

C.4.1 Domestic Price Indices by I-O Sectors

First, we construct domestic price indices for each disaggregated I-O sector using the Producer Price Index (PPI). The US PPI consists of two datasets: "industry data" and "commodity data," both derived from the same underlying data. While the commodity data are more suitable for measuring price changes in inputs used by each sector, the BLS commodity classification system differs from the BEA Industry Code. The industry data measure changes in prices received for the industry's output sold outside the industry. This dataset is classified into sectors based on the 2017 North American Industry Classification System (NAICS), which forms the basis of the BEA Industry Code, enabling a straightforward mapping between the two systems. In our study, we use the industry data to construct the domestic price indices for each sector in the I-O table.

We match the PPI data, classified by the 2017 NAICS codes, with the 2012 BEA codes in the I-O table. Initially, we match the 2012 and 2017 BEA codes using the 2017 I-O Accounts. Next, we match these codes with the 2017 concordance table between the 2017 BEA codes and related 2017 NAICS codes, published by the BEA. Table C.1 summarizes the 2012 BEA codes for which the corresponding NAICS (related NAICS) codes changed between the 2012 and 2017 classifications. Of the 409 BEA Industry Codes at the "detail" level in the 2012 I-O table, 393 are mapped to one or more related NAICS codes. Finally, we link the PPI data with the NAICS codes corresponding to the 393 BEA codes based on the following four criteria.

1. Related NAICS with exact matching: If the price time series corresponding to the related NAICS code exist in the PPI dataset, we link these time series to the corresponding BEA sector. E.g.: Oil and gas extractions (2012 BEA: 211000, Related NAICS: 211, NAICS in price data: 211, NAICS we use: 211).

2. Related NAICS matched with lower-level classifications: A related NAICS code is not in the PPI dataset, but lower-level classification codes belonging to the related NAICS are included. In these cases, we match the price index of the most aggregated classification among them with the corresponding BEA code. E.g.: Forestry and logging (2012 BEA: 113000, Related NAICS: 113, NAICS in price data: 1133, 11331, 113310, NAICS we use: 1133).

Table C.1: BEA Codes with NAICS Changes Between 2012 to 2017

2012 BEA	Related 2012 NAICS	Related 2017 NAICS
33391A	333911, 333913	333914
335221	335221	335220
335222	335222	335220
335224	335224	335220
335228	335228	335220
517110	5171	517311
517210	5172	517312

3. Related NAICS matched with upper-level classifications: A related NAICS is not present in the PPI dataset, but its upper-level classifications are included. In these cases, we do not match any price indices with the corresponding BEA code. E.g.: Automobile Manufacturing (2012 BEA: 336111, Related NAICS: 336111, NAICS in price data: 33611, NAICS we use: None).

4. Related NAICS with no matching: If the related NAICS cannot be matched with the PPI data based on criteria 1–3, the price index for the corresponding BEA code is treated as missing. E.g.: Oilseed farming (2012 BEA: 1111A0, Related NAICS: 11111 and 11112, NAICS in price data: None, NAICS we use: None).

As the final step, we calculate the domestic price indices at the BEA "detail" level by aggregating the monthly PPI for each related NAICS code. The PPI time series employed in this aggregation are normalized by the average value of each series for the year 2015.[5] If multiple NAICS codes correspond to a single "detail" code, the price index for this code is calculated as the simple average of the corresponding time series.

As a result, we construct the domestic price indices for 318 out of the 393 codes at the "detail" level. The sample period runs from January 2000 to July 2023.

C.4.2 Import Price Indices by I-O Sectors

Second, we construct the import price index at the "detail" level using the International Price Index. This dataset also includes indices based on both industry and commodity classifications, with the industry index classified according to the 2017 NAICS codes. We use the NAICS-based "Industry Import Index" as the import price index.

Following the same aggregation procedure used for the PPI, we construct import price indices for 26 "detail" codes from December 2005 to July 2023.

[5]Time series lacking observations for the year 2015 are excluded from the aggregation.

C.4.3 Wage Indices by I-O Sectors

Third, we outline the methodology for calculating wage indices for each "detail" code using the Current Employment Statistics (CES) published by the BLS. The CES provides various data on employment, hours, and wages, published monthly by CES industry, which corresponds to NAICS codes. Specifically, we use the seasonally adjusted "Average Hourly Earnings of All Employees" as the wage index due to its high compatibility with our model. And the sample period used in this study runs from March 2006 to July 2023.

The CES data are classified according to the 2022 NAICS codes. To construct wage indices based on the 2012 BEA codes, it is necessary to map the 2022 NAICS codes to the 2012 BEA codes. Therefore, in addition to Table C.1, we use the concordance table between the 2017 and 2022 NAICS codes published by the NAICS Association. The following two criteria are used when extracting the 2022 NAICS codes corresponding to the BEA codes.

1. BEA codes associated with disaggregated NAICS codes: If the 2012 BEA codes are matched with the related 6-digit NAICS codes, the relavant 6-digit 2022 codes are extracted using the concordance table between the 2017 and 2022 NAICS codes.

   - E.g.: Plumbing fixture fitting and trim manufacturing (2012 BEA: 332913, Related NAICS: 332913, 6-digit 2017 NAICS: 332913, 6-digit 2022 NAICS: 332913).

2. BEA codes associated with aggregated NAICS codes: The 2012 BEA codes are mapped to the related NAICS codes at a level higher than the 6-digit code. In such cases, the first step is to enumerate the 6-digit 2017 NAICS codes that fall under the related NAICS. Then, extract the corresponding 6-digit 2022 NAICS codes using the NAICS 2017–2022 concordance. If the related NAICS is classified at the N-digit level, all N-digit classifications of the extracted 2022 codes are mapped to the BEA code.

   - E.g.: Oil and gas extraction (2012 BEA: 211000, Related NAICS: 211, 6-digit 2017 NAICS: 211111, 6-digit 2022 NAICS: 211120 and 211300, N-digit NAICS: 211).
   - E.g.: Nonstore retailers (2012 BEA: 454000, Related NAICS: 454, 6-digit 2017 NAICS: 454110, 454210, 454310, and 454390, 6-digit 2022 NAICS: forty-three 6-digit codes classified into nine 3-digit codes, N-digit NAICS: 441, 444, 445, 449, 455, 456, 457, 458, and 459.)

The wage indices by NAICS code are aggregated by "detail" codes in the I-O table using the same method as applied to the PPI. As a result, we construct wage indices for 163 BEA "detail" codes.

C.5 Constructing the Price and Wage indices for Japan

In this subsection, we construct price indices on domestic prices, import prices, and wages for sectors in Japan's I-O table. Specifically, the domestic and import price indices are constructed using the 2015 Corporate Goods Price Index (CGPI), 2015 Services Producer Price Index (SPPI), and 2015 Wholesale Services Price Index (WSPI), as published by the Bank of Japan (BOJ). The wage indices are derived from the 2020 Monthly Labour Survey published by the Ministry of Health, Labour, and Welfare.

C.5.1 Domestic and Import Price Indices by I-O Sectors

First, we construct domestic and import price indices for each I-O sector using the CGPI, SPPI, and WSPI. The CGPI consists of monthly data on the prices of domestic, imported, and exported goods. Specifically, we use the 2015 Producer Price Index for domestic prices, and the 2015 Import Price Index (Yen basis) for import prices. The sample period for these datasets runs from January 2000 to April 2022.

The SPPI and WSPI are datasets that provide price information for business-related services. The WSPI specifically focuses on the prices of wholesale services, which are not covered by the SPPI, and consist of quarterly data from 2015 onwards.[6] Since there is only one wholesale sector in the Japanese I-O table, we use only the aggregated wholesale price index in the WSPI.

The SPPI is a monthly dataset that covers a broad range of services. We use the SPPI data for four reference years: 2000, 2005, 2010, and 2015. This is because the SPPI does not publish long-term item-level time series that link price indices from different base years. Therefore, we construct the linked index for the SPPI using the following two steps.

In the first step, we reclassify all price data for each base year according to the commodity classifications used in the 2015 data. The concordance table linking commodities across different base years is published by the BOJ. Let P_{it}^{y} denote the price index for commodity i in month t, with respect to the base year $y \in \{2000, 2005, 2010, 2015\}$. Additionally, let Θ_j^y represent the set of commodities in base year y corresponding to commodity j in the 2015 data. The price index for commodity j, calculated using the data for base year y, is given by

$$P_{jt}^{y,2015} = \sum_{i \in \Theta_j^{y,2015}} \omega_i^y P_{it}^y, \tag{C.15}$$

where ω_i^y is the weight used when aggregating commodity i into commodity j.

In the second step, we combine the price indices for commodity j across each base year y. For the price indices of two different base years $y = y_1$ and y_2 $(> y_1)$, we calculate the following link coefficient using the overlapping period of these two time series:

[6] The WSPI used in our analysis is data that has been converted from quarterly to monthly using the Last Observation Carried Forward method.

$$c_j^{y_1,y_2} = \frac{\sum_{t \in T_{y_2}} P_{jt}^{y_2,2015}}{\sum_{t \in T_{y_2}} P_{jt}^{y_1,2015}}, \tag{C.16}$$

where T_y is the set of months in year y. And the 2015 based-linked SPPI for commodity j is calculated as

$$P_{jt}^{SP} = \begin{cases} P_{jt}^{2015,2015}, & \text{if } t \geq \text{Jan.2015}, \\ c_j^{2010,2015} \times P_{jt}^{2010,2015}, & \text{if } t \in [\text{Jan.2010}, \text{Dec.2014}], \\ c_j^{2005,2010} \times c_j^{2010,2015} \times P_{jt}^{2005,2015}, & \text{if } t \in [\text{Jan.2005}, \text{Dec.2009}], \\ c_j^{2000,2005} \times c_j^{2005,2010} \times c_j^{2010,2015} \times P_{jt}^{2000,2015}, & \text{if } t \in [\text{Jan.2000}, \text{Dec.2004}]. \end{cases} \tag{C.17}$$

As a result, the 2015-based linked SPPI we construct covers the period from January 2000 to December 2022.

Next, by harmonizing the commodities included in the CGPI, WSPI, and linked SPPI data with the sectors in the I-O table, we construct the domestic and import price indices for each I-O sector. This harmonization is primarily carried out using the commodity concordance table between the 2011 I-O table and the 2015 price indices published by the BOJ. If multiple price indices correspond to a single I-O commodity code, those price indices are aggregated using the weights provided by the concordance table. Furthermore, for some I-O sectors that are not matched with price indices in the concordance table, we manually match them by referring to the price indices adopted by the Cabinet Office of Japan for the basic unit deflator in the national accounts.[7]

By completing the above steps, time series of price indices are constructed for 372 domestic sectors and 160 import sectors, respectively, out of the 517 supply sectors in the I-O table.

C.5.2 Wage Indices by I-O Sectors

Next, we construct wage indices for each demand sector in the Japanese I-O table using the 2020 Monthly Labour Survey published by the Ministry of Health, Labour, and Welfare. This is Japan's monthly labor market statistics, categorized by industry classification, size of establishments, and type of employment.[8]

Specifically, we use seasonally adjusted data for all establishment sizes and employment types.[9] And the sample period runs from January 2000 to October 2022.

We define the wage price index for each sector j using two variables from this dataset, as follows.

[7] Table 8-1 "List of Corresponding Price Indices for the Basic Unit Deflators (2011-based)" Heisei 23-nen kijun kihon tani defureta hinmoku taio kakaku shisu ichiran reiwa gannen 8-nen jiten (in Japanese), Cabinet Office: https://www.esri.cao.go.jp/jp/sna/data/reference1/h23/pdf/chap_8_2_201908.pdf (accessed on December 27, 2024).

[8] For a detailed description of classifications, see "The interpretation of symbols in the data" Jissu·Shisu ruiseki deta ni okeru kigo no mikata (in Japanese): https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00450071&tstat=000001011791&stat_infid=000031913619 (accessed on December 26, 2024)

[9] size of establishments: establishments with 5 employees or more, type of employment: total.

Table C.2: Harmonized Sector Classification with Corresponding Sectors in the US and Japan

Code	Name	US sectors	Japan's sectors
1	AGRICULTURE, FORESTRY, FISHING, AND HUNTING	11	1
2	MINING	21	2
3	UTILITIES	22	5
4	CONSTRUCTION	23	4
5	DURABLE GOODS	33DG	25 to 39[1]
6	NONDURABLE GOODS	31ND	11 to 22, 39, 68[2]
7	COMMERCE	42, 44RT	51
8	TRANSPORTATION AND WAREHOUSING	48TW	9
9	INFORMATION	51	10
10	FINANCE AND INSURANCE	52	7
11	REAL ESTATE AND RENTAL AND LEASING	53	8
12	SERVICES	54 to 81[3]	12
13	GOVERNMENT	G	11
14	SCRAP, USED AND SECONDHANDS GOODS	Used	–
15	NONCOMPARABLE IMPORTS AND REST-OF-THE-WORLD ADJUSTMENT	Other	–

1 Use 12 "2-digit Aggregated Sector Classification" codes.
2 Use 8 "2-digit Aggregated Sector Classification" codes.
3 Use 8 "Sector" codes.

$$\text{Wage index}_j \equiv \frac{\text{Total cash earnings}_j}{\text{Total of hours actually worked}_j}. \tag{C.18}$$

The industry classification in this dataset follows the "Japan Standard Industry Classification," which is used for the sector classification in the I-O table. However, the classification in this dataset is more aggregated compared to the I-O table, which comprises 83 industries. Therefore, we manually match these 83 industries to 361 out of 396 demand sectors in the I-O table.

C.6 Sectoral Aggregation

We aggregate the I-O tables and price indices to ensure consistent sector classifications between the US and Japan.

First, we harmonize the commodity classifications of the two countries with the 15 sectors presented in Table C.2. In this table, the US codes correspond to 23 "sector" codes, with the 409 "detail" codes assigned to one of these "sectors." The Japanese codes represent either the 2-digit classifications or the special classifications, with 517 supply sectors and 396 demand sectors assigned to one of these classification codes.

Second, we aggregate the I-O matrices and price indices for the domestic and import sectors according to our sector classifications. The method for aggregating these data does not depend on whether the data are for Japan or the US, or whether they pertain to domestic or import sectors. Therefore, we simply refer to the I-O matrix as $\mathbf{X}_{N_r \times N_c} = (x_{ij})_{1 \le i \le N_r, 1 \le j \le N_c}$, and the price indices as $\{P_{it}\}_{1 \le i \le N_r}$. Let the I-O table aggregated by sector $i' = 1, ..., N'$ be denoted as $\mathbf{X}_{N' \times N'} = (x_{i'j'})_{1 \le i', j' \le N'}$. Each element of this matrix is calculated as follows:

$$x_{i'j'} = \sum_{i \in \Theta_{i'}, j \in \Theta_{j'}} x_{ij}, \tag{C.19}$$

where $\Theta_{i'}$ is the set of commodities classified into sector i'. Additionally, using the total intermediate demand for each supply sector i, denoted by $x_i = \sum_j x_{ij}$, the price index for each sector i' is given by

$$P_{i't} = \frac{\sum_{\{i | i \in \Theta_{i'}, P_{it} \neq \text{missing}\}} x_i P_{it}}{\sum_{\{i | i \in \Theta_{i'}, P_{it} \neq \text{missing}\}} x_i}. \tag{C.20}$$

By applying these aggregations separately to the domestic and import sectors, we obtain the domestic I-O matrix, the import matrix, the domestic price indices, and the import price indices, represented by $\mathbf{X}^d_{N' \times N'}$, $\mathbf{X}^*_{N' \times N'}$, $P_{i't}$, and $P^*_{i't}$, respectively.[10]

Third, we aggregate the wage index for each demand sector j as follows:

$$W_{j't} = \frac{\sum_{\{j | j \in \Theta_{j'}, W_{jt} \neq \text{missing}\}} x^w_j W_{jt}}{\sum_{\{j | j \in \Theta_{j'}, W_{jt} \neq \text{missing}\}} x^w_j}, \tag{C.21}$$

where W_{jt} and x^w_j are the wage index and the compensation of employees, respectively, in the demand sector j. We also construct a diagonal matrix $\mathbf{X}^w_{N' \times N'} = \text{diag}(x^w_1, ..., x^w_{N'})$, where the diagonal elements are given by $x^w_{j'} = \sum_{j \in \Theta_{j'}} x^w_j$ for $j = 1, ..., N'$.

C.7 Construction of I-O Linkage Parameters and Aggregate Inflation

The three matrices for I-O linkage parameters $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$ are constructed from the I-O matrices $\mathbf{X}^d_{N' \times N'}$, $\mathbf{X}^*_{N' \times N'}$, and $\mathbf{X}^w_{N' \times N'}$. While the (i, j) entry of the parameter matrices reflects the input share of commodity/labor j for sector i, the (i', j') entry of the matrices $\mathbf{X}^d_{N' \times N'}$, $X^*_{N' \times N'}$, and $\mathbf{X}^w_{N' \times N'}$ shows the input <u>value</u> of commodity/labor $\underline{i'}$ for sector $\underline{j'}$. And the total value of inputs for each sector j' is represented by $s'_j = \sum_{i'} x^d_{i'j'} + \sum_{i'} x^*_{i'j'} + x^w_{j'}$. Therefore, the parameter matrices $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$ are calculated as follows:

$$\mathbf{\Omega} = \mathbf{S}^{-1} \mathbf{X}^{d\top}_{N' \times N'} - \mathbf{I}_{N'}, \tag{C.22}$$

$$\mathbf{\Omega}^* = \mathbf{S}^{-1} (\mathbf{X}^*_{N' \times N'})^\top, \tag{C.23}$$

$$\mathbf{\Omega}_w = \mathbf{S}^{-1} (\mathbf{X}^w_{N' \times N'})^\top, \tag{C.24}$$

[10] If the aggregated I-O matrices contain negative elements, they are replaced with zero.

Table C.3: Weights for Aggregating Sectoral Inflation

Weight	US I-O table (use table)	Japan's I-O table
Total output	Total Commodity Output	Domestic production (gross output)
Final demand	Total Final Uses (GDP) + Imports of goods and services (≥ 0)	Total final demand
Personal consumption expenditure	Personal consumption expenditures	Consumption expenditure of households

Notes: This table lists possible weights used for aggregating sectoral inflation. The first column shows the names of the weights used in this study, while the second and third columns summarize the correspondence between these variables and the components listed in the I-O Accounts of Japan and the US, respectively.

where $\mathbf{S} = \text{diag}(\mathbf{s})$ is the diagonal matrix of vector $\mathbf{s} = (s_1, ..., s_{N'})$.

Lastly, we introduce three weights for aggregating sectoral inflation: "Total output," "Final demand," and "Personal consumption expenditures," as shown in Table C.3. Specifically, we aggregate sectoral values using the relative share of each sector for each variable as a weight.

"Total output" represents the gross output for each commodity, including both intermediate and final products. This metric encompasses all stages of production and functions as a weight that indicates the relative importance of each sector within the entire production network. "Final demand" captures the total value of goods and services consumed or invested as final products. This weight is used for aggregating the price index based on the demand from final users. "Personal consumption expenditures" reflect the value of final products purchased by households. This measure is suitable as a weight to capture how the prices of goods and services consumed by households fluctuate at the production stage.

D Sequential Monte Carlo Algorithm

To approximate the posterior distribution of model parameters, we employ the generic SMC algorithm with likelihood tempering described in Herbst and Schorfheide (2014, 2015). In the algorithm, a sequence of tempered posteriors is defined as

$$\varpi_n(\boldsymbol{\theta}) = \frac{[p(\mathbf{Y}^T|\boldsymbol{\theta}, \mathbf{M})]^{\tau_n} p(\boldsymbol{\theta}, \mathbf{M})}{\int [p(\mathbf{Y}^T|\boldsymbol{\theta}, \mathbf{M})]^{\tau_n} p(\boldsymbol{\theta}, \mathbf{M}) d\boldsymbol{\theta} d\mathbf{M}}, \quad n = 0, ..., N_\tau,$$

where N_τ denotes the number of stages and is set at $N_\tau = 200$. The tempering schedule $\{\tau_n\}_{n=0}^{N_\tau}$ is determined by $\tau_n = (n/N_\tau)^\mu$, where μ is a parameter that controls the shape of the tempering schedule and is set at $\mu = 2$, following Herbst and Schorfheide (2014, 2015). The SMC algorithm generates parameter draws $\{\boldsymbol{\theta}_n^{(i)}, \mathbf{M}_n^{(i)}\}$ and associated importance weights $w_n^{(i)}$, called particles, from the sequence of posteriors $\{\varpi_n\}_{n=1}^{N_\tau}$; *i.e.*, at each stage, $\varpi_n(\boldsymbol{\theta})$ is represented by a swarm of particles $\{\boldsymbol{\theta}_n^{(i)}, \mathbf{M}_n^{(i)}, w_n^{(i)}\}_{i=1}^N$, where N denotes the number of particles. In the subsequent estimation, the algorithm uses $N = 10,000$ particles. For $n = 0, ..., N_\tau$, the algorithm sequentially updates the swarm of particles $\{\boldsymbol{\theta}_n^{(i)}, \mathbf{M}_n^{(i)}, w_n^{(i)}\}_{i=1}^N$ through importance sampling.[11]

Posterior inferences on model parameters are made based on the particles $\{\boldsymbol{\theta}_{N_\tau}^{(i)}, \mathbf{M}_{N_\tau}^{(i)}, w_{N_\tau}^{(i)}\}_{i=1}^N$ from the final importance sampling. The SMC-based approximation of the marginal data density is given by

$$p(\mathbf{Y}^T) = \prod_{n=1}^{N_\tau} \left(\frac{1}{N} \sum_{i=1}^{N} \tilde{w}_n^{(i)} w_{n-1}^{(i)} \right),$$

where $\tilde{w}_n^{(i)}$ is the incremental weight defined as $\tilde{w}_n^{(i)} = [p(\mathbf{Y}^T | \boldsymbol{\theta}_{n-1}^{(i)}, \mathbf{M}_{n-1}^{(i)})]^{\tau_n - \tau_{n-1}}$.

E Additional Empirical Results

E.1 Posterior Estimates of Parameters

Table E.1 presents the posterior mean of each parameter and the 90% credible interval along with the marginal data density in the estimation for the US and Japan, respectively. This table reveals notable differences between the two countries.

Table E.1: Posterior Estimates of Parameters

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
κ_1	6.387	[4.916, 7.420]	24.198	[20.417, 27.681]
κ_2	3.444	[2.754, 4.197]	29.744	[26.944, 32.449]
κ_3	8.253	[6.374, 9.837]	27.408	[23.862, 30.745]
κ_4	28.027	[26.471, 29.591]	19.884	[17.001, 23.088]
κ_5	23.122	[21.543, 24.755]	26.912	[23.960, 30.085]
κ_6	34.223	[32.910, 35.769]	23.835	[20.601, 27.087]
κ_7	31.063	[28.233, 33.332]	22.961	[19.402, 26.340]
κ_8	16.712	[15.721, 17.714]	24.267	[21.294, 27.477]
κ_9	17.151	[15.479, 18.699]	30.999	[28.253, 33.903]
κ_{10}	30.258	[28.285, 32.339]	39.300	[36.347, 42.632]
κ_{11}	27.760	[25.327, 30.132]	32.814	[29.033, 36.819]
κ_{12}	31.137	[30.045, 32.292]	33.944	[30.460, 37.615]
κ_{13}	31.694	[30.416, 33.026]	19.323	[16.323, 22.457]
κ_{14}	10.095	[8.887, 11.457]	-	-
κ_{15}	40.717	[39.263, 41.922]	-	-
ρ_1^ϵ	0.622	[0.572, 0.672]	0.848	[0.800, 0.896]
ρ_2^ϵ	0.593	[0.559, 0.629]	0.826	[0.782, 0.868]
ρ_3^ϵ	0.754	[0.705, 0.801]	0.910	[0.875, 0.949]

[11] This process includes one step of a single-block random-walk Metropolis–Hastings algorithm.

Parameter	US		Japan	
	Mean	90% interval	Mean	90% interval
ρ_4^ϵ	0.793	[0.767, 0.822]	0.301	[0.145, 0.451]
ρ_5^ϵ	0.749	[0.677, 0.807]	0.858	[0.812, 0.906]
ρ_6^ϵ	0.653	[0.618, 0.683]	0.643	[0.561, 0.720]
ρ_7^ϵ	0.967	[0.940, 0.996]	0.599	[0.511, 0.682]
ρ_8^ϵ	0.880	[0.835, 0.920]	0.699	[0.626, 0.772]
ρ_9^ϵ	0.726	[0.653, 0.799]	0.522	[0.446, 0.608]
ρ_{10}^ϵ	0.754	[0.698, 0.818]	0.472	[0.396, 0.550]
ρ_{11}^ϵ	0.806	[0.756, 0.856]	0.696	[0.634, 0.762]
ρ_{12}^ϵ	0.685	[0.643, 0.724]	0.958	[0.936, 0.981]
ρ_{13}^ϵ	0.638	[0.549, 0.734]	0.594	[0.472, 0.730]
ρ_{14}^ϵ	0.645	[0.603, 0.689]	-	-
ρ_{15}^ϵ	0.821	[0.759, 0.882]	-	-
ρ_1^*	0.979	[0.969, 0.987]	0.973	[0.963, 0.983]
ρ_2^*	0.426	[0.340, 0.514]	0.642	[0.493, 0.797]
ρ_3^*	0.249	[0.194, 0.300]	0.256	[0.142, 0.377]
ρ_5^*	0.850	[0.794, 0.904]	0.353	[0.213, 0.503]
ρ_6^*	0.061	[0.028, 0.095]	0.548	[0.455, 0.631]
ρ_7^*	-	-	0.272	[0.156, 0.385]
ρ_8^*	0.376	[0.299, 0.456]	0.152	[0.079, 0.228]
ρ_9^*	0.301	[0.193, 0.404]	0.116	[0.030, 0.194]
ρ_{10}^*	0.663	[0.602, 0.717]	0.532	[0.390, 0.662]
ρ_{12}^*	0.191	[0.102, 0.278]	0.639	[0.461, 0.803]
ρ_{13}^*	0.618	[0.570, 0.668]	-	-
ρ_{14}^*	0.981	[0.961, 0.998]	-	-
ρ_{15}^*	0.192	[0.140, 0.243]	-	-
ρ_1^w	0.873	[0.842, 0.903]	0.321	[0.207, 0.439]
ρ_2^w	0.875	[0.835, 0.906]	0.765	[0.714, 0.821]
ρ_3^w	0.028	[0.006, 0.047]	0.315	[0.241, 0.400]
ρ_4^w	0.278	[0.236, 0.323]	0.814	[0.763, 0.869]
ρ_5^w	0.977	[0.959, 0.997]	0.567	[0.486, 0.643]
ρ_6^w	0.405	[0.350, 0.457]	0.577	[0.496, 0.656]
ρ_7^w	0.863	[0.826, 0.902]	0.311	[0.222, 0.400]
ρ_8^w	0.953	[0.931, 0.976]	0.742	[0.686, 0.797]
ρ_9^w	0.892	[0.856, 0.929]	0.256	[0.159, 0.359]
ρ_{10}^w	0.965	[0.940, 0.990]	0.204	[0.134, 0.270]
ρ_{11}^w	0.669	[0.618, 0.714]	0.632	[0.555, 0.702]
ρ_{12}^w	0.088	[0.044, 0.136]	0.662	[0.602, 0.719]

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
ρ^w_{13}	0.889	[0.857, 0.920]	0.457	[0.339, 0.567]
ρ^w_{14}	0.484	[0.423, 0.544]	-	-
ρ^w_{15}	0.254	[0.195, 0.317]	-	-
σ^ϵ_1	2.592	[2.354, 2.864]	4.816	[4.210, 5.441]
σ^ϵ_2	10.756	[10.197, 11.415]	2.520	[2.216, 2.832]
σ^ϵ_3	12.194	[11.475, 13.018]	4.639	[3.980, 5.280]
σ^ϵ_4	3.093	[2.799, 3.433]	3.811	[2.332, 5.280]
σ^ϵ_5	2.065	[1.571, 2.586]	1.675	[1.386, 1.953]
σ^ϵ_6	5.072	[4.817, 5.342]	3.410	[2.940, 3.920]
σ^ϵ_7	2.025	[1.884, 2.157]	3.683	[2.995, 4.336]
σ^ϵ_8	1.863	[1.585, 2.119]	1.655	[1.385, 1.926]
σ^ϵ_9	1.329	[1.097, 1.547]	2.377	[2.013, 2.769]
σ^ϵ_{10}	3.369	[3.022, 3.712]	2.714	[2.353, 3.097]
σ^ϵ_{11}	1.946	[1.737, 2.174]	2.321	[1.933, 2.641]
σ^ϵ_{12}	1.183	[1.069, 1.281]	1.741	[1.518, 1.941]
σ^ϵ_{13}	2.953	[2.538, 3.332]	2.081	[1.426, 2.805]
σ^ϵ_{14}	3.783	[3.346, 4.215]	-	-
σ^ϵ_{15}	3.486	[3.139, 3.835]	-	-
σ^*_1	4.262	[4.025, 4.489]	3.482	[3.147, 3.789]
σ^*_2	4.671	[4.462, 4.850]	6.821	[6.258, 7.381]
σ^*_3	3.702	[3.225, 4.200]	6.841	[5.517, 8.215]
σ^*_5	0.372	[0.320, 0.426]	2.084	[1.892, 2.264]
σ^*_6	0.688	[0.619, 0.759]	2.652	[2.435, 2.856]
σ^*_7	-	-	3.328	[2.260, 4.395]
σ^*_8	6.715	[6.140, 7.336]	1.708	[1.150, 2.295]
σ^*_9	2.824	[2.326, 3.285]	1.295	[0.939, 1.711]
σ^*_{10}	1.052	[0.847, 1.274]	3.078	[2.157, 3.944]
σ^*_{12}	2.751	[2.368, 3.149]	3.598	[1.980, 4.979]
σ^*_{13}	3.446	[3.170, 3.711]	-	-
σ^*_{14}	5.966	[5.425, 6.504]	-	-
σ^*_{15}	2.430	[2.000, 2.901]	-	-
σ^w_1	1.467	[1.316, 1.626]	2.708	[1.723, 3.675]
σ^w_2	1.191	[1.020, 1.343]	3.994	[3.713, 4.303]
σ^w_3	2.483	[2.223, 2.697]	4.387	[4.085, 4.674]
σ^w_4	2.085	[1.847, 2.354]	2.351	[2.147, 2.543]
σ^w_5	0.414	[0.365, 0.461]	1.922	[1.771, 2.077]
σ^w_6	1.807	[1.578, 2.060]	1.878	[1.717, 2.033]

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
σ^w_7	0.669	[0.565, 0.780]	2.748	[2.526, 2.975]
σ^w_8	0.479	[0.420, 0.542]	2.198	[1.986, 2.407]
σ^w_9	0.872	[0.760, 0.976]	3.281	[3.011, 3.551]
σ^w_{10}	0.544	[0.471, 0.617]	3.744	[3.485, 3.990]
σ^w_{11}	0.946	[0.827, 1.060]	2.885	[2.648, 3.088]
σ^w_{12}	4.134	[3.809, 4.499]	2.348	[2.168, 2.527]
σ^w_{13}	2.591	[2.223, 2.946]	1.849	[1.013, 2.610]
σ^w_{14}	0.853	[0.705, 1.005]	-	-
σ^w_{15}	4.026	[3.593, 4.483]	-	-
$\log p(\mathbf{Y}^T)$	-10622.9		-12831.4	

Notes: The table reports the posterior mean and the 90% highest posterior density intervals based on $10,000$ particles from the final importance sampling in the SMC algorithm. $\log p(\mathbf{Y}^T)$ represents the SMC-based approximation of the log marginal data density.

E.2 Estimated Price Stickiness and the Frequency of Price Changes

In this subsection, we examine the consistency of our estimates for price stickiness κ_i with micro evidence as studied in Bils and Klenow (2004). To this end, we investigate whether our estimates of κ_i are negatively correlated with the frequency of price changes in the corresponding CPI items, presented by Bils and Klenow (2004) and Ueda (2024) for the US and Japan, respectively. Ueda (2024) compares the frequency of price changes for each CPI item in Japan with those in the US, as provided by Bils and Klenow (2004). We manually match these data to the disaggregated I-O sectors and then aggregate to the 15 harmonized sectors. If more than two CPI items are matched to a disaggregated I-O sector, we calculate the weighted frequency of these items using the CPI weights provided in Ueda (2024). Then, we aggregate these frequencies to the 15 harmonized sectors based on the weights defined by the domestically produced portion of total intermediate demand for each disaggregated sector.

Figure E.1 shows the scatter plots between our estimates of price stickiness κ_i and the observed frequency of price changes derived from micro price data for both the US and Japan. Because of missing sectoral data on the frequency of price changes, each panel excludes several sectors: Mining, Commerce, Finance and Insurance, Real Estate and Rental and Leasing, and Government, Scrap, Used and Secondhand Goods, and Others for the US; and Mining, Commerce, Finance and Insurance, and Government for Japan. The Pearson correlation coefficients for these plots are -0.06 and -0.32 for the US and Japan, respectively, which are indeed negative but insignificant.

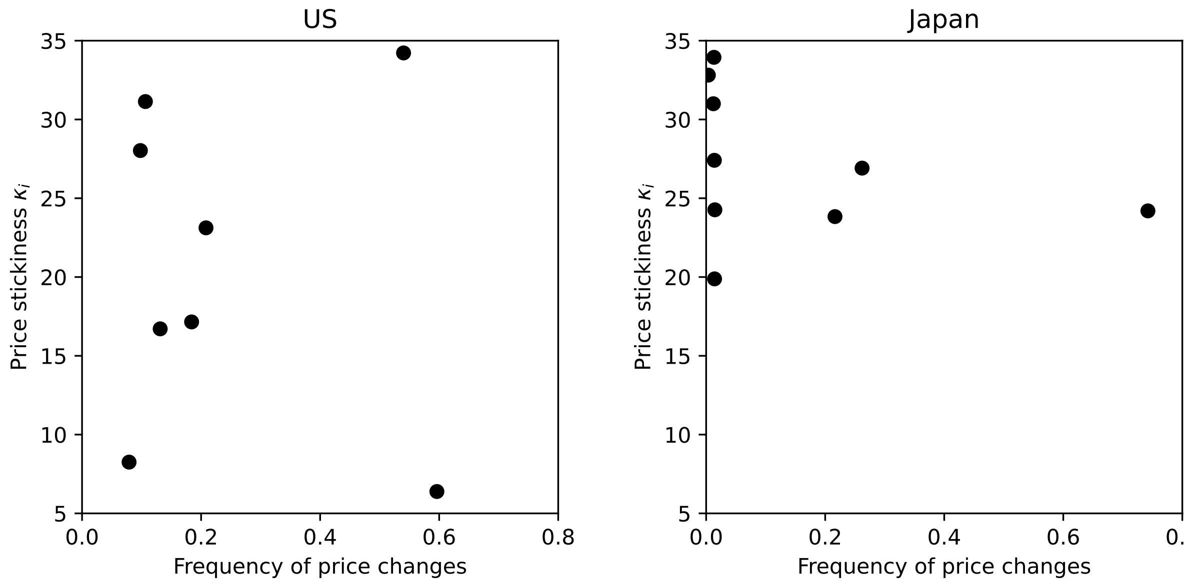


Figure E.1: Correlation Between Estimated Price Stickiness (κ_i) and Frequency of Price Changes

Note: Each dot represents the combination of the estimated price stickiness and the frequency of price changes in each harmonized sector, excluding 7 sectors for the US and 4 sectors for Japan.

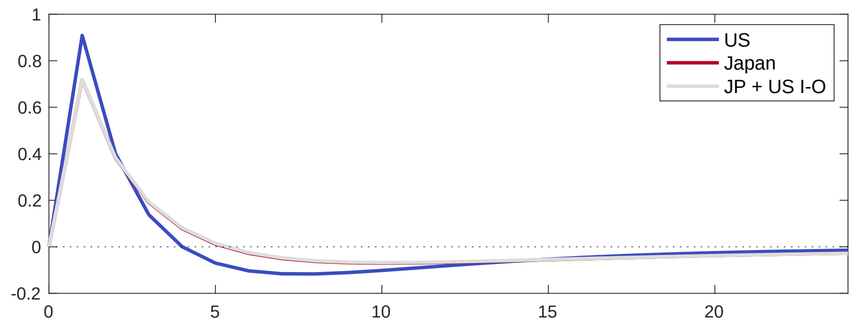
E.3 Responses of Aggregate Inflation Under Alternative Weights

This subsection presents the responses of aggregate inflation based on alternative weights that are listed in Table C.3 of Appendix C.7. Figures E.2–E.4 display the responses to the one-standard-deviation shocks to productivity, import prices, and wages.

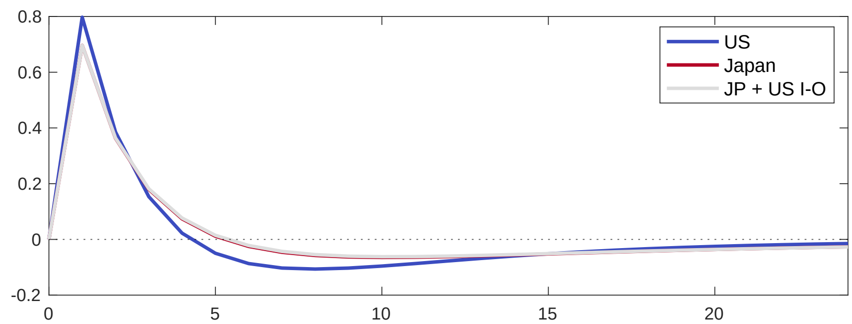
The top panels in these figures show the results based on the total output weights, which are presented in Section 4.2 as our main findings. The middle and bottom panels display results using the final demand and personal consumption expenditure (PCE) weights, respectively. While the initial responses differ slightly, the overall results remain consistent across these alternative weights.

E.4 Counterfactual Responses of Sectoral Inflation: The Role of Structural Parameters

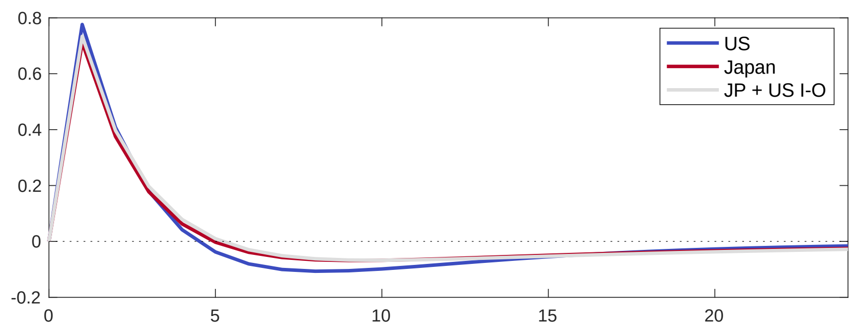
This subsection presents the counterfactual responses of sectoral inflation to various types of shocks, based on the estimated model for Japan with a subset of parameters being replaced with the US estimates. Figures E.5–E.7 display the responses to the one-standard-deviation productivity, import price, and wage shocks, respectively. Light gray lines represent counterfactual responses of the Japanese economy with the US price stickiness parameters. Dark gray lines are those with the US persistence parameters. As addressed in Section 4.3, these counterfactual exercises do not make significant differences at the aggregate level. However, we find noticeable differences at the sectoral level.



(a) Total Output



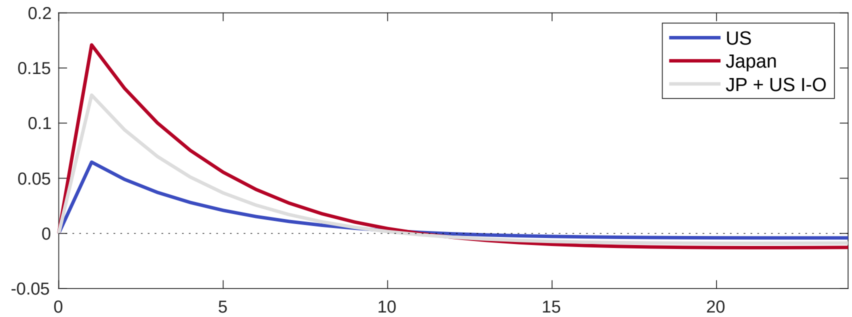
(b) Final Demand



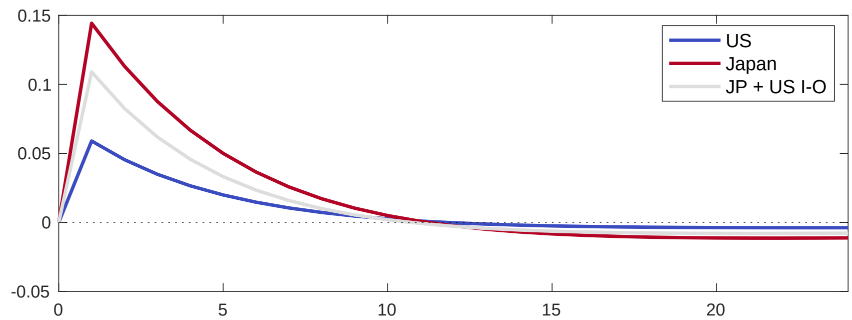
(c) PCE

Figure E.2: Responses of Aggregate Inflation to Productivity Shocks Under Alternative Weights

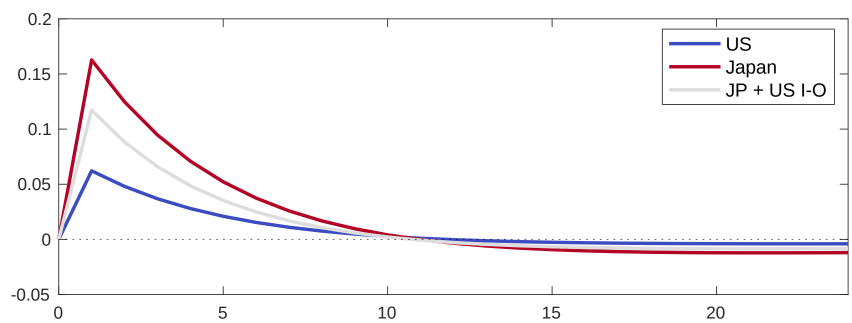
Notes: The figure compares the responses of aggregate inflation to the one-standard-deviation negative productivity shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines) under three alternative weights: total output, final demand, and PCE weights. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.



(a) Total Output



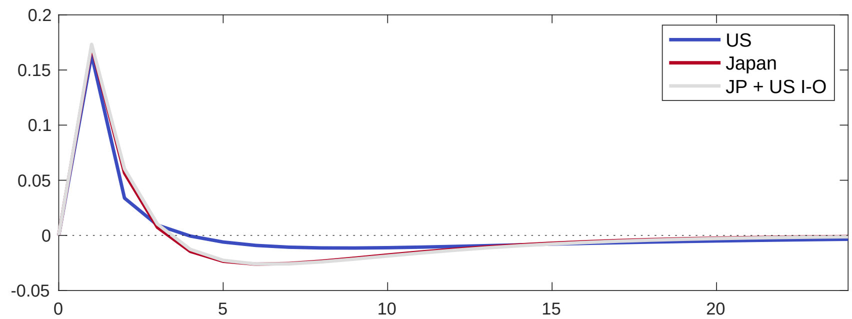
(b) Final Demand



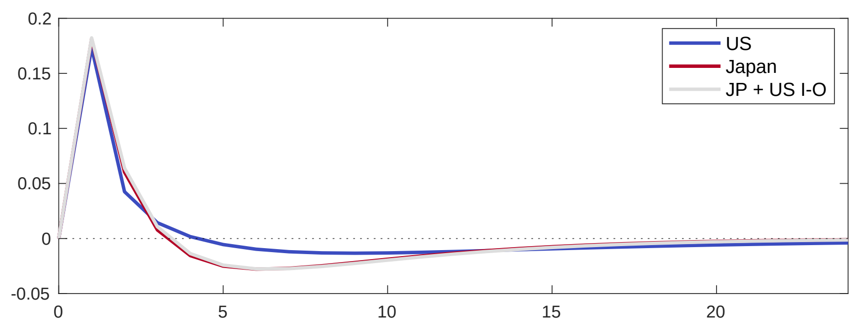
(c) PCE

Figure E.3: Responses of Aggregate Inflation to Import Price Shocks Under Alternative Weights

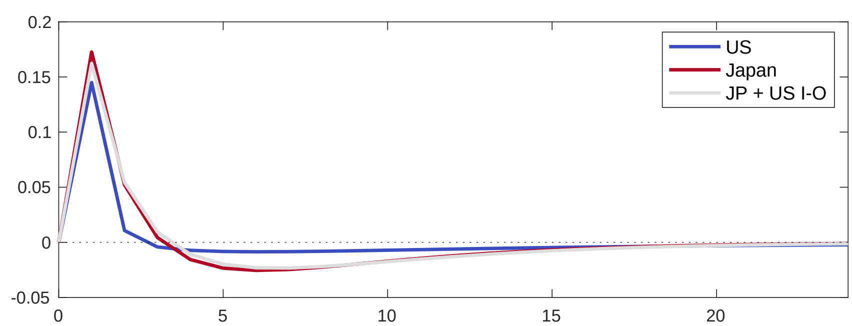
Notes: The figure compares the responses of aggregate inflation to the one-standard-deviation import price shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines) under three alternative weights: total output, final demand, and PCE weights. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.



(a) Total Output



(b) Final Demand



(c) PCE

Figure E.4: Responses of Aggregate Inflation to Wage Shocks Under Alternative Weights

Notes: The figure compares the responses of aggregate inflation to the one-standard-deviation wage shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US I-O linkages (light gray lines) under three alternative weights: total output, final demand, and PCE weights. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

With the US price stickiness parameters (light gray lines), the Agriculture, Mining, and Utilities sectors demonstrate more pronounced responses to the shocks. These are sectors where prices are estimated to be stickier in Japan than in the US, as shown in Figure 2. There are other sectors whose price stickiness differs across the two economies. However, their differences do not make noticeable differences in terms of IRFs.

With the US persistence parameters, the Construction and Commerce sectors exhibit more pronounced responses to productivity shocks (dark gray lines in Figure E.5). At the same time, the Utilities and Services sectors show more muted responses. These responses are somewhat offsetting each other at the aggregate level. Regarding the responses to import price shocks, because imported input shares are not large, replacing the persistence parameters for import price shocks with the US ones does not make significant differences in the IRFs (dark gray lines in Figure E.6). As shown in Figure 2, there are large variations in the estimates for the persistence parameters of wage shocks across the two economies. While we find stronger responses in the Agriculture, Durable Goods, Commerce, Information, Finance and Insurance sectors, more muted responses are observed in the Construction and Services sectors (dark gray lines in Figure E.7). As a result, the aggregate inflation responds stronger with the US estimates of wage persistence parameters.

E.5 Variance Decomposition of Aggregate Inflation Under Alternative Weights

Tables E.2 and E.3 report the forecast error variance decomposition of aggregate inflation into each sectoral shock in the US and Japan, respectively, at various forecast horizons: one month, quarter, year, and infinity, given the posterior mean estimates of each model's parameters. In aggregating sectoral inflation, we consider three weights: total output (TO), final demand (FD), and personal consumption expenditure (PCE). For details on the aggregation, see Appendix C.7.

Compared with the baseline results shown in Table 5, which are based on the weights for TO, the results in Tables E.2 reveal that the variance decomposition of the US aggregate inflation based on the weights for FD and PCE results in lower contributions of productivity shocks and higher contributions of wage shocks at all forecast horizons. In Japan, on the other hand, applying the weights for FD and PCE leads to slightly higher contributions of productivity shocks and lower contributions of wage shocks at all forecast horizons, as shown in Table E.3. However, the differences in the results across the three weights are relatively small in both countries, and the overall patterns of the variance decomposition are robust to the choice of weights.

E.6 Historical Decomposition of Aggregate Inflation Under Alternative Weights

Figures E.8 and E.9 show the historical decomposition of aggregate inflation in the US and Japan, respectively, based on the posterior mean estimates of the model's parameters. In the aggregation of sectoral inflation, three weights are considered: total output (TO), final demand (FD), and personal consumption expenditure (PCE). Each contribution is the sum of contributions of corresponding sectoral shocks.

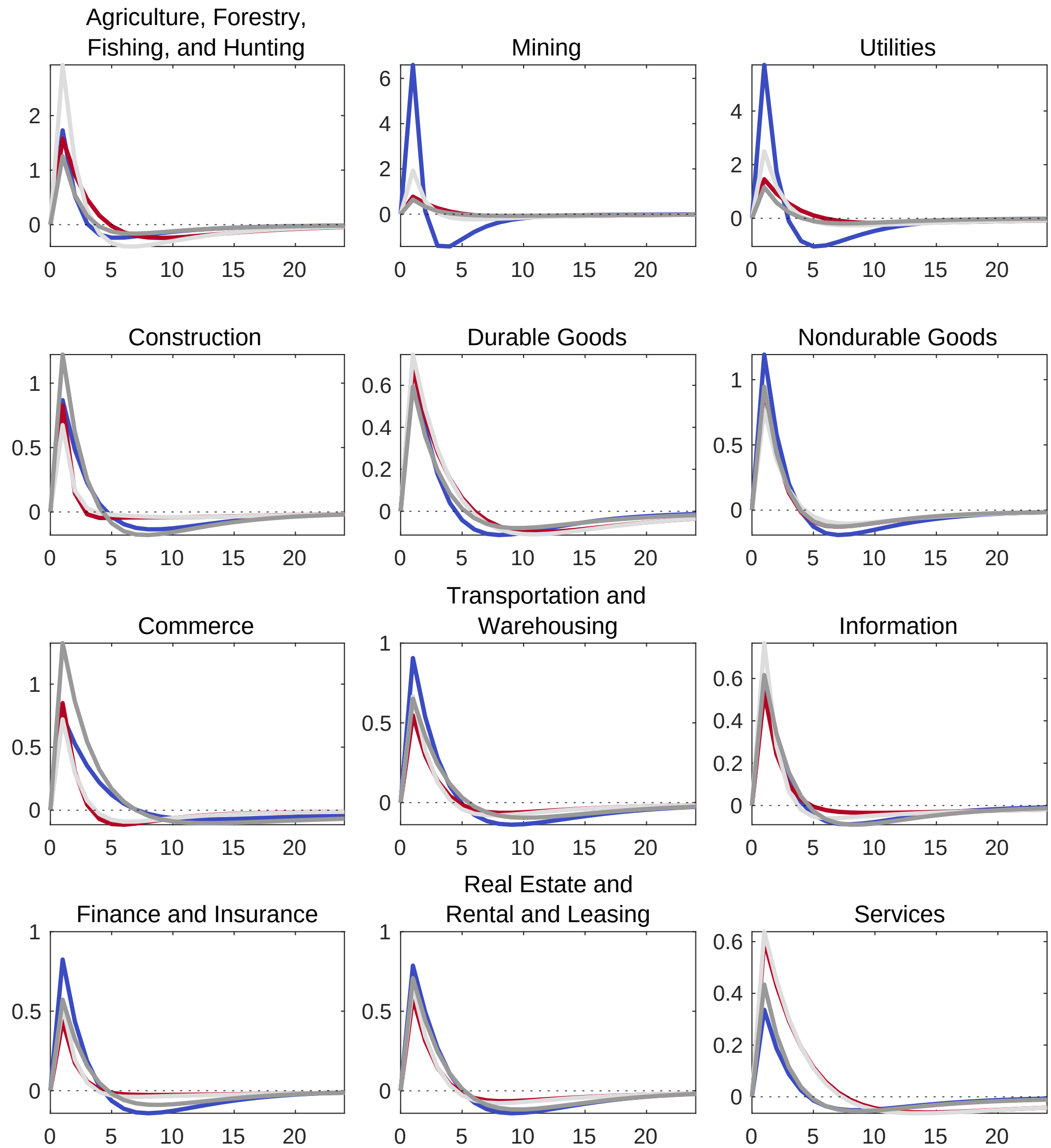


Figure E.5: Responses to Productivity Shocks

Notes: The figure shows the responses of sectoral inflation to the one-standard-deviation negative productivity shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US κ_i's (light gray lines) and those with the US ρ_i's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

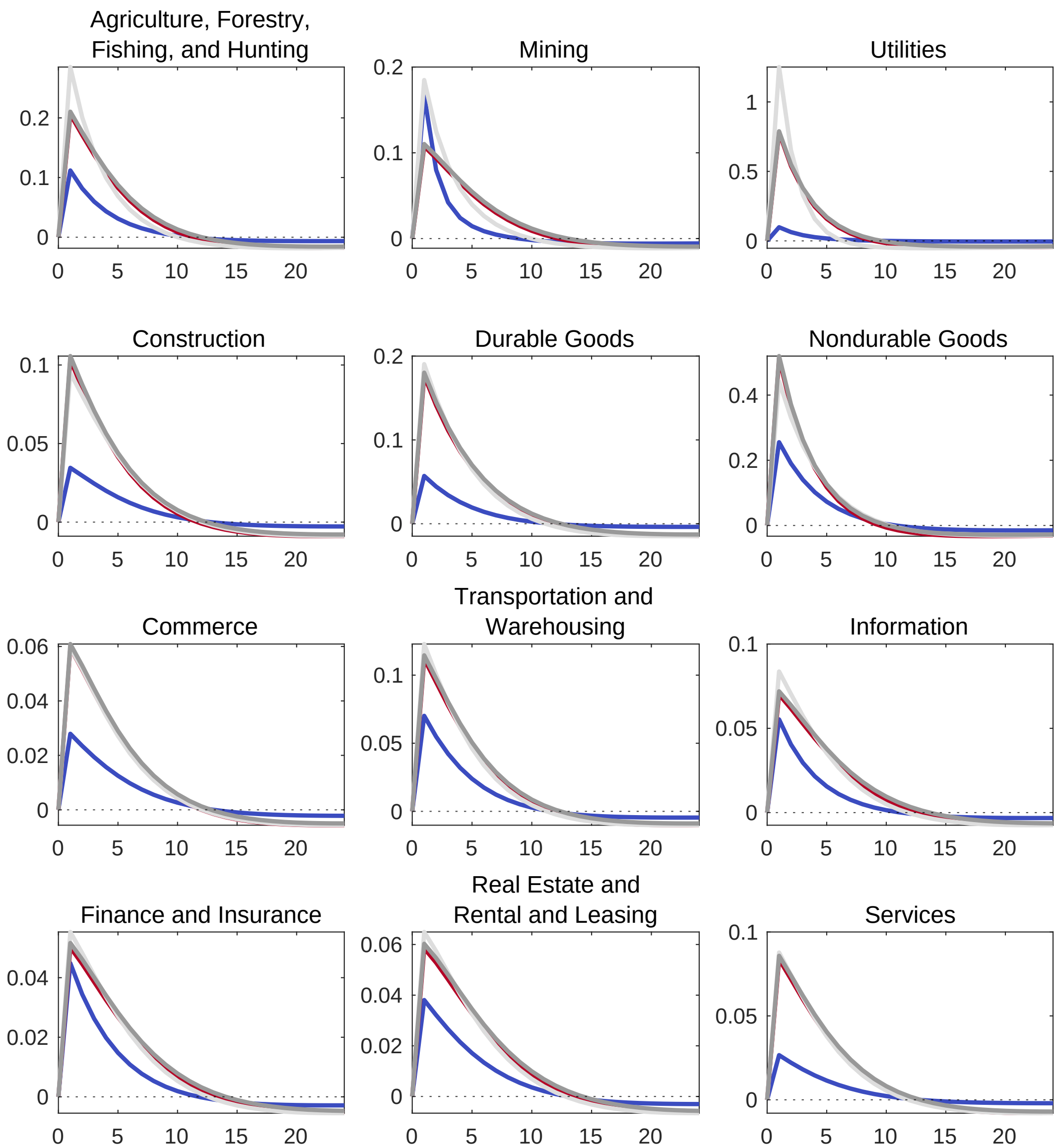


Figure E.6: Responses to Import Price Shocks

Notes: The figure shows the responses of sectoral inflation to the one-standard-deviation import price shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US κ_i's (light gray lines) and those with the US ρ_i's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

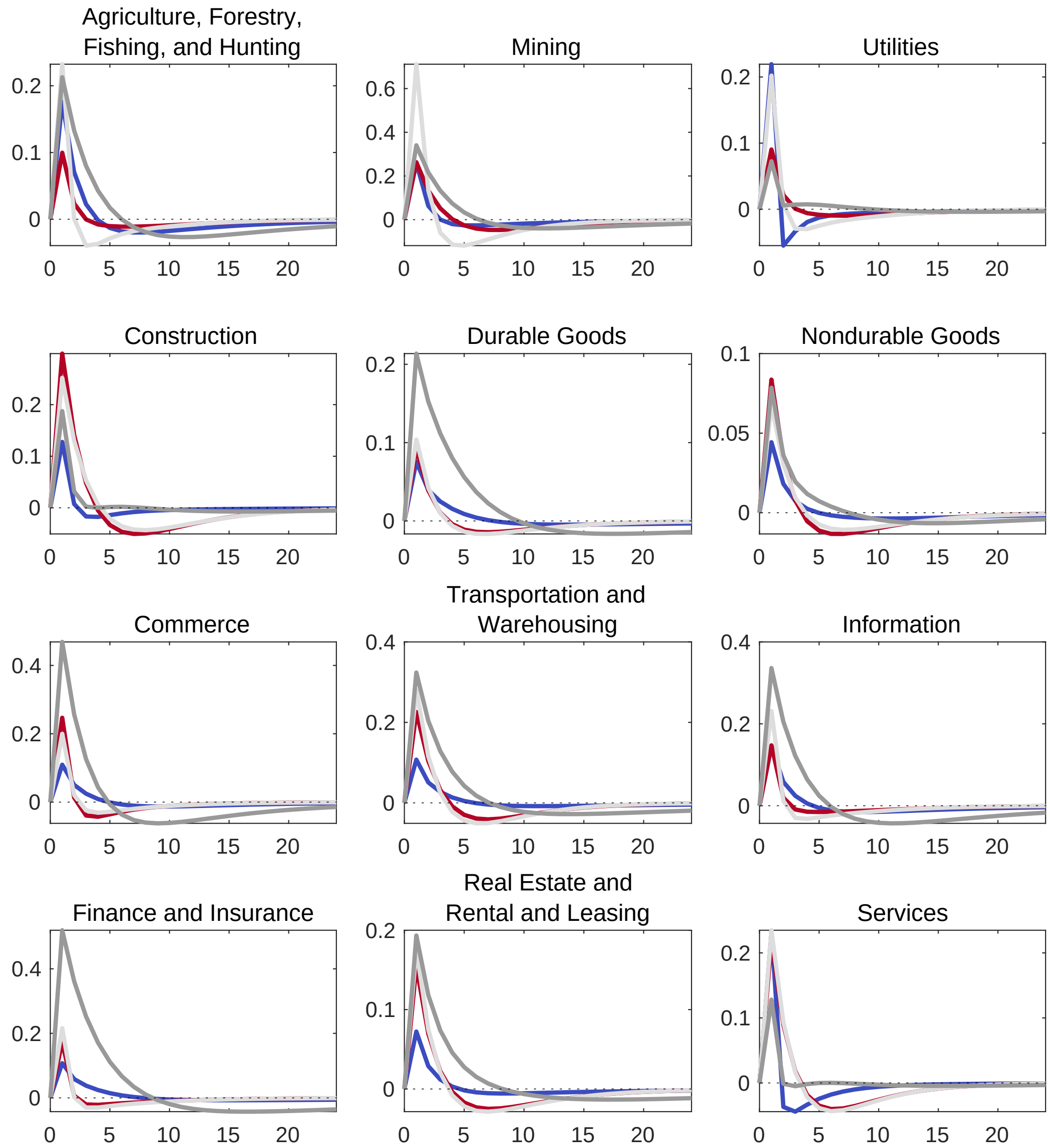


Figure E.7: Responses to Wage Shocks

Notes: The figure shows the responses of sectoral inflation to the one-standard-deviation wage shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses based on the estimated model for Japan with the US κ_i's (light gray lines) and those with the US ρ_i's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

Table E.2: Variance Decomposition of Aggregate Inflation Under Alternative Weights: US

Forecast horizons	1 month			1 quarter			1 year			∞		
Aggregation rule	TO	FD	PCE	TO	FD	PCE	TO	FD	PCE	TO	FD	PCE
Sum of productivity shocks	0.906	0.861	0.870	0.905	0.864	0.884	0.907	0.867	0.887	0.907	0.867	0.889
Sum of import shocks	0.014	0.016	0.015	0.023	0.024	0.023	0.025	0.026	0.025	0.025	0.027	0.026
Sum of wage shocks	0.079	0.124	0.115	0.072	0.112	0.093	0.068	0.107	0.088	0.068	0.106	0.085
Productivity shock												
Agriculture, etc.	0.006	0.002	0.002	0.005	0.002	0.002	0.005	0.002	0.002	0.005	0.002	0.002
Mining	0.243	0.114	0.012	0.203	0.091	0.013	0.200	0.089	0.013	0.195	0.087	0.013
Utilities	0.222	0.165	0.287	0.210	0.155	0.259	0.210	0.155	0.259	0.208	0.153	0.255
Construction	0.013	0.023	0.001	0.014	0.024	0.002	0.014	0.024	0.002	0.014	0.024	0.002
Durable Goods	0.032	0.061	0.010	0.034	0.060	0.011	0.034	0.061	0.011	0.034	0.060	0.011
Nondurable Goods	0.134	0.145	0.164	0.135	0.140	0.154	0.137	0.141	0.156	0.136	0.140	0.154
Commerce	0.067	0.102	0.117	0.099	0.142	0.158	0.100	0.144	0.158	0.106	0.150	0.164
Transportation; Warehousing	0.013	0.010	0.009	0.015	0.012	0.011	0.015	0.012	0.011	0.016	0.012	0.011
Information	0.003	0.004	0.004	0.003	0.004	0.003	0.003	0.004	0.003	0.003	0.004	0.003
Finance and Insurance	0.059	0.049	0.075	0.069	0.056	0.084	0.069	0.056	0.084	0.070	0.057	0.085
Real Estate; Rental and Leasing	0.038	0.052	0.089	0.044	0.056	0.094	0.043	0.056	0.094	0.044	0.057	0.095
Services	0.055	0.070	0.099	0.056	0.068	0.093	0.056	0.068	0.095	0.056	0.068	0.094
Government	0.021	0.063	0.000	0.019	0.054	0.000	0.019	0.056	0.000	0.019	0.054	0.000
Scrap; Used and Secondhands	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Others	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Import price shock												
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mining	0.013	0.014	0.014	0.020	0.021	0.021	0.022	0.024	0.023	0.023	0.024	0.024
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durable Goods	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nondurable Goods	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Transportation; Warehousing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Information	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Services	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Government	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Scrap; Used and Secondhands	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Others	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Wage shock												
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mining	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Construction	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durable Goods	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Nondurable Goods	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Commerce	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Transportation; Warehousing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Information	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Real Estate; Rental and Leasing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Services	0.064	0.082	0.112	0.054	0.065	0.089	0.050	0.061	0.084	0.049	0.060	0.082
Government	0.013	0.038	0.000	0.015	0.043	0.000	0.015	0.041	0.000	0.015	0.043	0.000
Scrap; Used and Secondhands	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Others	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The table presents the forecast error variance decomposition of aggregate inflation in the US, based on the posterior mean estimates of the model's parameters. In the aggregation of sectoral inflation, three weights are considered: total output (TO), final demand (FD), and personal consumption expenditure (PCE).

Table E.3: Variance Decomposition of Aggregate Inflation Under Alternative Weights: Japan

Forecast horizons	1 month			1 quarter			1 year			∞		
Aggregation rule	TO	FD	PCE	TO	FD	PCE	TO	FD	PCE	TO	FD	PCE
Sum of productivity shocks	0.775	0.806	0.787	0.751	0.792	0.758	0.742	0.782	0.753	0.743	0.783	0.752
Sum of import shocks	0.170	0.123	0.153	0.207	0.155	0.195	0.217	0.167	0.203	0.219	0.168	0.205
Sum of wage shocks	0.055	0.070	0.060	0.041	0.052	0.046	0.041	0.051	0.045	0.039	0.049	0.043
Productivity shock												
Agriculture, etc.	0.009	0.004	0.008	0.009	0.005	0.009	0.009	0.005	0.009	0.009	0.005	0.009
Mining	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	0.041	0.023	0.043	0.046	0.027	0.050	0.045	0.027	0.049	0.047	0.029	0.051
Construction	0.016	0.032	0.000	0.011	0.021	0.000	0.010	0.020	0.000	0.009	0.019	0.000
Durable Goods	0.141	0.130	0.016	0.138	0.129	0.017	0.133	0.123	0.017	0.134	0.124	0.017
Nondurable Goods	0.159	0.109	0.182	0.121	0.084	0.143	0.119	0.083	0.141	0.113	0.079	0.135
Commerce	0.082	0.097	0.162	0.057	0.068	0.117	0.057	0.067	0.116	0.054	0.063	0.111
Transportation; Warehousing	0.007	0.005	0.006	0.006	0.004	0.005	0.006	0.004	0.005	0.006	0.004	0.005
Information	0.005	0.004	0.005	0.004	0.003	0.004	0.004	0.003	0.003	0.003	0.003	0.003
Finance and Insurance	0.002	0.002	0.007	0.002	0.002	0.005	0.002	0.002	0.005	0.002	0.002	0.005
Real Estate; Rental and Leasing	0.013	0.026	0.088	0.010	0.020	0.070	0.010	0.020	0.069	0.010	0.019	0.066
Services	0.294	0.362	0.270	0.345	0.422	0.337	0.346	0.420	0.338	0.354	0.429	0.350
Government	0.004	0.011	0.000	0.003	0.008	0.000	0.003	0.008	0.000	0.002	0.007	0.000
Import price shock												
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.001
Mining	0.160	0.115	0.146	0.196	0.145	0.186	0.206	0.156	0.193	0.207	0.157	0.195
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durable Goods	0.002	0.002	0.000	0.002	0.002	0.000	0.002	0.002	0.001	0.002	0.002	0.001
Nondurable Goods	0.007	0.006	0.006	0.009	0.008	0.008	0.009	0.008	0.008	0.009	0.008	0.009
Commerce	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Transportation; Warehousing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Information	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Services	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wage shock												
Agriculture, etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mining	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Utilities	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Construction	0.003	0.006	0.000	0.002	0.005	0.000	0.002	0.005	0.000	0.002	0.004	0.000
Durable Goods	0.002	0.002	0.000	0.002	0.001	0.000	0.002	0.001	0.000	0.001	0.001	0.000
Nondurable Goods	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.000	0.001
Commerce	0.008	0.010	0.016	0.005	0.006	0.011	0.005	0.006	0.011	0.005	0.006	0.010
Transportation; Warehousing	0.002	0.001	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Information	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Finance and Insurance	0.001	0.001	0.002	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001
Real Estate; Rental and Leasing	0.001	0.002	0.006	0.001	0.001	0.004	0.001	0.001	0.004	0.001	0.001	0.004
Services	0.036	0.046	0.032	0.028	0.035	0.026	0.027	0.035	0.026	0.026	0.033	0.025
Government	0.001	0.002	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000

Notes: The table presents the forecast error variance decomposition of aggregate inflation in Japan, based on the posterior mean estimates of the model's parameters. In the aggregation of sectoral inflation, three weights are considered: total output (TO), final demand (FD), and personal consumption expenditure (PCE).

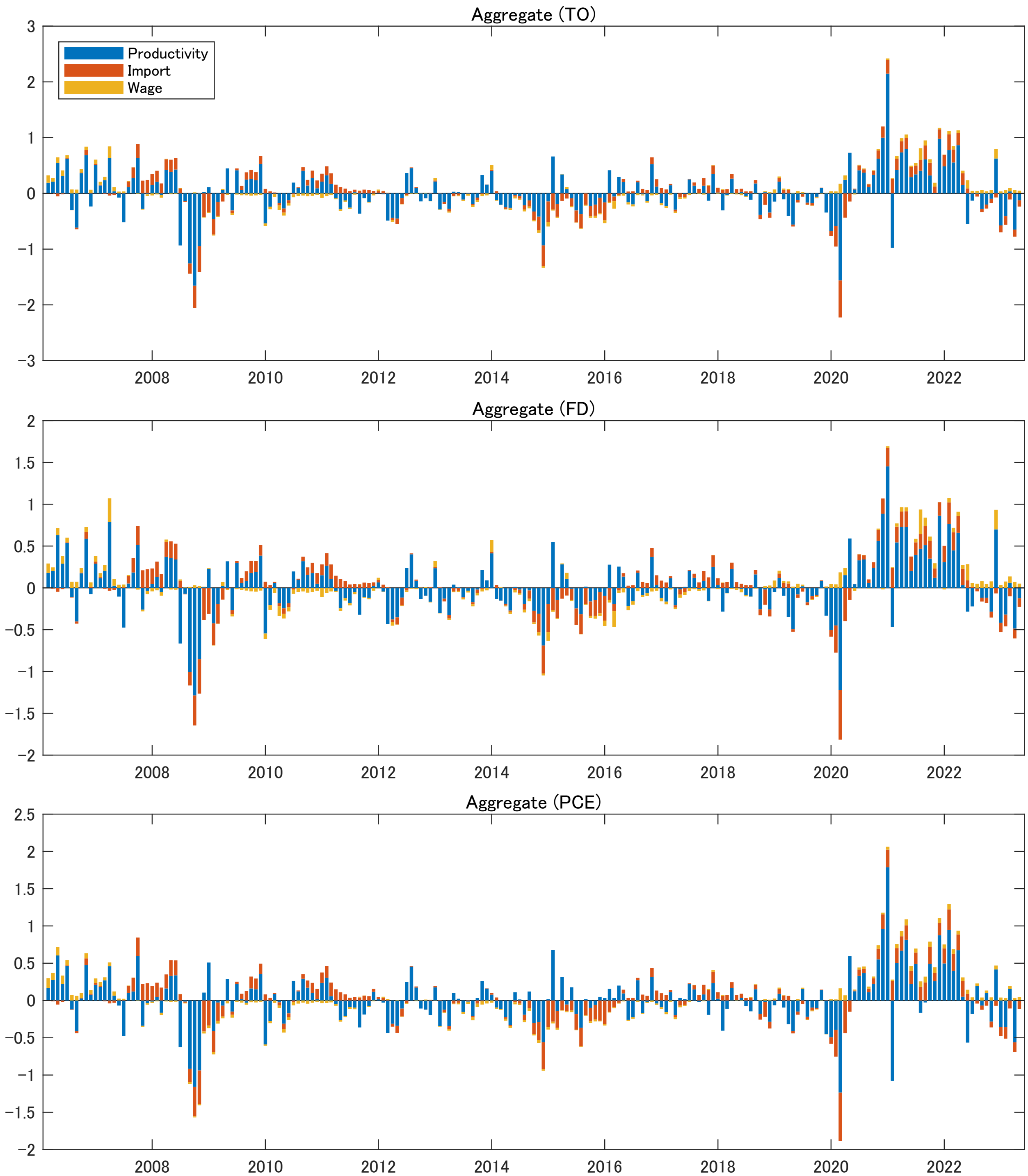


Figure E.8: Historical Decomposition of Aggregate Inflation Under Alternative Weights: US

Notes: The figure shows the historical decomposition of aggregate inflation in the US, based on the posterior mean estimates of the model's parameters. In the aggregation of sectoral inflation, three weights are considered: total output (TO), final demand (FD), and personal consumption expenditure (PCE). Each contribution is the sum of contributions of corresponding sectoral shocks.

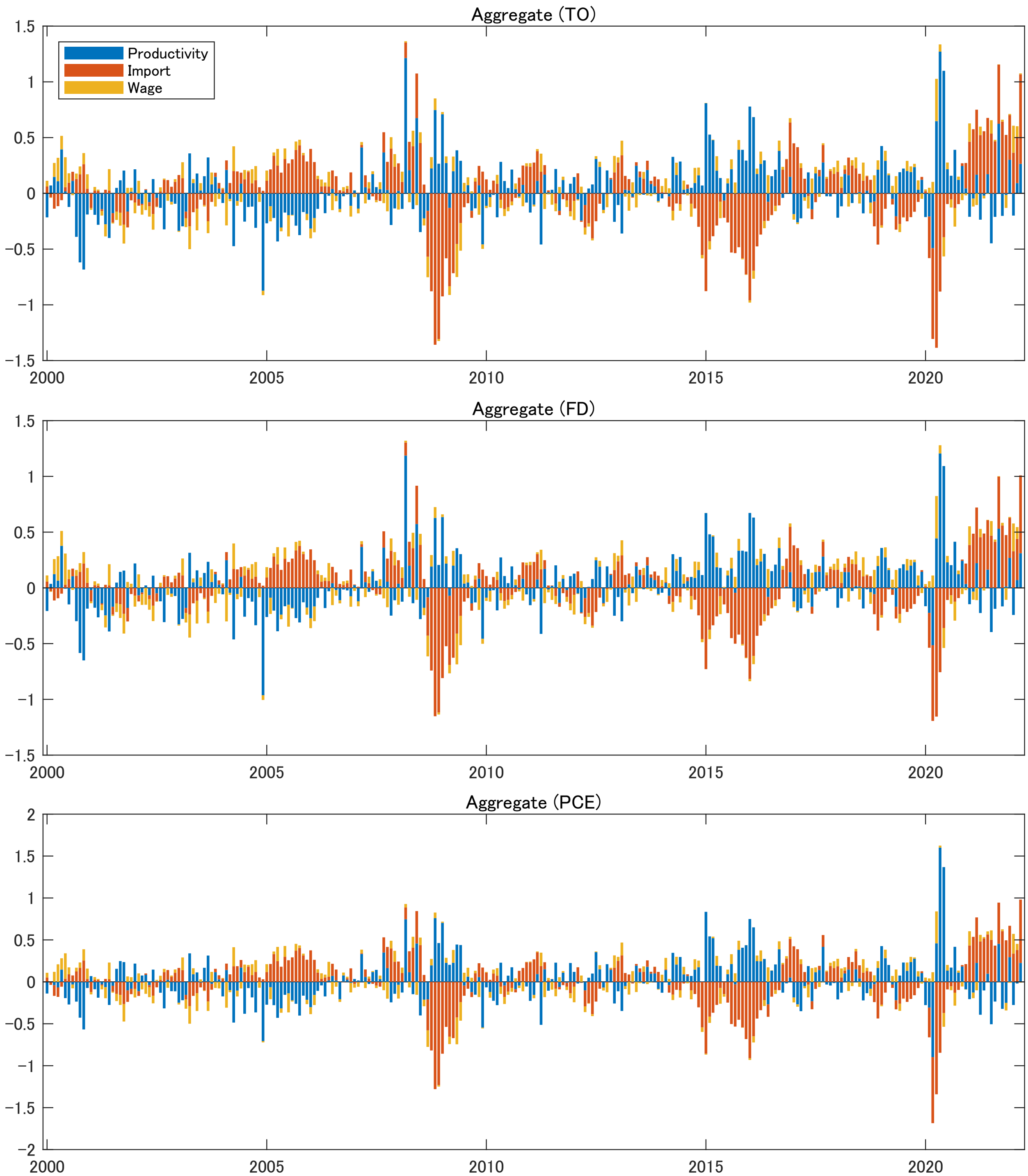


Figure E.9: Historical Decomposition of Aggregate Inflation Under Alternative Weights: Japan

Notes: The figure shows the historical decomposition of aggregate inflation in Japan, based on the posterior mean estimates of the model's parameters. In the aggregation of sectoral inflation, three weights are considered: total output (TO), final demand (FD), and personal consumption expenditure (PCE). Each contribution is the sum of contributions of corresponding sectoral shocks.

Compared with the baseline results in Figure E.9, which are based on the weights for TO, the results based on the weights for FD and PCE share a lot of similarities in both countries. Thus, as in the variance decomposition, the overall patterns of the historical decomposition are robust to the choice of weights.