Inflation Pass-Through in Production Networks*

Yasuo Hirose† Munechika Katayama‡ Kozo Ueda§ Kota Watanabe¶

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Abstract

This study empirically examines the differences in inflation pass-through 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 inflation pass-through operates. The model features that production interconnections generate inflation persistence across sectors, which is further enhanced by price stickiness in each sector. The full-information Bayesian estimation results show that impulse response functions to sectoral shocks are similar. Differences in inflation pass-through 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-throughs, whereas Japanese firms are inclined to set prices to absorb import price shocks.

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

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†Keio University, yhirose@econ.keio.ac.jp

‡Waseda University, mkatayama@waseda.jp

§Waseda University, kozo.ueda@waseda.jp

¶Canon Institute for Global Studies, watanabe.kota@canon-igs.org

1 Introduction



Figure 1: Inflation Rates in the US and Japan Based on Final Demand-Intermediate Demand (FD-ID) Prices

Notes: The FD-ID indices are price indices that aggregate inter-firm transaction prices for each commodity, categorized by the final and intermediate demand sectors in which the commodity is predominantly used. The intermediate demand sectors are subdivided into four stages—stage 1 (ID1), stage 2 (ID2), stage 3 (ID3), and stage 4 (ID4)—consistent with the production flow depicted in the I-O table. The price index for stage 1 intuitively represents price changes at the most upstream stage in the production flow, while the index for stage 4 corresponds to the most downstream stage, closest to final demand (FD). While the US FD-ID indices cover only domestically produced goods and services, the Japanese indices include both domestically produced and imported commodities. For further details, refer to "A new, experimental system of indexes from the PPI program" by the Bureau of Labor Statistics (February 2011) and "Explanation of Final Demand-Intermediate Demand price indexes (FD-ID indexes) (2015 base)" by the Bank of Japan (June 2022).

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 product categories. Figure 1 compares the inflation rates of products at various stages of production (from upstream to downstream) between the US and Japan. The figure reveals that the US economy experienced rapid and substantial inflation increases in all the production stages from upstream to final demand, implying a high degree of inflation pass-through. In contrast, those in Japan exhibit markedly larger differences in inflation rates across production stages, indicating a lower degree of inflation pass-through. Consequently, inflation at the consumer level remains relatively modest in Japan.

The objective of this study is to explore and provide a comprehensive explanation for why inflation pass-through 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. By addressing these key dimensions, our study aims to shed light on the mechanisms governing inflation pass-through and dynamics in distinct economic environments.

More specifically, we first 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 multi-dimensional matrices 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.

Then, we estimate the model while explicitly incorporating 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 differences in impulse responses to various shocks and conduct variance decomposition of shocks for the US and Japanese economies. To the best of our knowledge, this study is the first attempt to estimate a structural model with price stickiness and production networks in a full-information Bayesian approach.

The dataset used for our empirical analysis includes sector-level indices for producer prices, import prices, and wages, covering 12 main sectors from January 2000 to April 2022. The I-O tables are based on the structures as of 2012 for the US and 2011 for Japan. To enable a direct comparison between the two countries, we constructed a new dataset by standardizing the sector classifications into 12 main categories for both economies, with reference to more highly disaggregated sectoral data. In particular, we restructured Japan's I-O table to separate certain existing categories (e.g., to distinguish durable and non-durable goods in the manufacturing sector) and generated sector-level time series for producer prices, import prices, and wages that align with the harmonized sector classification. We plan to make these data available to other researchers through our companion website.

Our main findings are twofold. 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) to shocks—imported price shocks, wage shocks, and productivity shocks (all shocks are sectoral)—are surprisingly similar between the U.S. and Japanese economies. 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 inflation pass-through.

The divergence in inflation pass-through between the US and Japan can be explained by two key factors. 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 pass-through 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, productivity

shocks and import price shocks generally move in the same direction, while in Japan, these shocks often move in opposite directions. 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.

Existing studies on inflation pass-through and 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; Forbes, Hjortsoe, and Nenova, 2020; Chin and Lin, 2023).

On a theoretical front, this study is most closely related to Rubbo (2023) and Afrouzi and Bhattarai (2023).[1] 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) and La'O and Tahbaz-Salehi (2022) explore optimal monetary policy in multi-sector settings under sticky prices and incomplete information, respectively. 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 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 based on calibrated parameters.

Conventional empirical studies on inflation pass-through 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 pass-through 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. In this regard, our study aligns closely with Bouakez, Cardia, and Ruge-Murcia (2009, 2014). While they employ the simulated method of moments for estimation, we utilize likelihood-based Bayesian techniques. Besides, Ruge-Murcia and Wolman (2022) estimate a 15-sector New Keynesian model using maximum likelihood, although their framework does not explicitly incorporate the 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.

[1] 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), and Baqaee and Farhi (2019, 2020). 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).

2 The Model

In this section, we develop a simple New Keynesian model incorporating production networks, designed to allow for estimation without imposing substantial computational demands. This model represents a partial equilibrium framework of monopolistic firms producing intermediate goods. Each firm uses a diverse array of intermediate goods across multiple sectors, imported goods from various sectors, and labor as inputs. For tractability, we treat the following as exogenous: the I-O linkages, import prices, and wages. Under specific conditions, we demonstrate that a rational expectations equilibrium for sectoral and aggregate inflation can be derived in a tractable analytical form.

2.1 Setup

The model includes N intermediate-goods sectors, each indexed by i. Within each sector i, an infinite number of firms, indexed by f, produce intermediate goods using inputs that include N domestically-produced intermediate goods, M imported goods ($M \leq N$), and labor. Wages are heterogeneous across sectors and are treated as given. The production technology for intermediate goods follows a Cobb–Douglas form, with input coefficients sourced from the I-O table. We assume the price stickiness of the Rotemberg type. Trend inflation is assumed to be zero.

We impose two simplifying assumptions. First, we assume exogenous input price processes for imported goods and labor (i.e., wages), both following an AR(1) process. Sector-specific idiosyncratic productivity shocks are also exogenous and follow an AR(1) process. Second, we assume a constant returns-to-scale production technology. These assumptions are crucial for deriving a tractable analytical solution.

Goods are aggregated as

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

$$P_t = \left(\sum_i^N \frac{A_i}{N} P_{it}^{1-\theta} \right)^{\frac{1}{1-\theta}}, \tag{2}$$

where Y_t and P_t represent aggregate output and price, respectively, while Y_{it}, P_{it}, and A_i represent output, price, and taste for sector i. Parameter θ indicates the elasticity of substitution across sectors. We assume $\sum_i^N (A_i/N) = 1$. Sectoral output is aggregated as

$$Y_{it} = \left(\int_0^1 Y_{ift}^{\frac{\sigma_i - 1}{\sigma_i}} df \right)^{\frac{\sigma_i}{\sigma_i - 1}}, \tag{3}$$

where parameter σ_i indicates the elasticity of substitution among goods in sector i.

Under the Rotemberg-type price stickiness, 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 $Y_{ift+k} = (A_i/N) \left(P_{it+k}/P_{t+k} \right)^{-\theta_i} \left(P_{ift+k}/P_{it+k} \right)^{-\sigma_i} Y_{t+k}$, where RMC_{ift} represents real marginal costs for firm f in sector i in period t. For simplicity, we assume zero trend inflation by focusing on

fluctuations around the trend. While our analysis is robust to non-zero trend inflation, it requires that trend inflation be common across sectors.

We define the inflation rate by $\pi_{it} \equiv P_{it}/P_{it-1} - 1$ and relative price by $p_{it} \equiv P_{it}/P_t$. Deriving the first-order condition with respect to reset price P_{ift} and log-linearizing the equation yields the Phillips curve:

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

where $\widehat{RMC}_{it} \equiv RMC_{it} - (\sigma_i - 1)p_{it}/\sigma_i$. Hereafter, we omit firm subscript f, because firm f in sector i is symmetric under the Rotemberg-type price stickiness. Real marginal costs are derived from the following Cobb–Douglas production function:

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

where Y_{imt} represents imported inputs from sector m, L_{it} represents labor input to sector i, and ε_{it} represents a productivity shock in sector i. It satisfies constant returns to scale: $\Sigma_j \omega_{ij} + \Sigma_k \omega_{ik} + \omega_{iw} = 1$. Although this equation may appear to imply that sector i goods are used to produce sector i goods, the interpretation is that a firm in sector i produces output using inputs aggregated at the sector level. Therefore, the sector-level input aggregation is exogenous to the individual firm.

We assume the following exogenous AR(1) processes:

$$\widehat{P}^*_{mt} = \rho^*_m \widehat{P}^*_{mt-1} + \mu^*_{mt} \tag{6}$$

$$\widehat{W}_{it} = \rho^w_i \widehat{W}_{it-1} + \mu^w_{it} \tag{7}$$

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \mu_{it}, \tag{8}$$

where $\widehat{x}_t$ represents the log-linearization of x_t, and P^*_{mt} and W_{it} indicate exogenous import price of sector m and wage in sector i, respectively. Parameters ρ's indicate the shock persistence. We assume $\mathbb{E}_t \mu^*_{mt+k} = \mathbb{E}_t \mu^w_{it+k} = \mathbb{E}_t \mu_{it+k} = 0$ for $k = 1, 2, \cdots$, and define $\pi^*_{mt} \equiv \widehat{P}^*_{mt} - \widehat{P}^*_{mt-1}$, and $\pi^w_{it} \equiv \widehat{W}_{it} - \widehat{W}_{it-1}$.

Assuming an AR(1) process for costs allows for analytical tractability in solving the model. While variables like wages are endogenous, we consider the AR(1) process a reasonable approximation of cost dynamics, provided that we have data on import prices and wages at the sectoral level. This assumption also provides robustness to model misspecifications, which are more prevalent in DSGE frameworks.

2.2 Inflation Dynamics

We can obtain the following rational expectations equilibrium for inflation from equation (4). Table 1 summarizes the definitions of vectors and matrices used to describe this proposition. Appendix A provides the proof for the proposition.

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

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

Table 1: Definition of Vectors and Matrices

Name	Dimensions	Elements	Notes
$\mathbf{\Pi}_t$	$N \times 1$	i-th element is π_{it}	Data
$\mathbf{\Pi}_t^*$	$M \times 1$	m-th element is π_{mt}^*	Data
$\mathbf{\Pi}_t^w$	$N \times 1$	i-th element is π_{it}^w	Data
$\mathbf{e}_t$	$N \times 1$	i-th element is ε_{it}	Unobservable AR(1) shocks
$\mathbf{G}$	$N \times N$	Element (i,j) is Γ_{ij}	To be estimated
$\mathbf{G}^*$	$N \times M$	Element (i,m) is Γ_{im}^*	To be estimated
$\mathbf{G}_w$	$N \times N$	Element (i,j) is Γ_{ij}^w	To be estimated
$\mathbf{G}_L$	$N \times N$	Element (i,j) is Γ_{ij}^L	To be estimated
$\mathbf{P}$	Diagonal $N \times N$	Element (i,i) equals ρ_j	To be estimated
$\mathbf{P}^*$	Diagonal $M \times M$	Element (m,m) equals ρ_m^*	To be estimated
$\mathbf{P}_w$	Diagonal $N \times N$	Element (i,i) equals ρ_i^w	To be estimated
$\mathbf{K}$	Diagonal $N \times N$	Element (i,i) equals $\frac{\sigma_i - 1}{\kappa_i}$	To be estimated
$\mathbf{\Omega}$	$N \times N$	Element (i,j) equals $\omega_{ii} - 1$ for $j = i$; ω_{ij} for $j \neq i$	Set from the I-O table
$\mathbf{\Omega}^*$	$N \times M$	Element (i,m) equals ω_{im}	Set from the I-O table
$\mathbf{\Omega}_w$	Diagonal $N \times N$	Element (i,i) equals ω_{iw}	Set from the I-O table

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

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

and

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

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

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

Equation (9) indicates that the rational expectations equilibrium for the inflation rate can be expressed in terms of the minimum state variables, which include sectoral productivity shocks in the previous and current periods, import price shocks, wage shocks, and the inflation rate in the previous period. In other words, the equilibrium is expressed as a simple VARMA process. Although the coefficient matrix $\mathbf{G_L}$ is not available in closed form due to its quadratic nature, we can readily obtain three other coefficient matrices once $\mathbf{G_L}$ is determined.

Equation (9) is useful for estimation purposes. Given the data on inflation variables up to period t, and assuming knowledge of the idiosyncratic shock $\mathbf{e}_{t-1}$, we can compute the likelihood of observing $\mathbf{\Pi}_t$. Specifically, this allows us to estimate parameters such as price stickiness $\mathbf{K}$, persistence $\mathbf{P}$, $\mathbf{P}^*$, and $\mathbf{P}_w$, and the standard error of shocks, based on the known I-O linkages represented by $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$.

In the model, pass-through is explicitly defined using the coefficient matrices $\mathbf{G}$, $\mathbf{G}^*$, and $\mathbf{G_w}$, which represent the pass-through in response to 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 structural shocks. Moreover, although pass-through is frequently compared to the benchmark of 100%, this model demonstrates that pass-through is naturally below 100% due to two key factors: price stickiness with $\kappa > 0$ and the I-O linkages with $\omega < 1$.

Inflation Persistence Coefficient matrix $\mathbf{G_L}$ represents the degree of inflation persistence or the response of inflation to the past inflation rate. From equation (10), $\mathbf{G_L}$ can be written as

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

When production networks are interconnected (i.e., $\omega_{ij} > 0$), $\mathbf{G_L}$ becomes non-diagonal. That is, inflation persistence is influenced by that in other sectors. Further, note that $\mathbf{\Omega}$ is negative considering that the diagonal element $\omega_{ii} - 1$ is negative. Thus, this expression shows that as price becomes flexible (i.e., κ decreases), $\mathbf{K}$ increases and then $\mathbf{G_L}$ decreases toward zero. In other words, inflation persistence decreases.

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 at the demand side as is 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 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, the own inflation persistence in sector 1 (g_{11}) 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, 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 λ equals g_{11} or g_{12}. Suppose $g_{11} \geq g_{12} \geq 0$. A small increase in g_{12} and g_{21} from zero (given g_{11} and g_{22}) increases one λ from g_{11}, while decreasing the other λ from g_{22}.*

This lemma suggests that the two eigenvalues diverge by non-diagonal elements of $\mathbf{G_L}$. This likely contributes to an increase in aggregate inflation persistence, as a sector with the highest price stickiness tends to drive aggregate inflation dynamics (see Aoki, 2001; Carvalho, 2006).

2.3 Aggregate Inflation

From equation (9) for sectoral inflation, we can describe aggregate inflation dynamics. Equation (2) leads to the aggregate inflation rate π_t, given by

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

where $\mathbf{A}$ is the 1 by N unit vector, with element i equal to A_i/N and $\sum(A_i/N)^2 = 1$ (i.e., $\mathbf{AA}^t = 1$).

Combining this with Equation (9), the aggregate inflation rate can be expressed as

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

We focus on the coefficient of inflation persistence, represented by the last term on the right-hand side, $\mathbf{AG_L}$. 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), 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 the weights of $\mathbf{A}$ in terms of eigenvectors. Then, we can write

$$\begin{aligned}\mathbf{AG_L} &= (\mathbf{WP})(\mathbf{P}^{-1}\mathbf{\Lambda P}) \\ &= \mathbf{W\Lambda P}.\end{aligned}$$

A special case arises when $\mathbf{A}$ corresponds to one eigenvector of $\mathbf{G_L}$ (i.e., one of the rows of $\mathbf{P}$). In this case, $\mathbf{AG_L} = \lambda\mathbf{A}$, indicating that inflation persistence is determined entirely by the eigenvalue λ. More generally, $\mathbf{AG_L} \neq \lambda\mathbf{A}$ for any specific λ.

This expression mirrors the concept of the divine coincidence index in Rubbo (2023), where inflation is weighted by sales share and price rigidity across sectors. While both studies rely on similar weights (sales share ($\mathbf{A}$ or $\mathbf{W}$) and price stickiness ($\mathbf{\Lambda}$)), a key difference lies in the measurement of price stickiness. Rubbo (2023) uses Calvo-type stickiness, whereas this study uses a more complicated form given by the eigenvalue of $\mathbf{G_L}$, which is influenced by sectoral interactions through the I-O linkages, not just the stickiness parameter κ_i within individual sectors.

3 Empirical Strategy

3.1 Data

We construct data primarily for 12 sectors in the US and Japan, as shown in Table 2. These sectors include mining, durable goods, nondurable goods, and services.[2] Although the official statistics of the two countries employ different sectoral classifications, we harmonize them to enable meaningful comparison. In this subsection, we briefly outline the data construction process, with detailed explanations provided in Appendix C.

We derive the I-O linkage parameters $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, and $\mathbf{\Omega}_w$ from the I-O tables for 2012 and 2011 for the US and Japan, respectively. 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 total supply of each product. Second, we aggregate the detailed I-O matrix into mainly 12 sectoral levels by summing the figures corresponding to each sector.

The monthly inflation indices $\mathbf{\Pi}_t$ and $\mathbf{\Pi}_t^*$ are constructed from 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 wage inflation index $\mathbf{\Pi}_t^w$ is 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.

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

[2] Although the government sector is incorporated, we do not show the results on this sector because it has no contribution to other sectors as intermediate goods. Further, the U.S. dataset includes two minor categories, scrap and incomparable imports.

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	Noncomparable Imports and Rest-of-the-World Adjustment	< 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 index for each sector: domestic prices (D), import prices (M), and wages (W). The hyphen (–) indicates that the corresponding price data are not available.

Table 3 presents a summary of the I-O tables for the US and Japan used in this study, corresponding to the ω's in the model. 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 United States (6.5%). This discrepancy reflects Japan's dependence on imported energy resources, whereas the US primarily produces its own energy.

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 P_{it}, import price P^*_{mt}, and nominal wage W_{it} in each sector, but not all the sectoral series are available in our data set. All 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

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	–	–	–
Noncomparable Imports and Rest-of-the-World Adjustment	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.

US:

$$\begin{bmatrix} 100\Delta \log P_{1t} \\ \vdots \\ 100\Delta \log P_{13t} \\ 100\Delta \log P^*_{1t} \\ 100\Delta \log P^*_{2t} \\ 100\Delta \log P^*_{5t} \\ 100\Delta \log P^*_{6t} \\ 100\Delta \log W_{1t} \\ \vdots \\ 100\Delta \log W_{12t} \end{bmatrix} = \begin{bmatrix} \hat{\pi}_{1t} \\ \vdots \\ \hat{\pi}_{13t} \\ \hat{\pi}^*_{1t} \\ \hat{\pi}^*_{2t} \\ \hat{\pi}^*_{5t} \\ \hat{\pi}^*_{6t} \\ \hat{\pi}^w_{1t} \\ \vdots \\ \hat{\pi}^w_{12t} \end{bmatrix},$$

Japan:

$$\begin{bmatrix} 100\Delta \log P_{1t} \\ \vdots \\ 100\Delta \log P_{3t} \\ 100\Delta \log P_{5t} \\ \vdots \\ 100\Delta \log P_{12t} \\ 100\Delta \log P^*_{1t} \\ 100\Delta \log P^*_{2t} \\ 100\Delta \log P^*_{5t} \\ 100\Delta \log P^*_{6t} \\ 100\Delta \log W_{2t} \\ \vdots \\ 100\Delta \log W_{12t} \end{bmatrix} = \begin{bmatrix} \hat{\pi}_{1t} \\ \vdots \\ \hat{\pi}_{3t} \\ \hat{\pi}_{5t} \\ \vdots \\ \hat{\pi}_{12t} \\ \hat{\pi}^*_{1t} \\ \hat{\pi}^*_{2t} \\ \hat{\pi}^*_{5t} \\ \hat{\pi}^*_{6t} \\ \hat{\pi}^w_{2t} \\ \vdots \\ \hat{\pi}^w_{12t} \end{bmatrix}.$$

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 methods 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 the parameters and approximate the marginal data densities.

3.3 Fixed Parameters and Priors

To avoid identification issues, we fix several parameters in the model. Preliminary investigation of the I-O tables for the US and Japan indicates that there are no imported inputs from several sectors: sectors 4, 7, and 11 in the US; and sectors 4, 11, and 13 in Japan. For these sectors, we exclude the 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% 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 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, as determined by equation (4). This prior is deliberately chosen to be relatively diffuse, allowing the data to shape the posterior distribution of the parameters.

The priors for the persistence parameters ρ^ϵ_i, ρ^*_m, and ρ^w_i, 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 σ^ϵ_i, σ^*_m, and σ^w_i of the shocks, inverse Gamma priors are imposed with a

Table 4: Prior distributions of parameters

Parameter	Distribution	Mean	S.D.
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: Inverse gamma distributions are of the form $p(\sigma|\nu, s) \propto \sigma^{-\nu-1}e^{-\nu s^2/2\sigma^2}$, where ν and s are respectively set at the mean and standard deviation (S.D.) values in the table.

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 A4 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.

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.

In Appendix E.2, we examine the consistency of our price stickiness estimates κ_i with micro-level evidence presented in Bils and Klenow (2004) and Ueda (2024). As expected, our estimates of κ_i are negatively correlated with the frequency of price changes in the corresponding CPI items, but 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

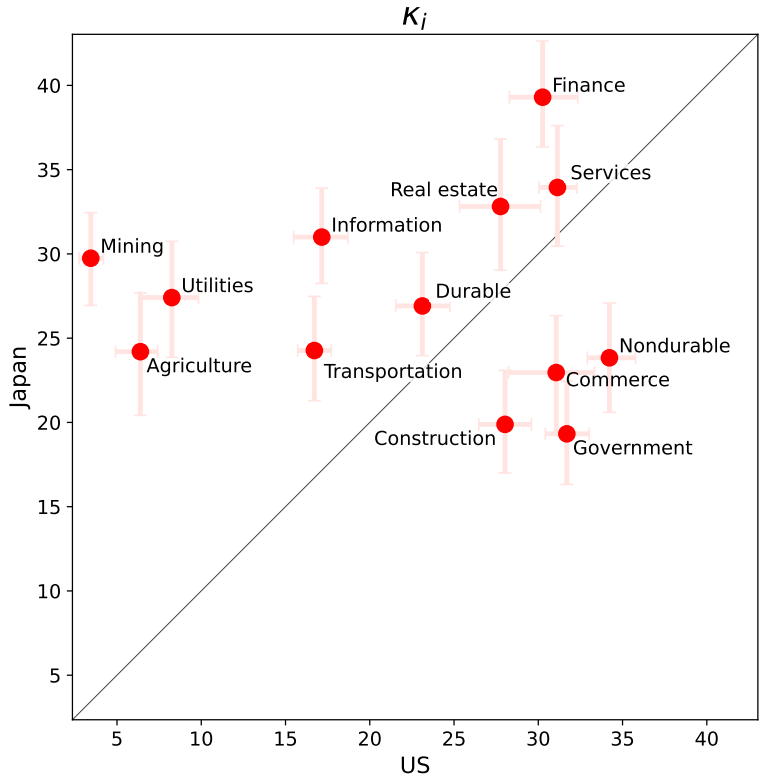


Figure 2: Posterior estimates of price stickiness in the US and Japan

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.

output weights gives almost the same averages: approximately 0.74 for both countries. The estimates for the persistence of import price shocks ρ_m^* exhibit large heterogeneity across sectors in both countries, but on average, they do not differ significantly: 0.49 for the US and 0.45 for Japan. In contrast, the estimates for the persistence of wage shocks ρ_i^w are generally higher in the US than in Japan: 0.63 and 0.51, respectively, on average. Besides, the US estimates are more dispersed 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 three types of shocks. We consider the one-standard-deviation productivity shocks, import price shocks, and wage shocks. We also conduct a counterfactual analysis to investigate the impact of I-O linkages by imposing the US I-O structure

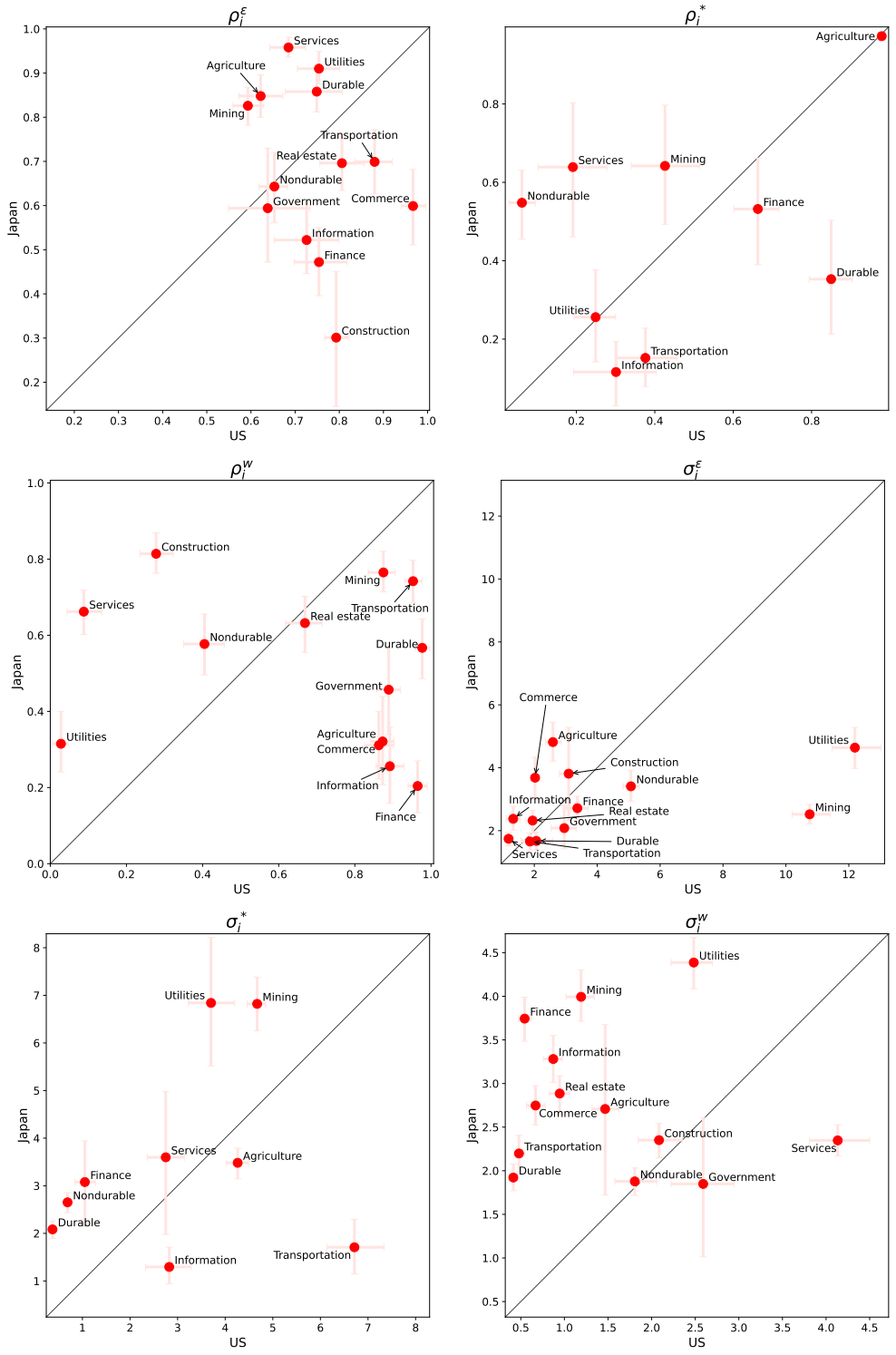


Figure 3: Posterior estimates of persistence and standard deviation parameters in the US and Japan

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.

on the Japanese economy.[3]

Figure 4 compares the responses of aggregate and sectoral inflation to the one-standard-deviation productivity shocks in 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). To derive aggregate responses, we aggregate sectoral inflation rates using the total output shares reported in Table 2.[4]

The top panel of Figure 4 shows the responses of aggregate inflation to the estimated one-standard-deviation productivity shocks to all domestic sectors. 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 of the Japanese economy with the US I-O linkages are almost identical to the actual responses of the Japanese economy (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 aggregate inflation dynamics in terms of productivity shocks.

The bottom panels of Figure 4 display the sectoral responses to the productivity shocks.[5] 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 shares. As a result, the aggregate responses are largely similar across the two economies. The counterfactual sectoral responses remain almost unchanged compared to the actual responses of the Japanese economy. At the sectoral level, the production structure does not play an important role in propagating sectoral productivity shocks to aggregate inflation.

Figure 5 compares the responses of aggregate and sectoral inflation to the one-standard-deviation import price shocks to all import sectors in 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).

The top panel of Figure 5 shows the responses of aggregate inflation to the estimated one-standard-deviation import price shocks. There is a noticeable difference in the responses of aggregate inflation in the US and Japan. The initial impact is much larger in Japan than in the US, although the persistence is similar in both economies. It is largely due to the estimated size of shocks that are bigger in Japan than in the US, as shown in Figure 3. However, the counterfactual responses of the Japanese economy with the US I-O linkages suggest that the industry structure of the Japanese economy also accounts for its vulnerability to import price shocks.

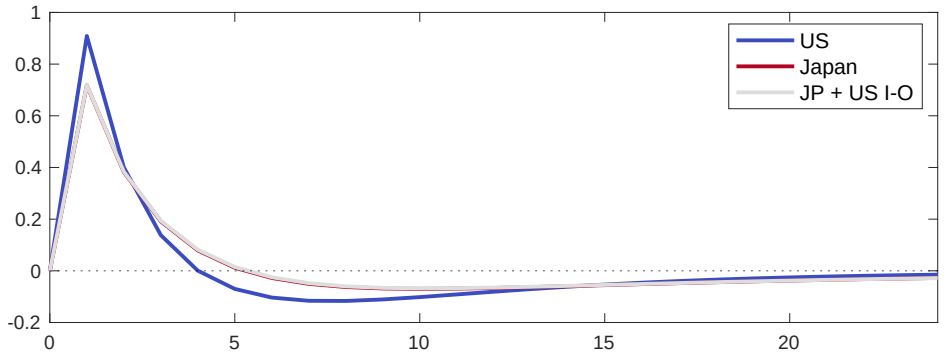
The bottom panels of Figure 5 display the sectoral responses to the import price shocks. As the estimated volatilities for the import price shocks are bigger in Japan, sectoral responses to the import price shocks are higher in Japan than in the US. The counterfactual responses with the US production network are relatively similar to the ones with the Japanese structure. However, a noticeable exception may be the responses of the Utilities sector in Japan. It is solely due to the industry structure, in which dependence on imported goods is higher in Japan than in the US. In fact, if the Utilities sector in Japan had the same production structure as in the US, the counterfactual responses would almost coincide with the US ones.

Figure 6 compares the responses of aggregate and sectoral inflation to the one-standard-deviation wage

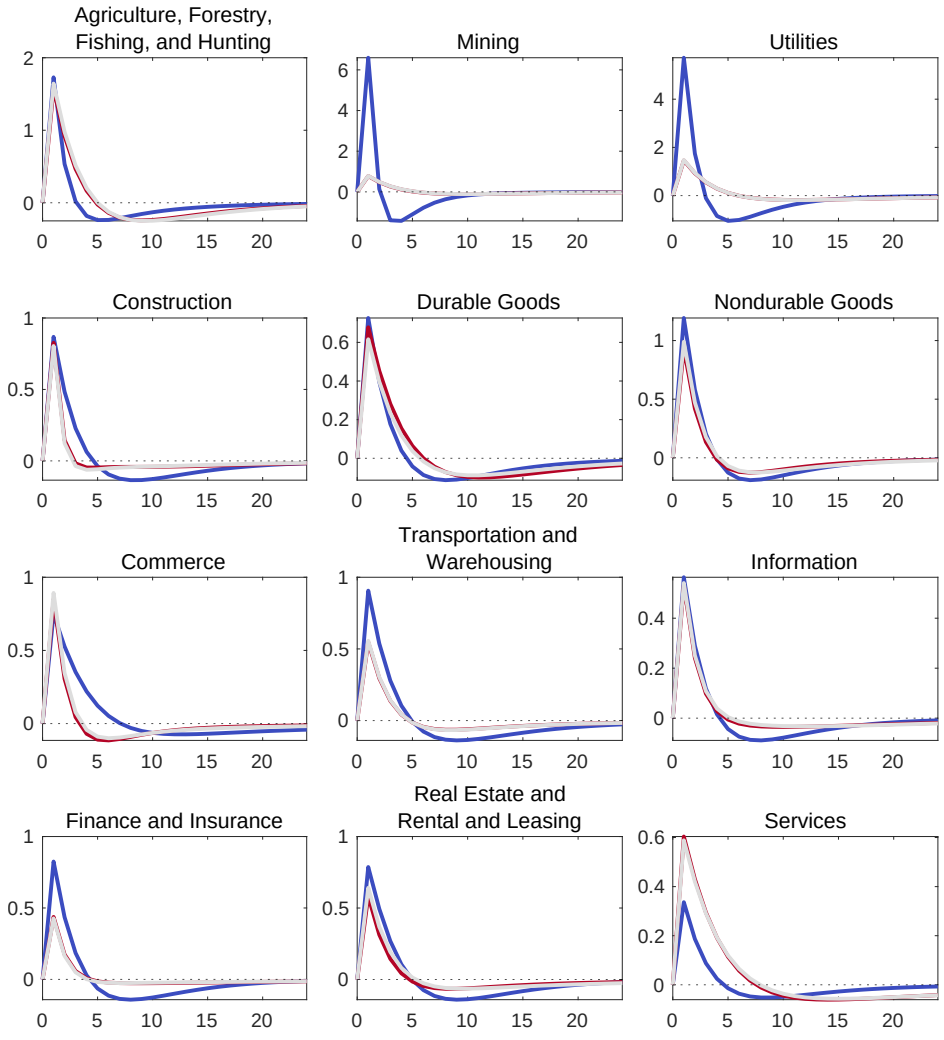
[3]The number of sectors is slightly different in the US and Japan. When we impose the US production network structure, we ignore Sectors 14 and 15 and normalize the shares, so that they sum to unity.

[4]All results are robust to different aggregation methods that are summarized in Table A3. Detailed results are presented in Section E.3.

[5]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.



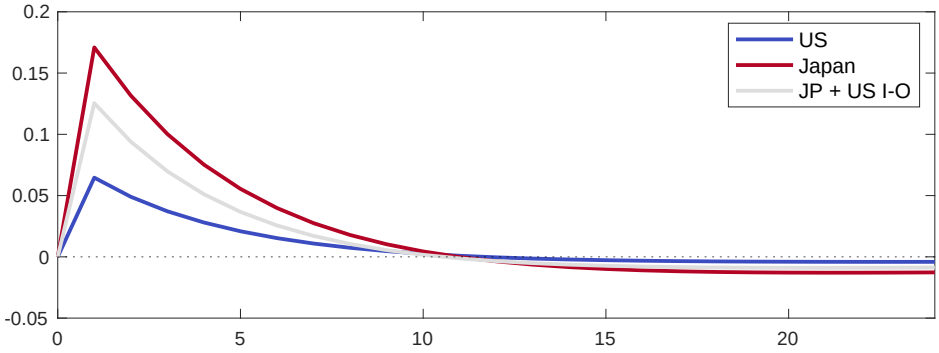
(a) Responses of Aggregate Inflation



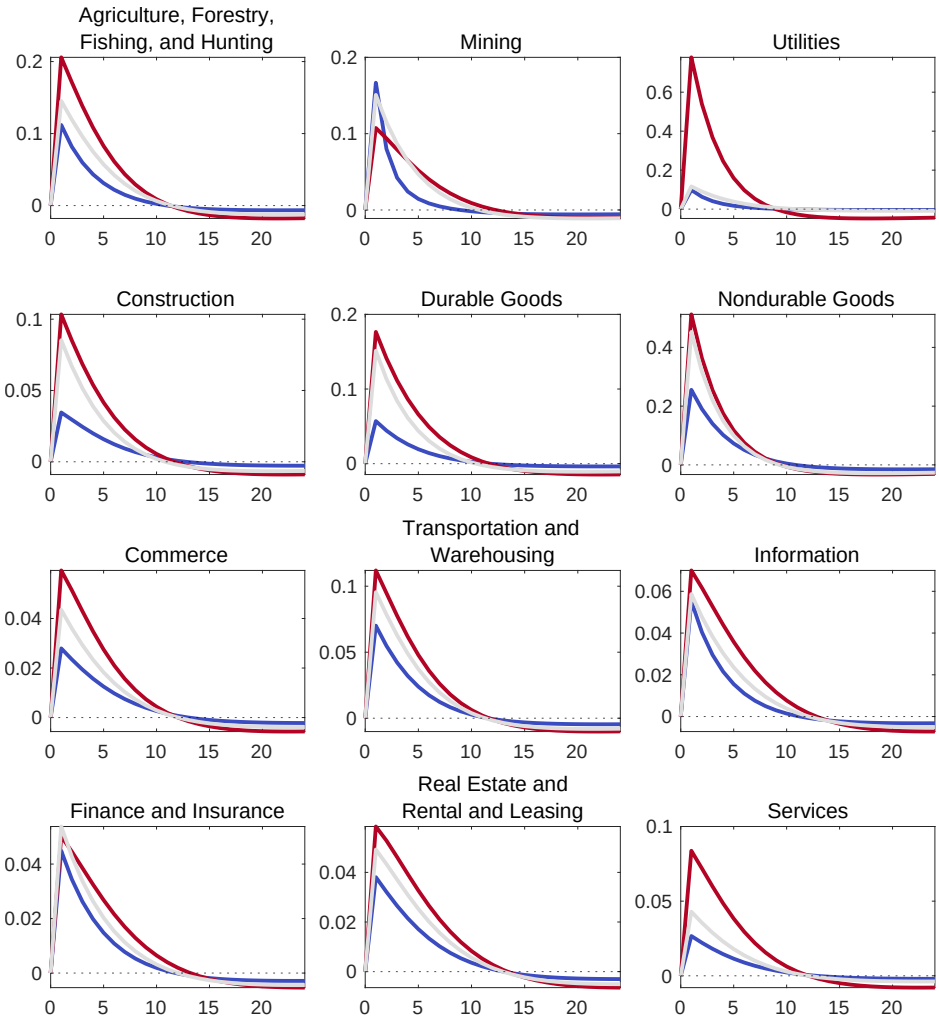
(b) Sectoral Responses

Figure 4: Responses to the Productivity Shocks

Notes: The figure shows the responses of aggregate and sectoral inflation to the one-standard-deviation productivity shocks in 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.



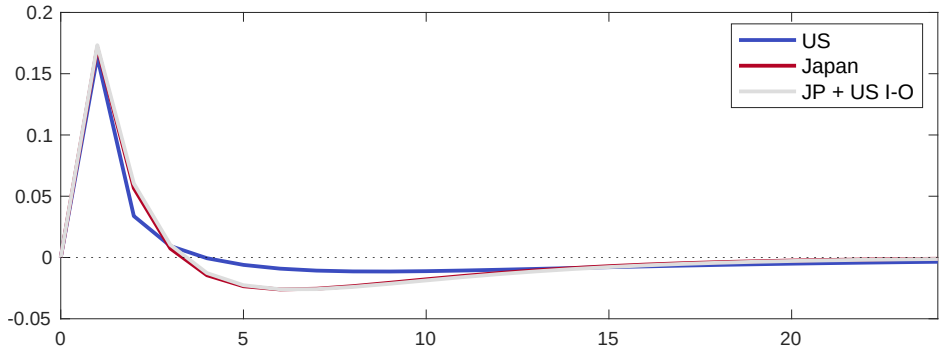
(a) Responses of Aggregate Inflation



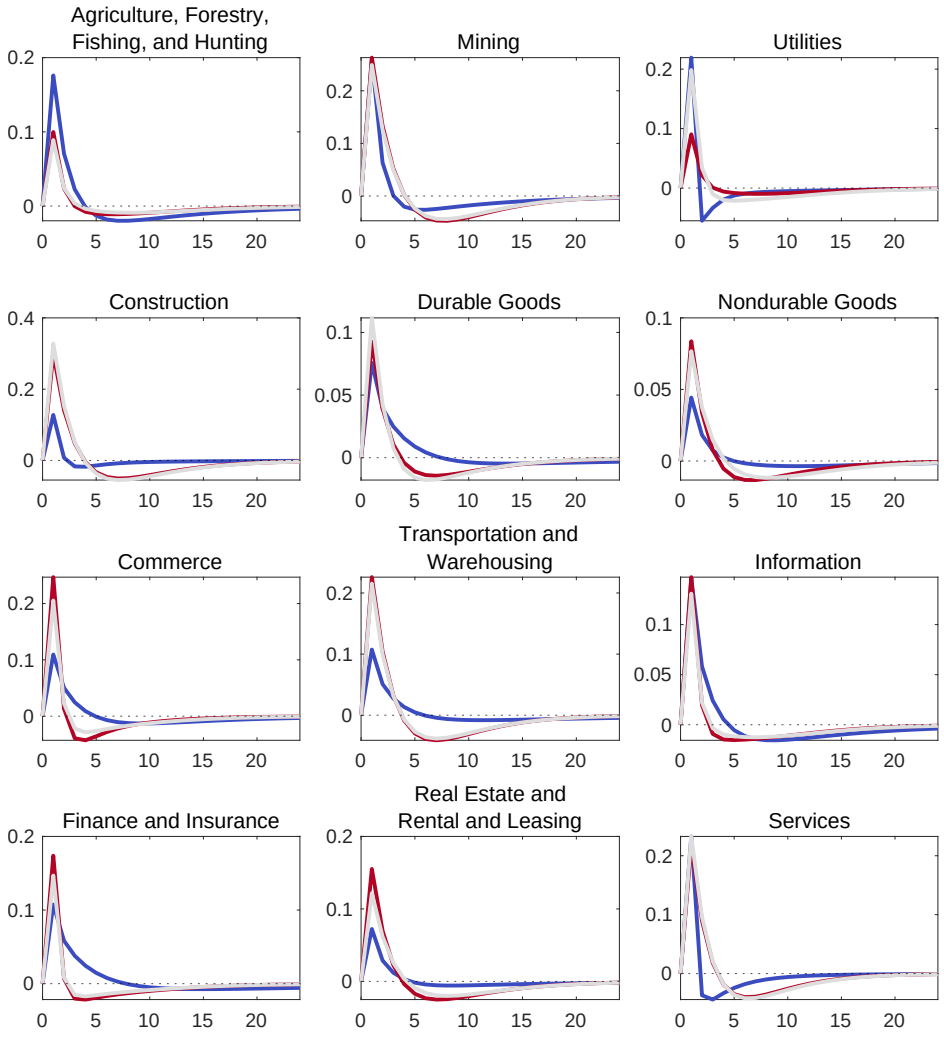
(b) Sectoral Responses

Figure 5: Responses to the 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 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.



(a) Responses of Aggregate Inflation



(b) Sectoral Responses

Figure 6: Responses to the 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 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.

shocks to all sectors in 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).

The top panel of Figure 6 shows the responses of aggregate inflation to the estimated one-standard-deviation wage shocks. Unlike import price shocks, the responses of aggregate inflation to the wage shocks in the US and Japan are quantitatively similar. The counterfactual responses of the Japanese economy with the US I-O structure are almost identical to the actual responses of the Japanese economy.

The bottom panels of Figure 6 display the sectoral responses to the wage shocks. There is heterogeneity in terms of the importance of wage shocks at the sectoral levels. Wage shocks are more important in some sectors in the US than those in Japan (and vice versa). However, such heterogeneity does not contribute to differences in the aggregate responses, as we observe in the top panel of Figure 6. The counterfactual responses with the US production network are similar to the actual responses with the Japanese structure, except for the Utilities sector.

There are two takeaways from this exercise. First, differences in domestic production structure (either the I-O linkages or wage shares) do not account for differences in the aggregate inflation dynamics. Second, differences in import-good structure play an important role in explaining the aggregate inflation dynamics. In particular, both the estimated size of import price shocks and reliance on imported intermediate goods create sizable differences in the aggregate dynamics.

4.3 Counterfactual Impulse Response Functions

In this subsection, we look at the counterfactual responses of the Japanese economy with the estimated US parameters. We consider two cases. One is to replace the price-stickiness parameters of the Japanese economy with the US estimates,[6] while keeping the rest of the parameters unchanged. The other is to replace all persistence parameters in Japan with the US estimates.[7] The aggregate responses to different shocks are shown in Figure 7.

Similar to the I-O linkages, differences in price stickiness in 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 total output weighted degrees of price stickiness are very close to each other in the US and Japan. The same applies to differences in the degree of shock persistence. 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 differences in the aggregate dynamics, counterfactual responses at the sectoral level are heterogeneous. Detailed results are shown in Appendix E.4.

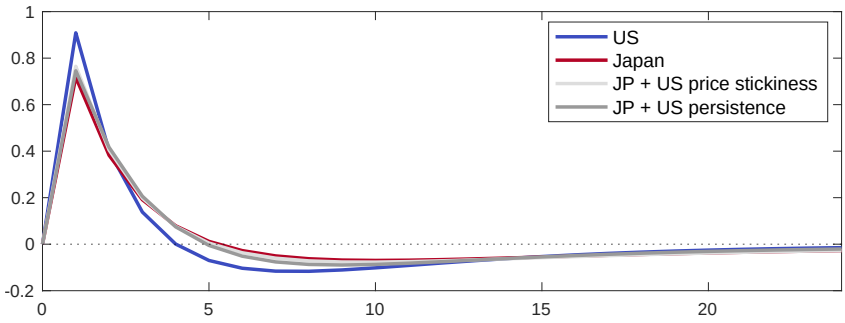
4.4 Variance Decomposition

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.[8] The decomposition of aggregate inflation based on alternative weights is presented in Appendix E.5.

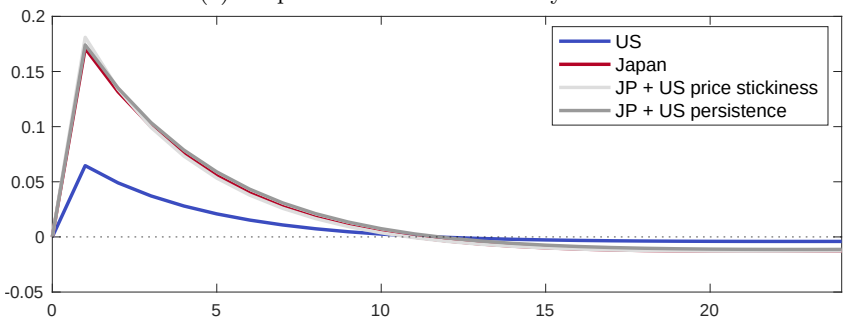
[6] We can also look at 100% pass-through scenarios with κ's being zero. Under such scenarios, initial responses become five to eleven times bigger than the actual responses.

[7] In practice, we cannot replace all Japanese persistence parameters with the US counterparts. Because there is no US estimate for the persistence parameter for the import-good in Commerce (i.e., ρ_7^*), we keep the Japanese estimate.

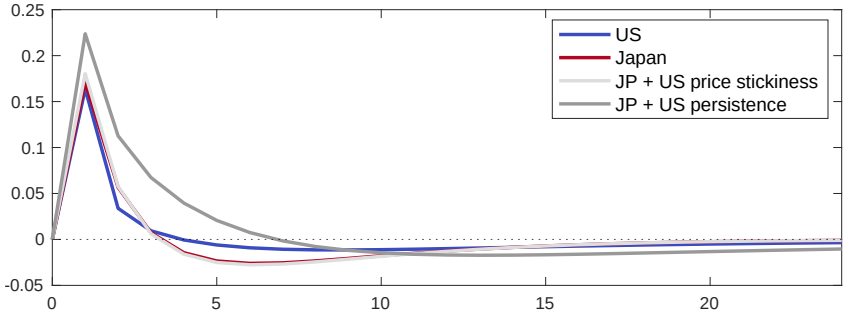
[8] For details on the aggregation, see Appendix C.6.



(a) Responses to the Productivity Shocks



(b) Responses to the Import Price Shocks



(c) Responses to the Wage Shocks

Figure 7: Counterfactural Responses of the Aggregate Inflation Rates

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 of the Japanese economy with the US κ's (light gray lines) and those with the US ρ's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

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.

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% to 7.9% of the variance of aggregate inflation. In contrast, import price shocks are the second most important in Japan, accounting for 17.0% to 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 the previous subsection, 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% to 2.5%. On the other hand, the contribution of wage shocks is small in Japan, ranging from 3.9% to 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.

4.5 Historical Decomposition

Figure 8 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 variance decomposition. Alternative weights for aggregate inflation are considered in Appendix E.6.

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

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	1.000	0.000
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	–	–
Noncomparable Imports and Rest-of-the-World Adjustment	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.

variance decomposition in the US that wage shocks are more important than import price shocks. However, this is because the effects of each sector's wage shocks offset one another, resulting in a diminished role in aggregate terms.

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, productivity shocks and import price shocks tend to contribute in opposite directions 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 a pricing behavior is identified as positive 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. Conversely, declining import prices that reduce inflationary pressures are tempered by negative productivity shocks that increase production costs and contribute to mitigating deflationary pressures.

This divergence reflects structural differences in production networks between the two economies, 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.

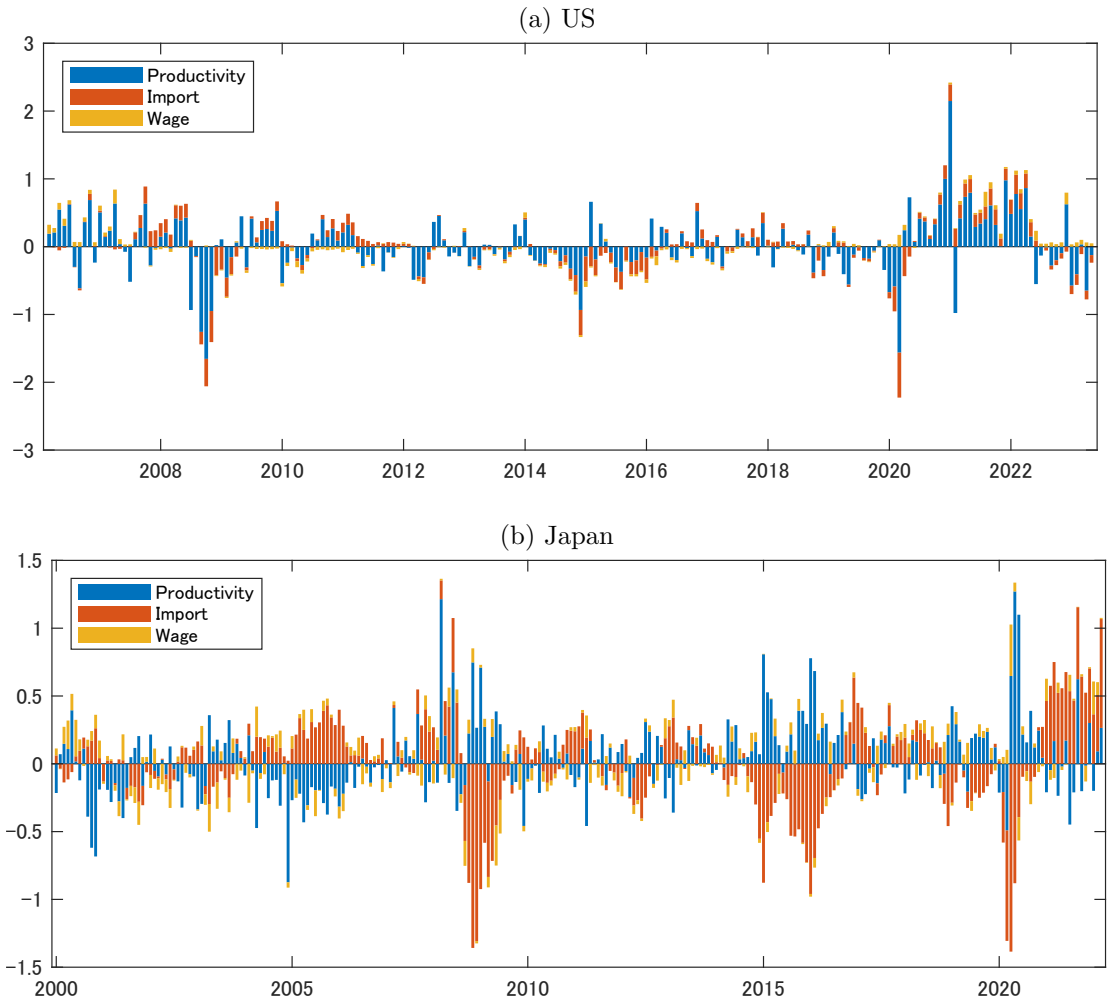


Figure 8: Historical decomposition of aggregate inflation: US and Japan

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.

Figure 9 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 Agriculture, etc.; Information; Finance and Insurance; and Government sectors.

The historical decomposition of sectoral inflation in Japan is shown in Figure 10. 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



Figure 9: Historical decomposition of sectoral inflation: US

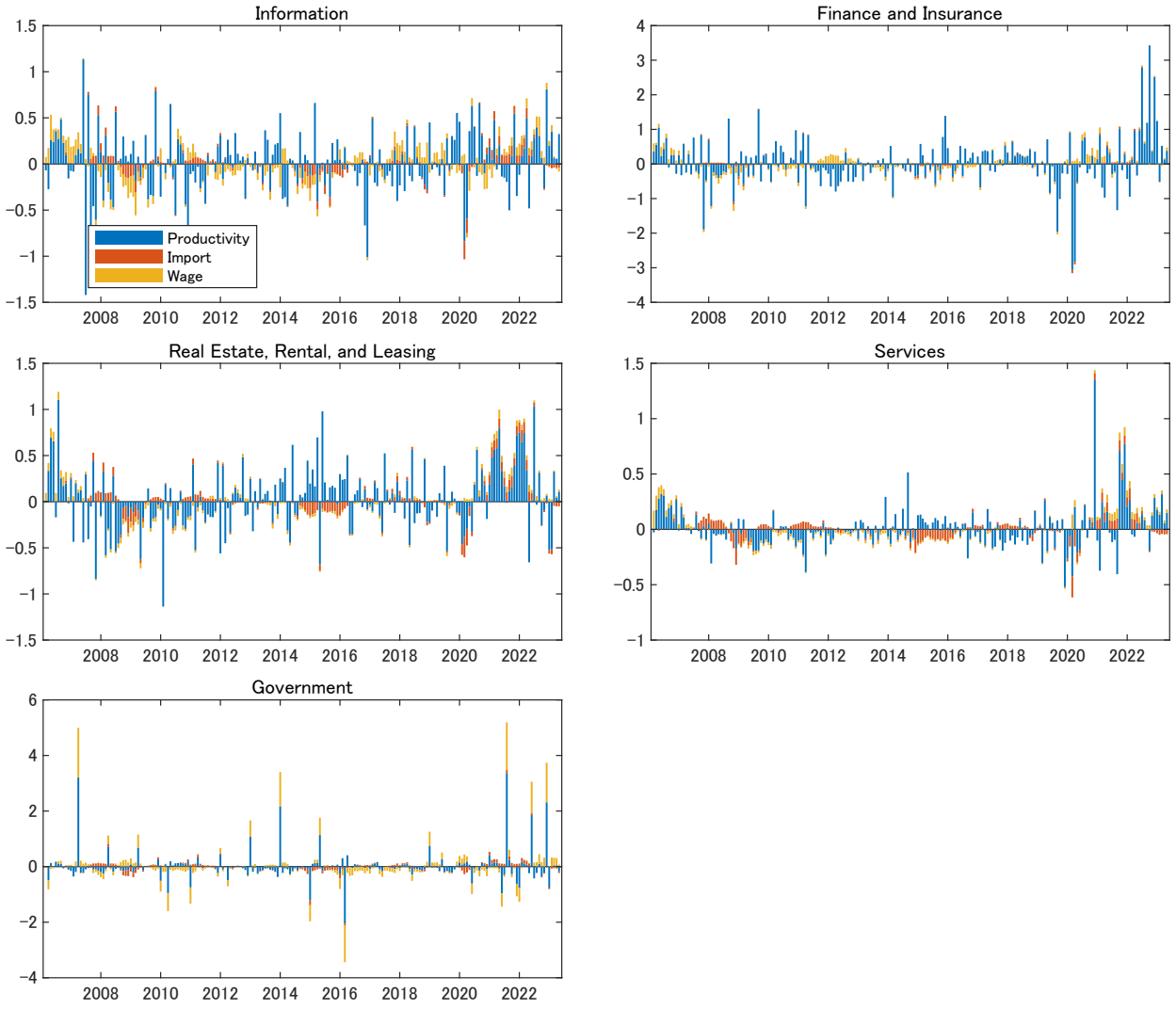


Figure 9: Historical decomposition of sectoral inflation: US (continued)

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.

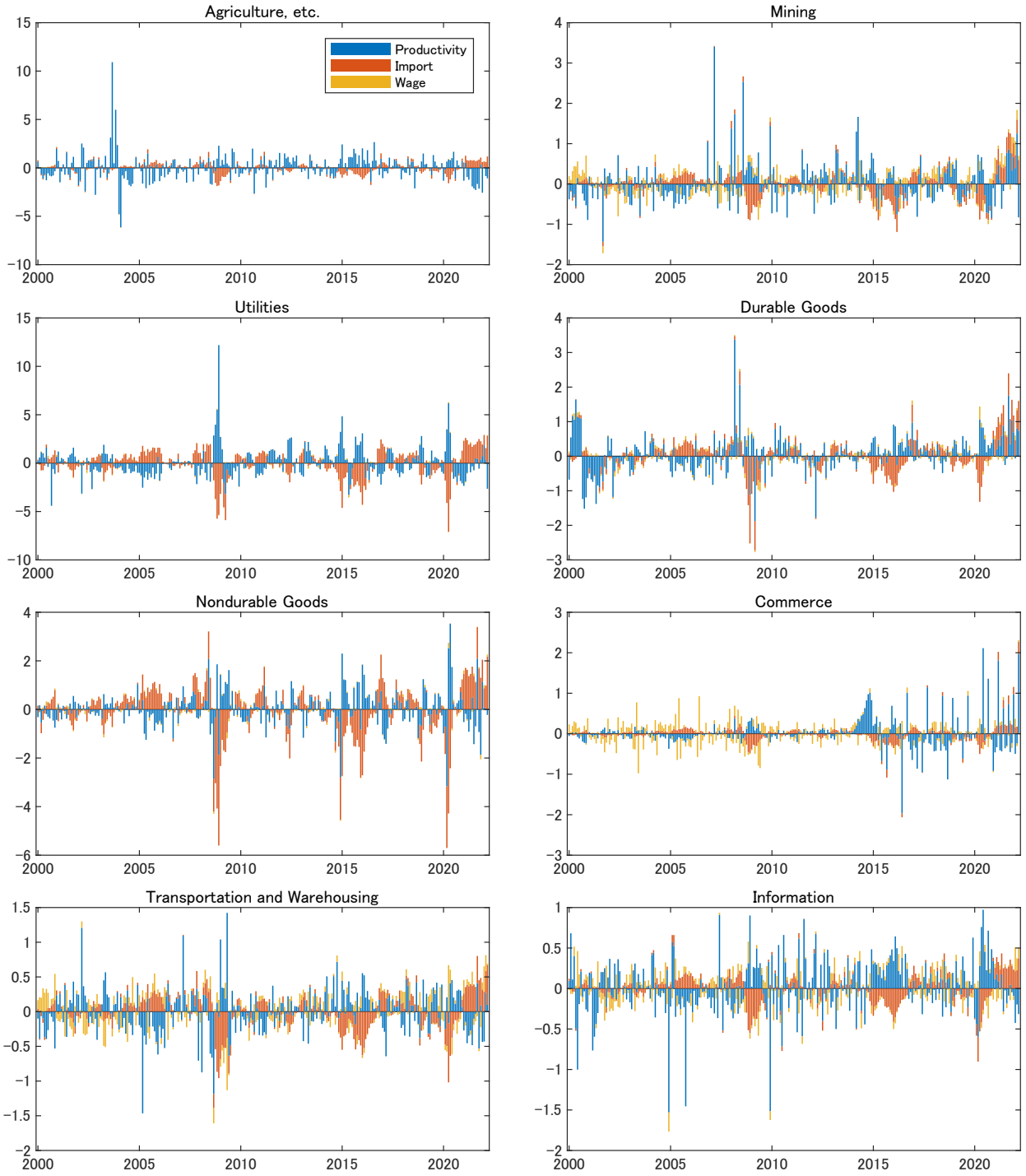


Figure 10: Historical decomposition of sectoral inflation: Japan

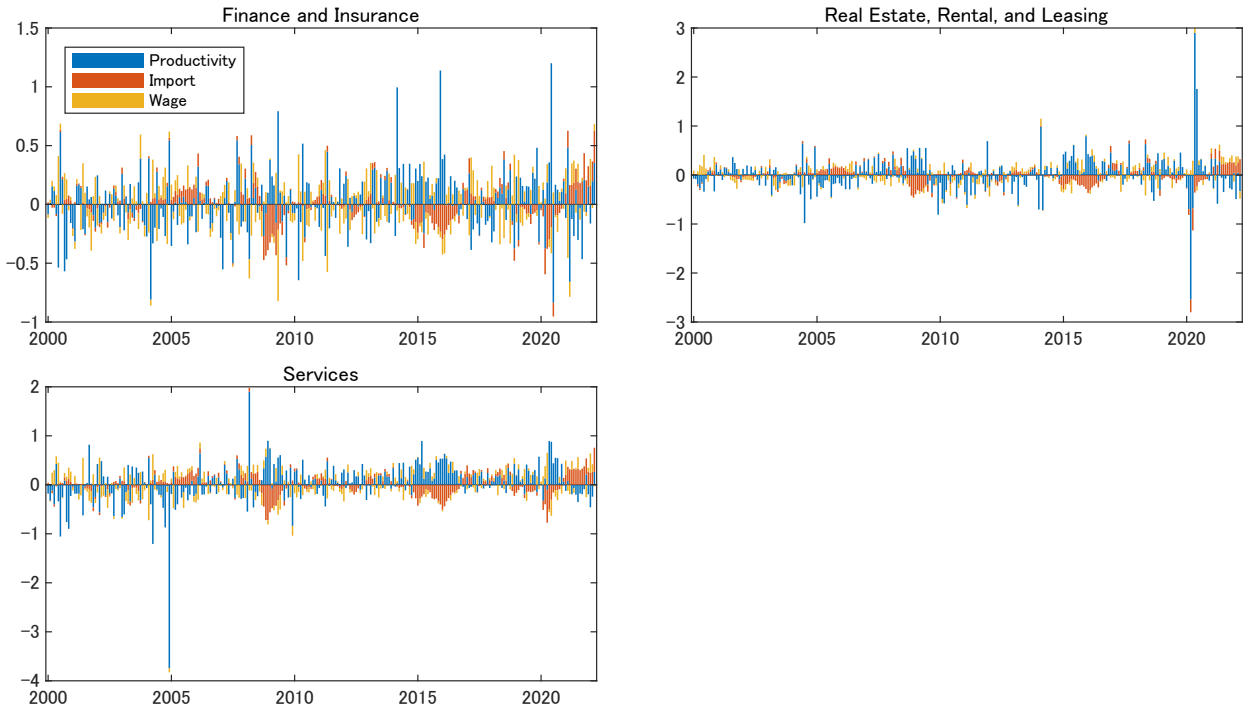


Figure 10: Historical decomposition of sectoral inflation: Japan (continued)

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.

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 pass-through and dynamics.

5 Conclusion

This paper has developed and estimated a structural model of sectoral inflation incorporating production networks to analyze inflation pass-through 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.

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Appendix

A Model

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

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

which becomes

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

Firm f in sector i are symmetric under the Rotemberg-type price stickiness, so that P_{it} equals P_{ift}. Thus, we omit subscript f hereafter. We define the inflation rate by $\pi_{it} \equiv P_{it}/P_{it-1} - 1$ and relative price by $p_{it} \equiv P_{it}/P_t$. The log-linearization yields

$$\pi_{it} = \frac{\sigma_i}{\kappa_i}\left(RMC_{it} - (\sigma_i - 1)p_{it}/\sigma_i\right) + \beta\mathbb{E}_t\pi_{it+1}, \tag{16}$$

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

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

$$Y_{it} = e^{\varepsilon_{it}}\left(\prod_{j=1}^{N} Y_{ijt}^{\omega_{ij}}\right)\cdot\left(\prod_{m=1}^{M} Y_{imt}^{\omega_{im}}\right)\cdot L_{it}^{\omega_{iw}}, \tag{17}$$

Then, the cost minimization yields

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

where P_{mt}^* is exogenous import price. Then, we have the log-linearized form:

$$\widehat{RMC}_{it} = \frac{\sigma_i - 1}{\sigma_i}\left(\sum_{j=1}^{N}\omega_{ij}\widehat{p}_{jt} + \sum_{m=1}^{M}\omega_{im}\widehat{p}_{mt}^* + \omega_{iw}\widehat{w}_{it} - \varepsilon_{it} - \widehat{p}_{it}\right), \tag{18}$$

where we assume $P_i = P$ for all i in the steady state and $\widehat{x}_t$ represents the log-linearization of x_t. This

becomes

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

$$\widehat{RMC}_{it} = \widehat{RMC}_{it-1} + \sum_{j=1}^{N}\omega^*_{ij}\pi_{jt} + \sum_{m=1}^{M}\omega^*_{im}\pi^*_{mt} + \omega^*_{iw}\pi^w_{it} - ()\varepsilon_{it} - \varepsilon_{it-1}), \tag{19}$$

where $\widehat{p}_{it} - \widehat{p}_{it-1} = \pi_{it} - \pi_t$ and ε_{it} is replaced by $\frac{\sigma-1}{\sigma}\varepsilon_{it}$ for simplicity and

$$\omega^*_{ii} = \frac{\sigma_i - 1}{\sigma_i}(\omega_{ii} - 1) \tag{20}$$

$$\omega^*_{ij} = \frac{\sigma_i - 1}{\sigma_i}\omega_{ij} \qquad (j \neq i) \tag{21}$$

$$\omega^*_{im} = \frac{\sigma_i - 1}{\sigma_i}\omega_{im}. \tag{22}$$

$$\omega^*_{iw} = \frac{\sigma_i - 1}{\sigma_i}\omega_{iw}. \tag{23}$$

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

$$\widehat{P}^*_{mt} = \rho^*_m\widehat{P}^*_{mt-1} + \mu^*_{mt} \tag{24}$$

$$\widehat{W}_{it} = \rho^w_i\widehat{W}_{it-1} + \mu^w_{it} \tag{25}$$

$$\varepsilon_{it} = \rho_i\varepsilon_{it-1} + \mu_{it}, \tag{26}$$

where $\mathbb{E}_t\mu^*_{mt+k} = \mathbb{E}_t\mu^w_{it+k} = \mathbb{E}_t\mu_{it+k} = 0$ for $k = 1, 2, \cdots$, $\pi^*_{mt} = \widehat{P}^*_{mt} - \widehat{P}^*_{mt-1}$, and $\pi^w_{it} = \widehat{W}_{it} - \widehat{W}_{it-1}$.

Then, the inflation rate of sector i, π_{it}, is expressed as

$$\pi_{it} = -\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt} - \varepsilon_{it-1}\right) + \sum_{m=1}^{M}\Gamma^*_{im}\pi^*_{mt} + \sum_{j=1}^{N}\Gamma^w_{ij}\pi^w_{jt} + \sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt-1}. \tag{27}$$

To see this, we insert the equation for $t+1$ to equation (16):

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

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

which becomes

$$
\begin{aligned}
&\sum_{j=1}^{N}\Gamma_{ij}\left(\varepsilon_{jt}-\varepsilon_{it-1}\right)+\sum_{m=1}^{M}\Gamma^*_{im}\pi^*_{mt}+\sum_{j=1}^{N}\Gamma^w_{ij}\pi^w_{jt}+\sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt-1}\\
&=\pi_{it-1}\\
&\quad-\beta\left(\sum_{j=1}^{N}(1-\rho_j)\Gamma_{ij}(\varepsilon_{jt}-\varepsilon_{jt-1})+\sum_{m=1}^{M}(1-\rho^*_m)\Gamma^*_{im}\pi^*_{mt}+(1-\rho^w_i)\sum_{j=1}^{N}\Gamma^w_{ij}\pi^w_{jt}+\sum_{j=1}^{N}\Gamma^L_{ij}\pi_{jt-1}\right)\\
&\quad+\sum_{j=1}^{N}\left(\beta\Gamma^L_{ij}+\frac{\sigma_i}{\kappa_i}\omega^*_{ij}\right)\left\{\sum_{l=1}^{N}\Gamma_{jl}\left(\varepsilon_{lt}-\varepsilon_{lt-1}\right)+\sum_{m=1}^{M}\Gamma^*_{jm}\pi^*_{mt}+\sum_{l=1}^{N}\Gamma^w_{jl}\pi^w_{lt}+\sum_{l=1}^{N}\Gamma^L_{jl}\pi_{lt-1}\right\}\\
&\quad+\frac{\sigma_i}{\kappa_i}\left(\sum_{m=1}^{M}\omega^*_{im}\pi^*_{mt}+\omega^*_{iw}\pi^w_{it}-\left(\varepsilon_{it}-\varepsilon_{it-1}\right)\right).
\end{aligned}
$$

Comparing coefficients of $\varepsilon_{jt}-\varepsilon_{it-1}$, π^*_{mt}, π^w_{jt}, and π_{jt-1} for $j=i$ and $j\neq i$ in the left- and right-hand side of the equations suggests

$$
\Gamma_{ii}=-\beta(1-\rho_i)\Gamma_{ii}+\sum_{l=1}^{N}\left(\beta\Gamma^L_{il}+\frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma_{li}+\frac{\sigma_i}{\kappa_i} \tag{28}
$$

$$
\Gamma_{ij}=-\beta(1-\rho_j)\Gamma_{ij}+\sum_{l=1}^{N}\left(\beta\Gamma^L_{il}+\frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma_{lj}\qquad(j\neq i) \tag{29}
$$

$$
\Gamma^*_{im}=-\beta(1-\rho^*_m)\Gamma^*_{im}+\sum_{l=1}^{N}\left(\beta\Gamma^L_{il}+\frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma^*_{lm}+\frac{\sigma_i}{\kappa_i}\omega^*_{im} \tag{30}
$$

$$
\Gamma^w_{ii}=-\beta(1-\rho^w_i)\Gamma^w_{ii}+\sum_{l=1}^{N}\left(\beta\Gamma^L_{il}+\frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma^w_{li}+\frac{\sigma_i}{\kappa_i}\omega^*_{iw} \tag{31}
$$

$$\Gamma^w_{ij} = -\beta(1-\rho^w_i)\Gamma^w_{ij} + \sum_{l=1}^{N}\left(\beta\Gamma^L_{il} + \frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma^w_{lj} \qquad (j \neq i) \tag{32}$$

$$\Gamma^L_{ii} = 1 - \beta\Gamma^L_{ii} + \sum_{l=1}^{N}\left(\beta\Gamma^L_{il} + \frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma^L_{li} \tag{33}$$

$$\Gamma^L_{ij} = -\beta\Gamma^L_{ij} + \sum_{l=1}^{N}\left(\beta\Gamma^L_{il} + \frac{\sigma_i}{\kappa_i}\omega^*_{il}\right)\Gamma^L_{lj} \qquad (j \neq i). \tag{34}$$

We define the following vectors and matrices:

- $\mathbf{\Pi}_t$: the N by 1 vector, where i-th element is π_{it} (data);
- $\mathbf{\Pi}^*_t$: the M by 1 vector, where m-th element is π^*_{mt} (data);
- $\mathbf{\Pi}^w_t$: the N by 1 vector, where i-th element is π^w_{it} (data);
- $\mathbf{e}_t$: the N by 1 vector, where i-th element is ε_{it} (unobservable AR(1) shocks);
- $\mathbf{G}$: the N by N matrix, where element (i,j) is Γ_{ij} (to be estimated);
- $\mathbf{G}^*$: the N by M matrix, where element (i,m) is Γ^*_{im} (to be estimated);
- $\mathbf{G_w}$: the N by N matrix, where element (i,j) is Γ^w_{ij} (to be estimated);
- $\mathbf{G_L}$: the N by N matrix, where element (i,j) is Γ^L_{ij} (to be estimated);
- $\mathbf{P}$: the diagonal N by N matrix, where element (i,i) equals ρ_j (to be estimated);
- $\mathbf{P}^*$: the diagonal M by M matrix, where element (m,m) equals ρ^*_m (to be estimated);
- $\mathbf{P_w}$: the diagonal N by N matrix, where element (i,i) equals ρ^w_i (to be estimated);
- $\mathbf{K}$: the diagonal N by N matrix, where element (i,i) equals $(\sigma_i - 1)/\kappa_i$ (to be estimated)
- $\mathbf{\Omega}$: the N by N matrix, where element (i,j) equals $\omega_{ii} - 1$ for $j = i$ and ω_{ij} for $j \neq i$ (set from the I-O table);
- $\mathbf{\Omega}^*$: the N by M matrix, where element (i,m) equals ω_{im} (set from the I-O table);
- $\mathbf{\Omega_w}$: the diagonal N by N matrix, where element (i,i) equals ω_{iw} (set from the I-O table);

Note that we used

$$\omega^*_{ii} = \frac{\sigma_i - 1}{\sigma_i}(\omega_{ii} - 1) \tag{35}$$

$$\omega^*_{ij} = \frac{\sigma_i - 1}{\sigma_i}\omega_{ij} \qquad (j \neq i) \tag{36}$$

$$\omega^*_{im} = \frac{\sigma_i - 1}{\sigma_i}\omega_{im} \tag{37}$$

$$\omega^*_{iw} = \frac{\sigma_i - 1}{\sigma_i}\omega_{iw}. \tag{38}$$

Then, equation (27) is rewritten as

$$\mathbf{\Pi}_t = -\mathbf{G}\left(\mathbf{e}_t - \mathbf{e}_{t-1}\right) + \mathbf{G}^*\mathbf{\Pi}^*_t + \mathbf{G_w}\mathbf{\Pi}^w_t + \mathbf{G_L}\mathbf{\Pi}_{t-1}, \tag{39}$$

where coefficients are given by

$$(1+\beta)\mathbf{G_L} = (\beta\mathbf{G_L} + \mathbf{K\Omega})\,\mathbf{G_L} + \mathbf{I} \tag{40}$$

and

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

The above three equations can be rewritten using $\mathbf{G_L}$ as

$$\begin{aligned}
((1+\beta)\mathbf{I} - (\beta\mathbf{G_L} + \mathbf{K\Omega}))\,\mathbf{G} &= \mathbf{K} + \beta\mathbf{GP} \\
{\mathbf{G_L}}^{-1}\mathbf{G} &= \mathbf{K} + \beta\mathbf{GP} \\
\mathbf{G} &= \mathbf{G_L}\,(\mathbf{K} + \beta\mathbf{GP}) \\
vec(\mathbf{G}) &= vec(\mathbf{G_L}\mathbf{K}) + \beta vec(\mathbf{G_L}\mathbf{GP}) \\
&= vec(\mathbf{G_L}\mathbf{K}) + \beta\,(\mathbf{P}' \otimes \mathbf{G_L})\,vec(\mathbf{G}) \\
vec(\mathbf{G}) &= (\mathbf{I} - \beta\,(\mathbf{P}' \otimes \mathbf{G_L}))^{-1}\,vec(\mathbf{G_L}\mathbf{K}),
\end{aligned} \tag{41}$$

$$\begin{aligned}
((1+\beta)\mathbf{I} - (\beta\mathbf{G_L} + \mathbf{K\Omega}))\,\mathbf{G}^* &= \mathbf{K\Omega}^* + \beta\mathbf{G}^*\mathbf{P}^* \\
{\mathbf{G_L}}^{-1}\mathbf{G}^* &= \mathbf{K}\Omega^* + \beta\mathbf{G}^*\mathbf{P}^* \\
\mathbf{G}^* &= \mathbf{G_L}\,(\mathbf{K\Omega}^* + \beta\mathbf{G}^*\mathbf{P}^*) \\
vec(\mathbf{G}^*) &= \left(\mathbf{I} - \beta\left(\mathbf{P}^{*\prime} \otimes \mathbf{G_L}\right)\right)^{-1} vec(\mathbf{G_L}\mathbf{K\Omega}^*),
\end{aligned} \tag{42}$$

$$\begin{aligned}
\mathbf{G_w} &= (-\beta\mathbf{P_w} + (1+\beta)\mathbf{I} - \beta\mathbf{G_L} - \mathbf{K\Omega})^{-1}\,\mathbf{K\Omega_w} \\
&= \left(-\beta\mathbf{P_w} + {\mathbf{G_L}}^{-1}\right)^{-1}\mathbf{K\Omega_w}.
\end{aligned} \tag{43}$$

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

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

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

which yields the solution given by

$$
\begin{aligned}
g_{11} &= \frac{1+\beta+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11}) - \sqrt{\left\{1+\beta+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11})\right\}^2 - 4\beta\left\{1+\left(\beta g_{12}+\frac{\sigma_1-1}{\kappa_1}\omega_{12}\right)g_{21}\right\}}}{2\beta} \\
g_{12} &= \frac{\frac{\sigma_1-1}{\kappa_1}\omega_{12}}{1+\beta-\beta g_{11}-\beta g_{22}+\frac{\sigma_1-1}{\kappa_1}(1-\omega_{11})}g_{22} \\
g_{21} &= \frac{\frac{\sigma_2-1}{\kappa_2}\omega_{21}}{1+\beta-\beta g_{11}-\beta g_{22}+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22})}g_{11} \\
g_{22} &= \frac{1+\beta+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22}) - \sqrt{\left\{1+\beta+\frac{\sigma_2-1}{\kappa_2}(1-\omega_{22})\right\}^2 - 4\beta\left\{1+\left(\beta g_{21}+\frac{\sigma_2-1}{\kappa_2}\omega_{21}\right)g_{12}\right\}}}{2\beta}.
\end{aligned}
\tag{44}
$$

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 big). 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 $\omega_{12}g_{22}$ equals zero.

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 $g_{22} \rightarrow$ my own sector),
- decreases g_{11} (given a positive ω_{12} and ω_{21}; third effect through my own sector $\rightarrow$ the other sector g_{21} $\rightarrow$ my own sector with κ_1).

The eigenvalues of $\mathbf{G_L}$ show 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 $g_{11} \geq g_{12} \geq 0$. A positive g_{12} and g_{21} (given g_{11} and g_{22}) increases one λ slightly from g_{11}, while decreases the other λ slightly from g_{22}. That is, the eigenvalues diverge, which contributes to an increase in aggregate inflation persistence.

Simulation Results

We numerically calculate parameter values for coefficients on inflation persistence $\mathbf{G_L}$ and responses to idiosyncratic shocks $\mathbf{G}$. We assume $N = 2$, $\beta = 0.96$, $\rho = 0.85$, $\sigma = 10$, $\kappa = 10$, $\omega_{11} = \omega_{22} = 0.4$, $\omega_{12} = \omega_{21} = 0.2$, $\omega_m = 0.2$, and $\omega_w = 0.2$ (i.e., $\omega_{ii} + \omega_{i-i} + \omega_m + \omega_w = 1$). The simulation results are shown in Figure A1. In each figure, we change parameter values for both ω_{12} and ω_{21}, only ω_{12}, only ω_{21}, κ in both sectors, and κ in sector 2 only, which is displayed in the horizontal axis.

C Data Appendix

This section provides a detailed explanation of how the matrices $\mathbf{\Omega}$, $\mathbf{\Omega}^*$, $\mathbf{\Omega_w}$, and the price inflation vectors $\mathbf{\Pi}_t$, $\mathbf{\Pi}_t^*$, $\mathbf{\Pi}_t^w$, which are used in model calibration, are constructed from datasets for the US and Japan.

Subsections C.1 and C.2 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 Subsections C.3 and C.4, we construct sectoral domestic price indices, import price indices, and wage indices for both countries. These indices are used in the calculation of $\mathbf{\Pi}_t$, $\mathbf{\Pi}_t^*$, and $\mathbf{\Pi}_t^w$. Subsection C.5 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 Subsection C.6, the matrices and vectors for the empirical analyses are derived using the constructed data.

C.1 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. Of 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

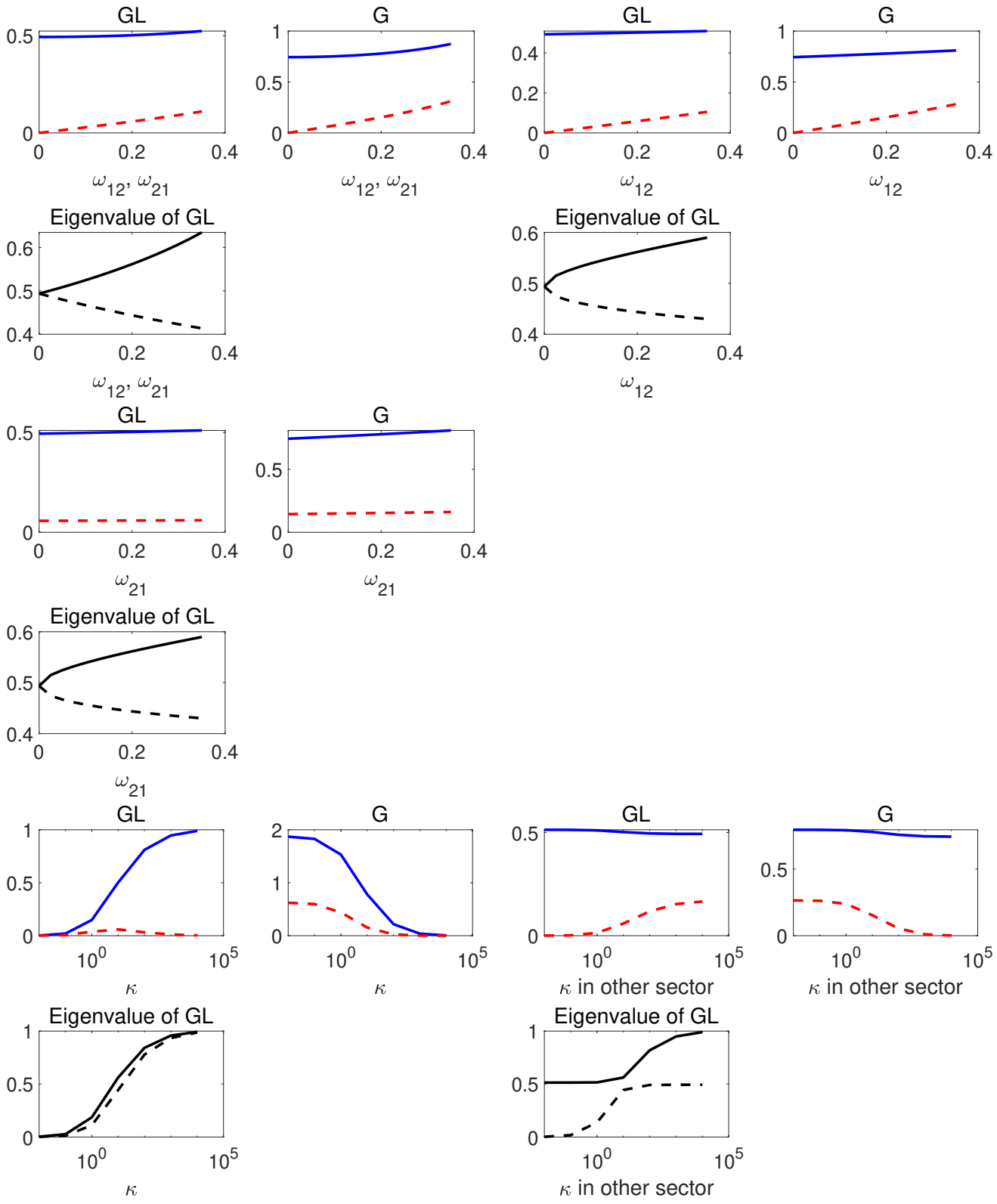


Figure A1: Inflation Dynamics

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

to the manual provided by the BLS. [9] [10] 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.

$$\begin{aligned} \mathbf{q} &= \mathbf{U}\mathbf{i}_N + \mathbf{e}, \\ &= \mathbf{V}^\top \mathbf{i}_N, \end{aligned} \tag{45}$$

$$\mathbf{g} = \mathbf{V}\mathbf{i}_N, \tag{46}$$

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.

$$\mathbf{B} = \mathbf{U} \times \text{diag}(\mathbf{g})^{-1}, \tag{47}$$

$$\mathbf{D} = \mathbf{V} \times \text{diag}(\mathbf{q})^{-1}, \tag{48}$$

where $\text{diag}(\mathbf{g})$ is the diagonal matrix of vector $\mathbf{g}$ and $\text{diag}(\mathbf{q})$ 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 (46)–(48), equation (45) can be rewritten as follows.

$$\mathbf{q} = \mathbf{B}\mathbf{D}\mathbf{q} + \mathbf{e}. \tag{49}$$

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

$$\mathbf{X} \equiv \mathbf{A} \times \text{diag}(\mathbf{q}). \tag{50}$$

C.1.1 Decomposing the I-O Matrix into the Domestic and Import Sectors

In our 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:

$$\mathbf{U}^d = \mathbf{U} - \mathbf{U}^*. \tag{51}$$

[9] 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.

[10] 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.

We use the decomposed matrices $\mathbf{U}^d$ and $\mathbf{U}^*$ instead of $\mathbf{U}$ when calculating $\mathbf{X}$ in equation (50). This allows us to obtain the commodity-by-commodity I-O matrix for both domestic and import sectors.

C.1.2 Constructing the Compensation of Employees for each Sector

In this subsection, 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:

$$\mathbf{g}^\top = \mathbf{y}^\top + \mathbf{i}_N^\top \mathbf{B} \times \text{diag}(\mathbf{g}), \tag{52}$$

$$\mathbf{q}^\top = \mathbf{z}^\top + \mathbf{i}_N^\top \mathbf{A} \times \text{diag}(\mathbf{q}), \tag{53}$$

where $\mathbf{y} = \mathbf{Y}^\top \mathbf{i}_3$ and $\mathbf{z} = \mathbf{Z}^\top \mathbf{i}_3$. Postmultiplying equation (53) by $\mathbf{V}^{-1} \times \text{diag}(\mathbf{g})$, we have

$$\mathbf{g}^\top = \mathbf{z}^\top \mathbf{V}^{-1} \times \text{diag}(\mathbf{g}) + \mathbf{i}_N^\top \mathbf{B} \times \text{diag}(\mathbf{g}). \tag{54}$$

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

$$\mathbf{Z} = \mathbf{Y} \times \text{diag}(\mathbf{g})^{-1} \mathbf{V}. \tag{55}$$

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

C.2 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. [11] 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 Subsection C.5.

C.2.1 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 value of "Total imports," denoted by $m_i \geq 0$, for each supply sector $i \in [1, 2, ..., N_r = 517]$. [12]

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

$$c_i = \frac{m_i}{m_i + D_i}, \tag{56}$$

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 $\mathbf{X}^*$.

$$\begin{aligned} \mathbf{X}_{N_r \times N_c} &= \{\mathbf{I}_{N_r} - \text{diag}(\mathbf{c})\} \mathbf{X}_{N_r \times N_c} + \text{diag}(\mathbf{c}) \mathbf{X}_{N_r \times N_c}, & (57) \\ &\equiv \mathbf{X}^d + \mathbf{X}^*, & (58) \end{aligned}$$

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

C.2.2 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:

$$\text{Compensation of employees}_j \equiv \text{Wages and salaries}_j$$

[11] 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.

[12] In the I-O tables, the value of "Total imports" is generally reported as the value obtained by multiplying the import amount by -1, that is, as $-m_i$.

$$+ \text{Contribution of employers to social insurance}_j$$
$$+ \text{Other payments and allowances}_j.$$

C.3 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 inflation rate vectors $\mathbf{\Pi}_t$, $\mathbf{\Pi}_t^*$, and $\mathbf{\Pi}_t^w$, as shown in Table 1. 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.3.1 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 A1 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).

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).

Table A1: 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

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. [13] 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. [14]

C.3.2 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.

C.3.3 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 A1, we use the concordance table between the 2017 and 2022 NAICS codes published

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

[14] There may be cases where a related NAICS code exists for a BEA code, but no data are available for the corresponding PPI (e.g., for farm sectors).

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.4 Constructing the Price and Wage indices for Japan

In this subsection, we construct three price index datasets—domestic prices, import prices, and wages—by sectors in Japan's I-O table. These price indices are essential for the development of the three inflation rate vectors, $\mathbf{\Pi}_t$, $\mathbf{\Pi}_t^*$, and $\mathbf{\Pi}_t^w$, as shown in Table 1. 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 index is derived from the 2020 Monthly Labour Survey published by the Ministry of Health, Labour, and Welfare.

C.4.1 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. [15] Since there is only one wholesale sector in the Japanese I-O table, we use only the aggregated wholesale price index in the WSPI.

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

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

$$p_{jt}^{y,2015} = \sum_{i \in \Theta_j^{y,2015}} \omega_i^y p_{it}^y, \tag{59}$$

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:

$$c_{y_1,y_2} = \frac{\sum_{t \in T_{y_2}} p_{jt}^{y_2,2015}}{\sum_{t \in T_{y_2}} p_{jt}^{y_1,2015}}, \tag{60}$$

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

$$p_{jt}^{SP} = \begin{cases} p_{jt}^{2015,2015}, & \text{if } t \geq Jan.2015, \\ c_{2010,2015} \times p_{jt}^{2010,2015}, & \text{if } t \in [Jan.2010, Dec.2014], \\ c_{2005,2010} \times c_{2010,2015} \times p_{jt}^{2005,2015}, & \text{if } t \in [Jan.2005, Dec.2009], \\ c_{2000,2005} \times c_{2005,2010} \times c_{2010,2015} \times p_{jt}^{2000,2015}, & \text{if } t \in [Jan.2000, Dec.2004]. \end{cases} \tag{61}$$

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. [16]

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.

[16] 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).

C.4.2 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. [17]

Specifically, we use seasonally adjusted data for all establishment sizes and employment types. [18] 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.

$$\text{Wage index}_j \equiv \frac{\text{Total cash earnings}_j}{\text{Total of hours actually worked}_j}. \tag{62}$$

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.5 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 A2. 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 tables 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 table as $\mathbf{X}_{N_r \times N_c} = (x_{ij})_{1 \leq i \leq N_r, 1 \leq j \leq N_c}$, and the price indices as $\{p_{it}\}_{1 \leq i \leq N_r}$. Let the I-O table aggregated by sector $i' = 1, ..., N'$ be denoted as $\mathbf{X}_{N' \times N'} = (x_{i'j'})_{1 \leq i', j' \leq N'}$. Each element of this matrix is calculated as follows:

$$x_{i'j'} = \sum_{i \in \Theta_{i'}, j \in \Theta_{j'}} x_{ij'}, \tag{63}$$

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

$$p_{i't} = \frac{\sum_{\{i | i \in \Theta_{i'}, p_{it} \neq \text{missing}\}} x_i p_{it}}{\sum_{\{i | i \in \Theta_{i'}, p_{it} \neq \text{missing}\}} x_i}. \tag{64}$$

By applying these aggregations separately to the domestic and import sectors, we obtain the domestic I-O

[17] 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)

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

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. [19]

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

$$p^{w}_{j't} = \frac{\sum_{\{j|j\in\Theta_{j'},p^{w}_{jt}\neq\text{missing}\}} x^{w}_{j} p^{w}_{jt}}{\sum_{\{j|j\in\Theta_{j'},p^{w}_{jt}\neq\text{missing}\}} x^{w}_{j}}, \tag{65}$$

where x^{w}_{j} is the compensation of employees for each demand sector j. And 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.6 Construction of the Empirical Data

In this subsection, we finally construct the three I-O linkage parameters $\mathbf{\Omega}$, $\mathbf{\Omega}^{*}$, and $\mathbf{\Omega}_{w}$, along with the three price inflation vectors $\mathbf{\Pi}_{t}$, $\mathbf{\Pi}^{*}_{t}$, and $\mathbf{\Pi}^{w}_{t}$, as shown in Table 1. First, the matrices $\mathbf{\Omega}$, $\mathbf{\Omega}^{*}$, 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 value of commodity/labor i' for sector 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:

$$\mathbf{\Omega} = \mathbf{S}^{-1}\mathbf{X}^{d\top}_{N'\times N'} - \mathbf{I}_{N'}, \tag{66}$$

$$\mathbf{\Omega}^{*} = \mathbf{S}^{-1}(\mathbf{X}^{*}_{N'\times N'})^{\top}, \tag{67}$$

$$\mathbf{\Omega}_{w} = \mathbf{S}^{-1}(\mathbf{X}^{w}_{N'\times N'})^{\top}, \tag{68}$$

where $\mathbf{S} = \text{diag}(\mathbf{s})$ is the diagonal matrix of vector $\mathbf{s} = (s_{1},...,s_{N'})$.

Next, we calculate the three price inflation vectors, $\mathbf{\Pi}_{t}$, $\mathbf{\Pi}^{*}_{t}$, and $\mathbf{\Pi}^{w}_{t}$ as follows:

$$\mathbf{\Pi}_{t} = \left(100\log\left(\frac{p_{1t}}{p_{1t-1}}\right),...,100\log\left(\frac{p_{N't}}{p_{N't-1}}\right)\right)^{\top}, \tag{69}$$

$$\mathbf{\Pi}^{*}_{t} = \left(100\log\left(\frac{p^{*}_{1t}}{p^{*}_{1t-1}}\right),...,100\log\left(\frac{p^{*}_{N't}}{p^{*}_{N't-1}}\right)\right)^{\top}, \tag{70}$$

$$\mathbf{\Pi}^{w}_{t} = \left(100\log\left(\frac{p^{w}_{1t}}{p^{w}_{1t-1}}\right),...,100\log\left(\frac{p^{w}_{N't}}{p^{w}_{N't-1}}\right)\right)^{\top}. \tag{71}$$

Lastly, we introduce three weights for aggregating sectoral inflation: "Total output," "Final demand," and "Personal consumption expenditures," as shown in Table A3. 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

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

Table A2: Harmonized Sector Classification with Corresponding Sectors in the US and Japan

Code	Name	Corr. US sectors	Corr. Japanese 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.

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.

Table A3: Weights for Aggregating Sectoral Inflation

Weight	US I-O table (use table)	Japanese 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 reports the 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 show the correspondence between these variables and the components listed in the I-O Accounts of Japan and the US, respectively.

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.[20]

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 A4 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 A4: 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]	-	-

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

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
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]
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]
ρ_{13}^w	0.889	[0.857, 0.920]	0.457	[0.339, 0.567]

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
ρ_{14}^{w}	0.484	[0.423, 0.544]	-	-
ρ_{15}^{w}	0.254	[0.195, 0.317]	-	-
σ_{1}^{ϵ}	2.592	[2.354, 2.864]	4.816	[4.210, 5.441]
σ_{2}^{ϵ}	10.756	[10.197, 11.415]	2.520	[2.216, 2.832]
σ_{3}^{ϵ}	12.194	[11.475, 13.018]	4.639	[3.980, 5.280]
σ_{4}^{ϵ}	3.093	[2.799, 3.433]	3.811	[2.332, 5.280]
σ_{5}^{ϵ}	2.065	[1.571, 2.586]	1.675	[1.386, 1.953]
σ_{6}^{ϵ}	5.072	[4.817, 5.342]	3.410	[2.940, 3.920]
σ_{7}^{ϵ}	2.025	[1.884, 2.157]	3.683	[2.995, 4.336]
σ_{8}^{ϵ}	1.863	[1.585, 2.119]	1.655	[1.385, 1.926]
σ_{9}^{ϵ}	1.329	[1.097, 1.547]	2.377	[2.013, 2.769]
σ_{10}^{ϵ}	3.369	[3.022, 3.712]	2.714	[2.353, 3.097]
σ_{11}^{ϵ}	1.946	[1.737, 2.174]	2.321	[1.933, 2.641]
σ_{12}^{ϵ}	1.183	[1.069, 1.281]	1.741	[1.518, 1.941]
σ_{13}^{ϵ}	2.953	[2.538, 3.332]	2.081	[1.426, 2.805]
σ_{14}^{ϵ}	3.783	[3.346, 4.215]	-	-
σ_{15}^{ϵ}	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_{1}^{w}	1.467	[1.316, 1.626]	2.708	[1.723, 3.675]
σ_{2}^{w}	1.191	[1.020, 1.343]	3.994	[3.713, 4.303]
σ_{3}^{w}	2.483	[2.223, 2.697]	4.387	[4.085, 4.674]
σ_{4}^{w}	2.085	[1.847, 2.354]	2.351	[2.147, 2.543]
σ_{5}^{w}	0.414	[0.365, 0.461]	1.922	[1.771, 2.077]
σ_{6}^{w}	1.807	[1.578, 2.060]	1.878	[1.717, 2.033]
σ_{7}^{w}	0.669	[0.565, 0.780]	2.748	[2.526, 2.975]
σ_{8}^{w}	0.479	[0.420, 0.542]	2.198	[1.986, 2.407]
σ_{9}^{w}	0.872	[0.760, 0.976]	3.281	[3.011, 3.551]
σ_{10}^{w}	0.544	[0.471, 0.617]	3.744	[3.485, 3.990]
σ_{11}^{w}	0.946	[0.827, 1.060]	2.885	[2.648, 3.088]

	US		Japan	
Parameter	Mean	90% interval	Mean	90% interval
σ_{12}^w	4.134	[3.809, 4.499]	2.348	[2.168, 2.527]
σ_{13}^w	2.591	[2.223, 2.946]	1.849	[1.013, 2.610]
σ_{14}^w	0.853	[0.705, 1.005]	-	-
σ_{15}^w	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 A2 shows the scatter plot between our estimates of price stickiness κ_i and the observed frequency of price changes derived from micro price data across the 15 sectors for both the US and Japan. In these figures, there are missing frequencies from several sectors: sectors 2, 7, 10, 11, 13, 14, and 15 in the US; and sectors 2, 7, 10, 13, 14, and 15 in Japan. The Pearson correlation coefficients are -0.06 and -0.32 for the US and Japan, respectively, which are indeed negative but insignificant.

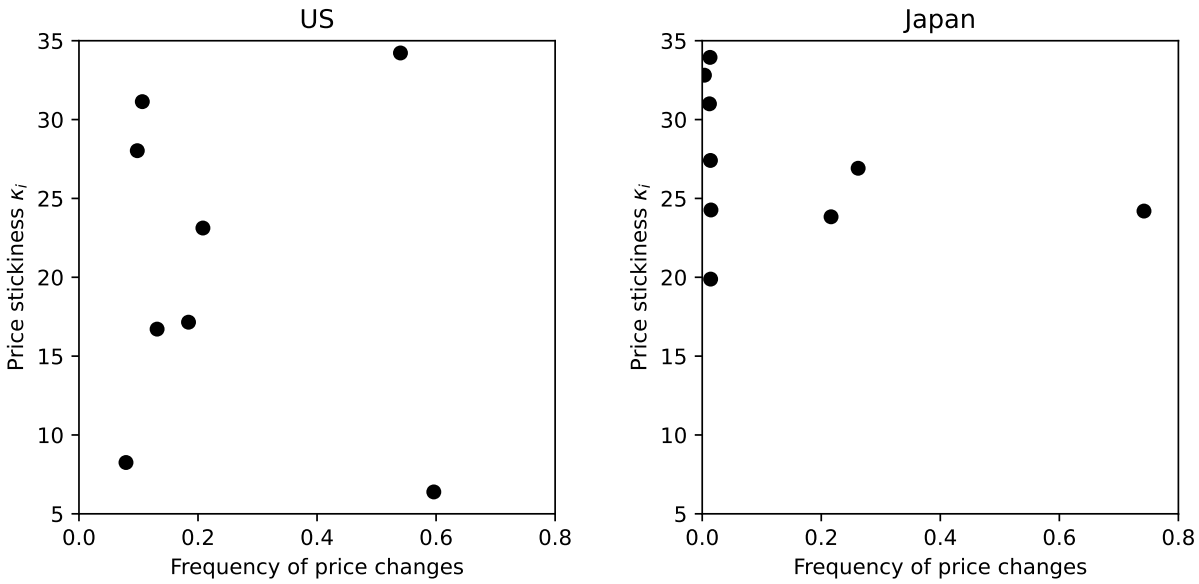


Figure A2: Correlation Between Estimated Price Stickiness (κ) and Frequency of Price Changes

Notes: Each dot represents a harmonized sector. Out of the 15 sectors, the frequency of price changes is not observed in 7 sectors in the US and 6 sectors in Japan.

E.3 Responses of Aggregate Inflation Based on Alternative Weights

This subsection presents responses of aggregate inflation based on different weights that are shown in Table A3. Figures A3–A5 display responses to productivity, import price, and wage shocks.

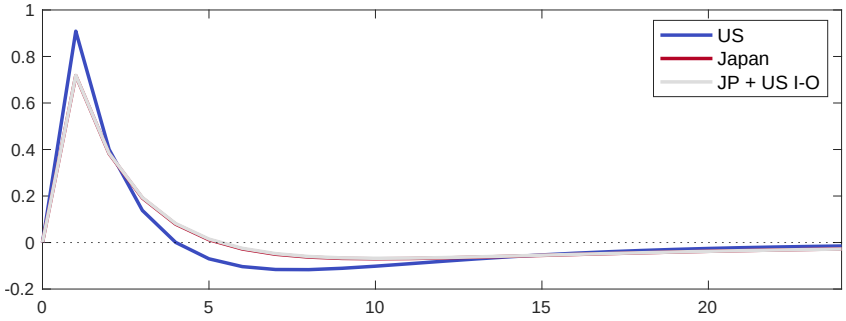
Top panels are the results based on the total output weights, which is shown in our main results. The middle and bottom panels are using the final demand weights and PCE weights, respectively. All quantitative results are robust to different weights.

E.4 Counterfactual Responses of Sectoral Inflation Rates

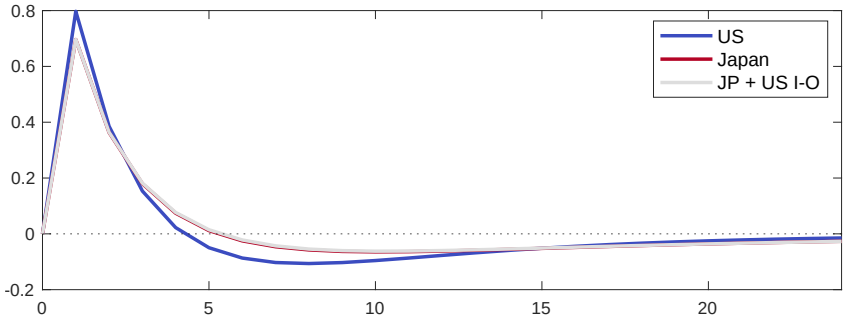
This subsection presents counterfactual responses of sectoral inflation in Japan with the estimated US parameters to various types of shocks. Figures A6–A8 show responses to the one-standard-deviation productivity, import price, and wage shocks, respectively. Light gray lines represent counterfactual responses of the Japanese economy with the US price stickiness parameters. Dark gray lines are those with the US persistence parameters. As we saw in Section 4.3, these counterfactual exercises do not make significant differences at the aggregate level. However, we observe noticeable differences at the sectoral level.

With the US price stickiness parameters (light gray lines), the Agriculture, Mining, and Utilities sectors show 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, small differences do not make noticeable differences in terms of IRFs.

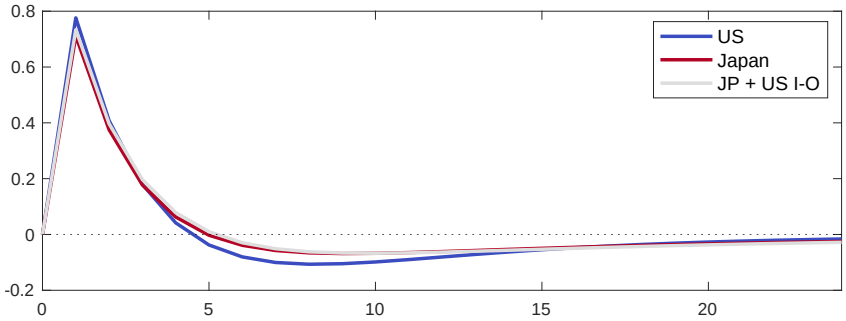
With the US persistence parameters for productivity shocks (dark gray lines in Figure A6), we observe that the Construction and Commerce sectors exhibit more pronounced responses. At the same time, the Utilities and Services sectors show more muted responses. These responses are somewhat offsetting each



(a) Total Output



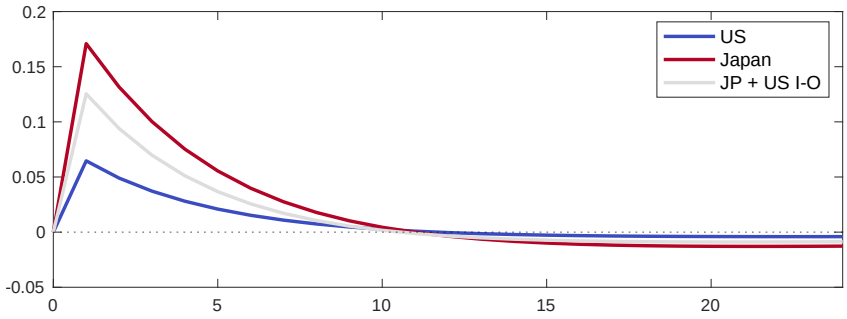
(b) Final Demand



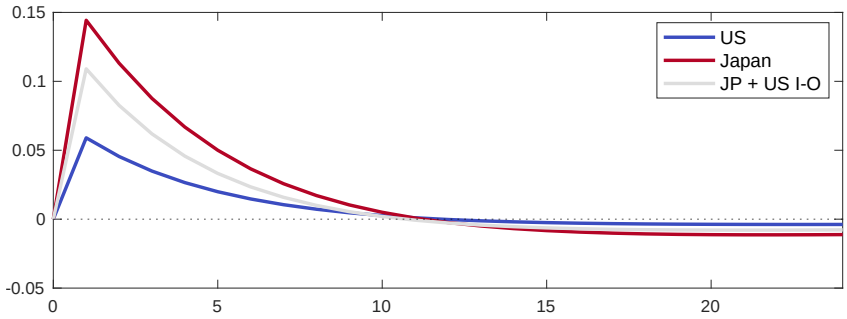
(c) PCE

Figure A3: Responses of Aggregate Inflation to the Productivity Shocks with Different Weights

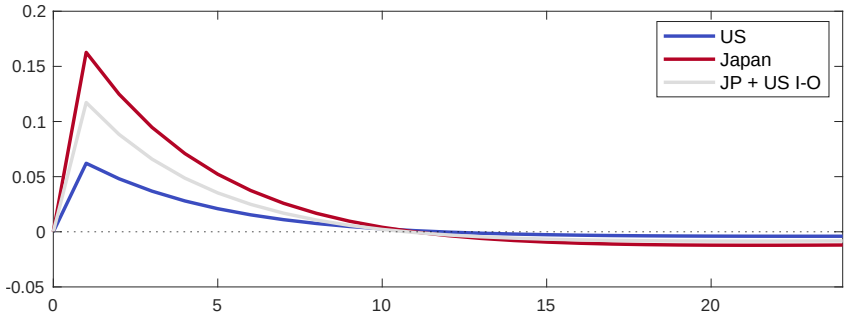
Notes: The figure compares the responses of aggregate inflation to the one-standard-deviation productivity shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses of the Japanese economy with the US I-O linkages (light gray lines). The top panel uses the total output weights. The middle panel employs the final demand weights. The bottom panel is based on the PCE weights. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.



(a) Total Output



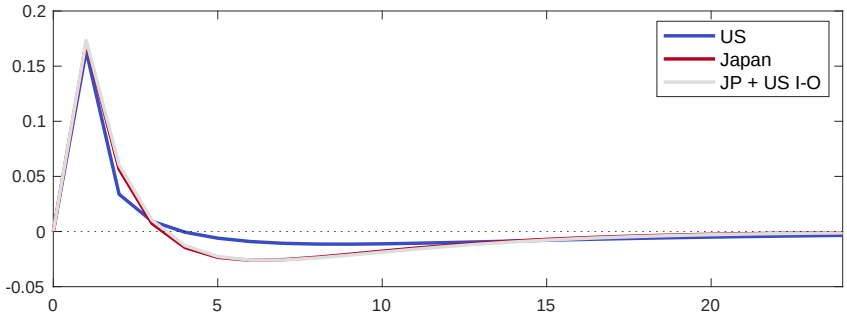
(b) Final Demand



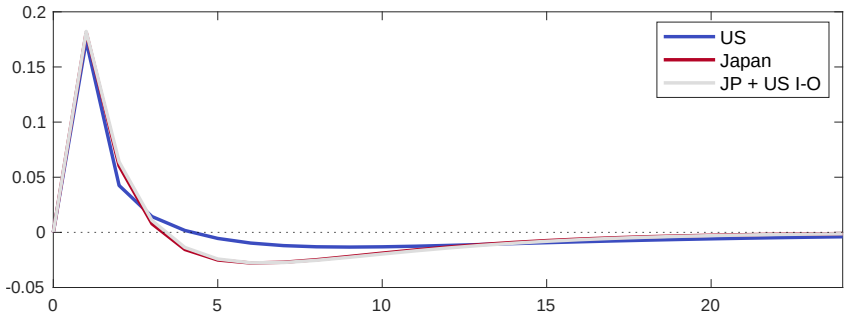
(c) PCE

Figure A4: Responses of Aggregate Inflation to the Import Price Shocks with Different Weights

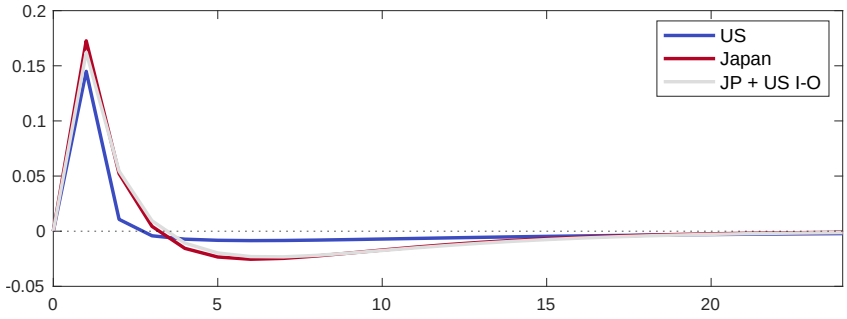
Notes: The figure compares the responses of aggregate inflation to the one-standard-deviation import price shocks in the US (blue lines) and Japan (red lines), together with the counterfactual responses of the Japanese economy with the US I-O linkages (light gray lines). The top panel uses the total output weights. The middle panel employs the final demand weights. The bottom panel is based on the 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 A5: Responses of Aggregate Inflation to the Wage Shocks with Different 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 of the Japanese economy with the US I-O linkages (light gray lines). The top panel uses the total output weights. The middle panel employs the final demand weights. The bottom panel is based on the PCE weights. Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

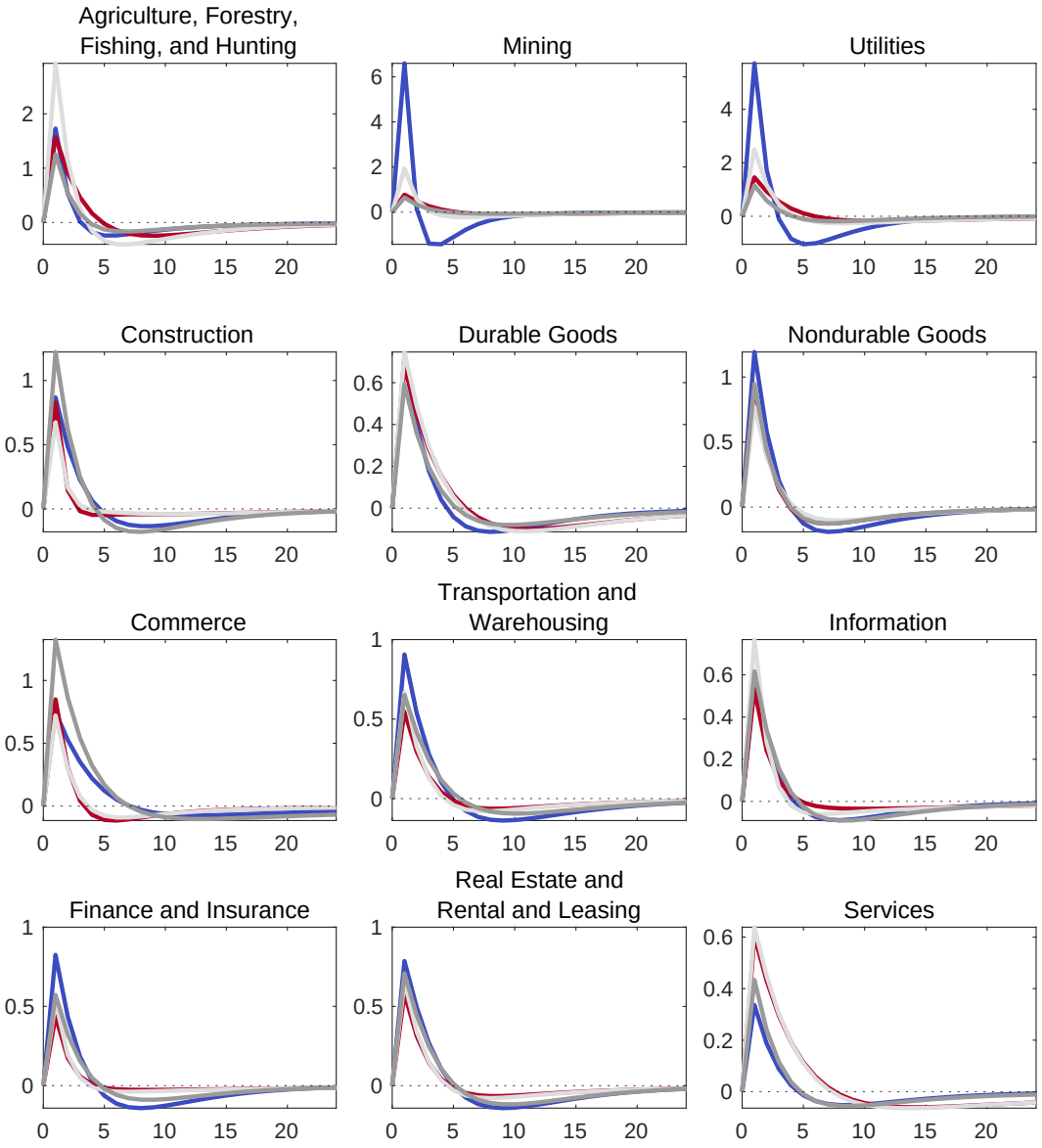


Figure A6: Responses to the Productivity Shocks

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

other. 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 IRFs (dark gray lines in Figure A7). As in Figure 2, there are large variations in the estimates for the persistence parameters for wage shocks in the two economies. While we observe much stronger responses in the Agriculture, Durable Goods, Commerce, Information, Finance and Insurance sectors, we see much muted responses in the Construction and Services sectors. As a result, the aggregate inflation responds stronger with the US estimates of persistence parameters for wage shocks.

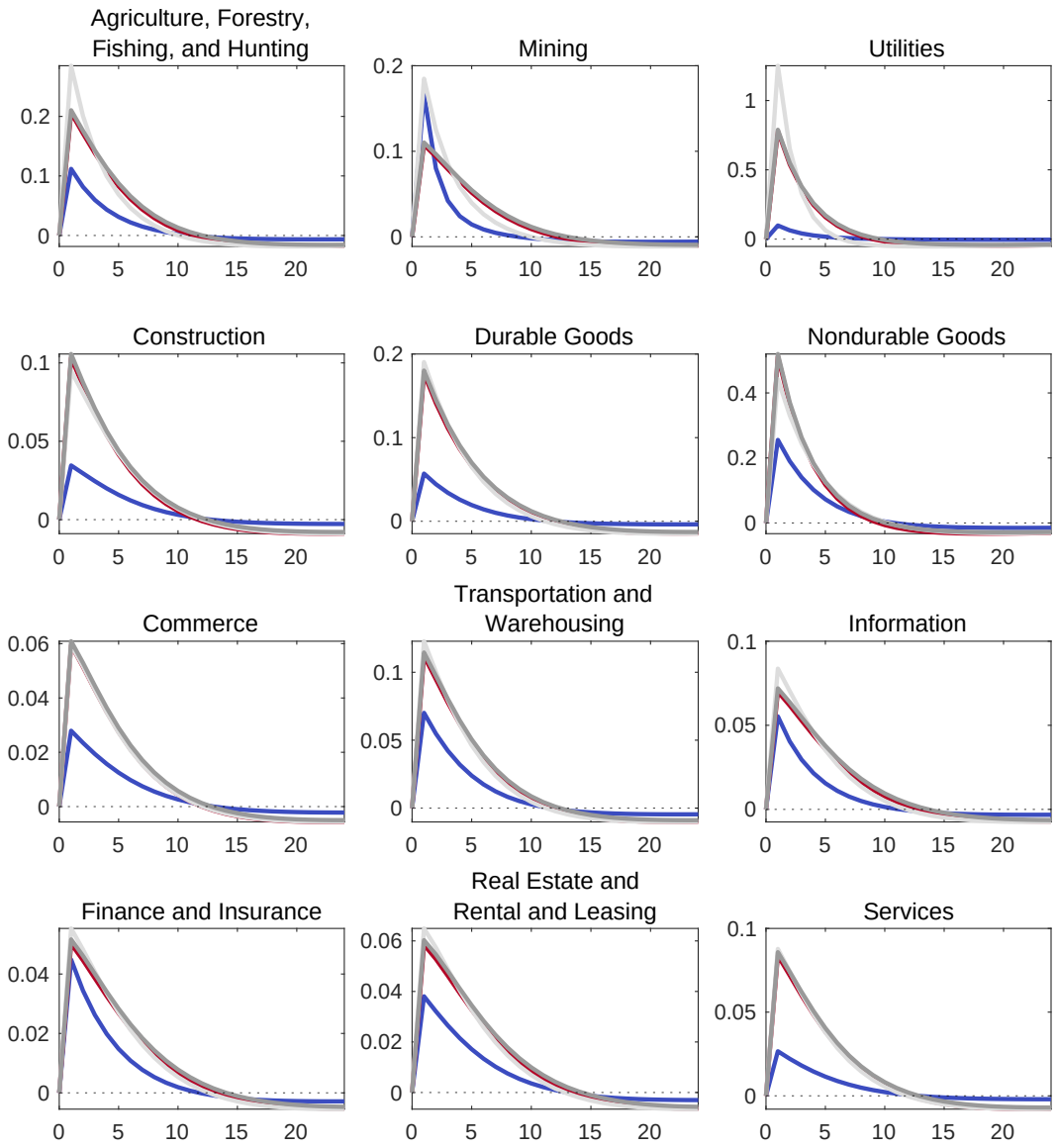


Figure A7: Responses to the Import Price Shocks

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 of the Japanese economy with the US κ's (light gray lines) and those with the US ρ's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

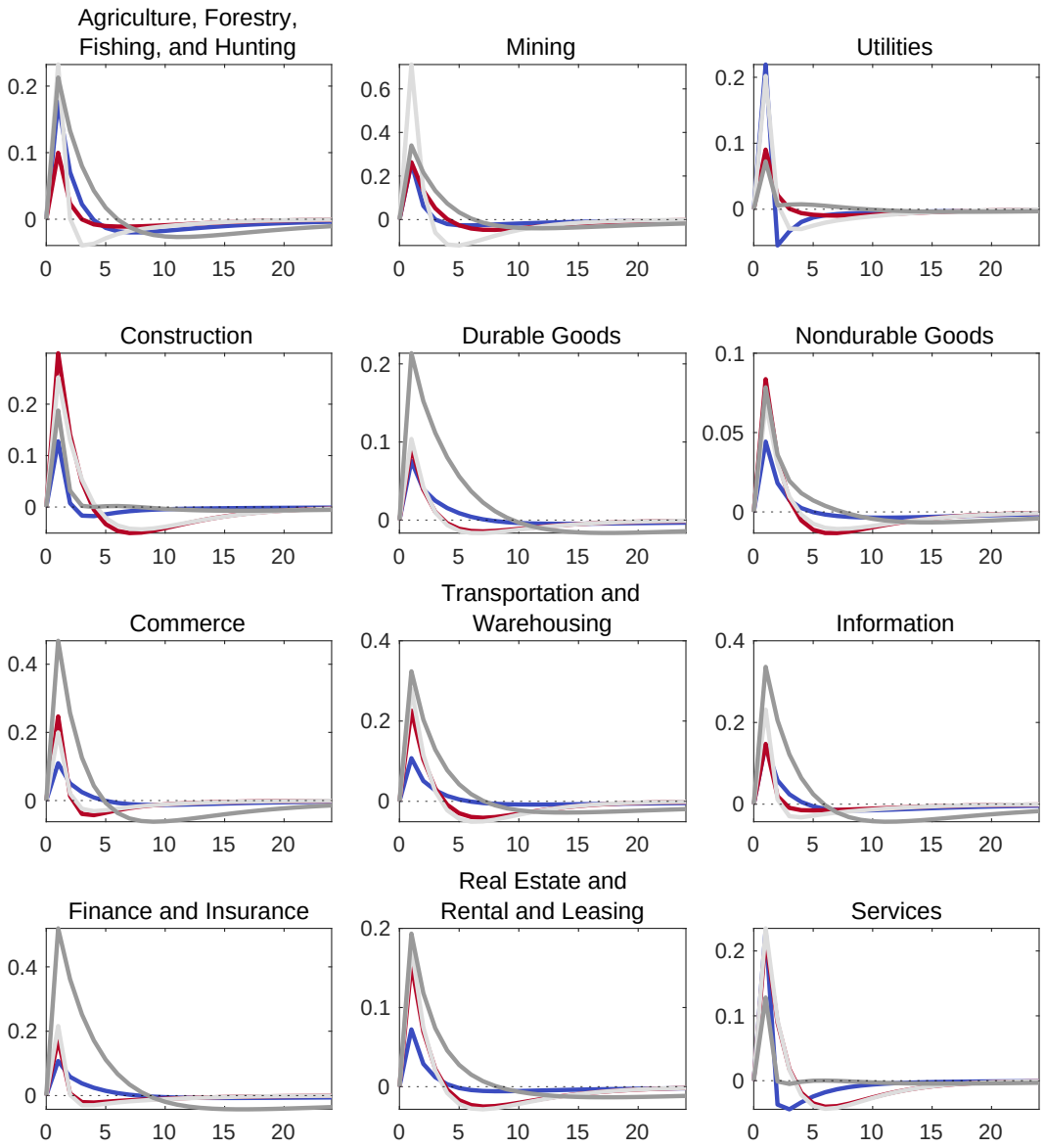


Figure A8: Responses to the Wage Shocks

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 of the Japanese economy with the US κ's (light gray lines) and those with the US ρ's (dark gray lines). Vertical axes represent the percentage deviation from the steady state. Horizontal axes represent the months after the shock.

E.5 Variance Decomposition of Aggregate Inflation Based on Alternative Weights

Tables A5 and A6 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.6.

Compared with the baseline results shown in Table 5, which are based on the weights for TO, the results in Tables A5 show 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 A6. 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

Figures A9 and A10 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.

Compared with the baseline results in Figure A10, 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.

Table A5: Variance Decomposition of Aggregate Inflation based on 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 A6: Variance Decomposition of Aggregate Inflation based on 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).

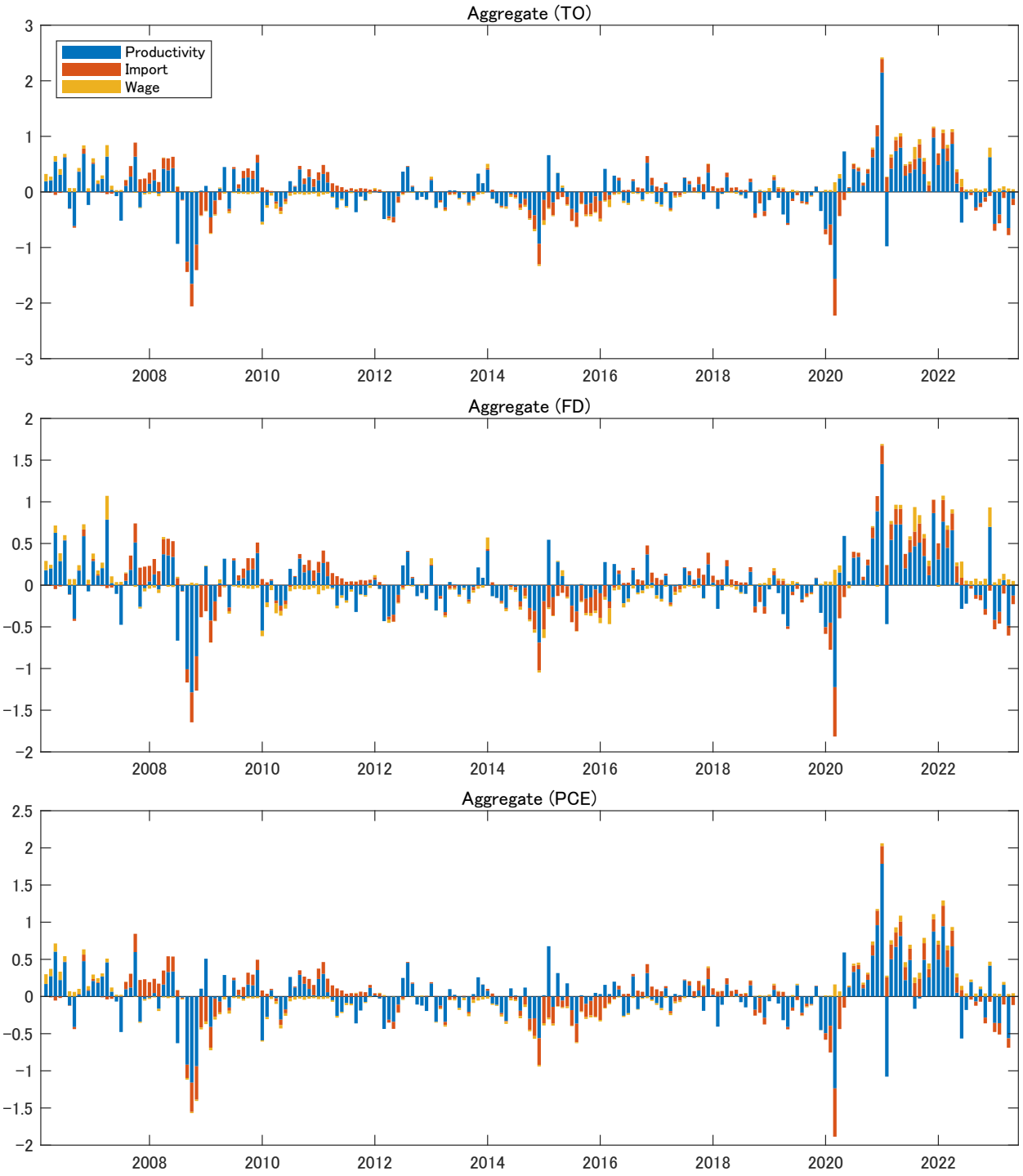


Figure A9: Historical decomposition of aggregate inflation: US

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.

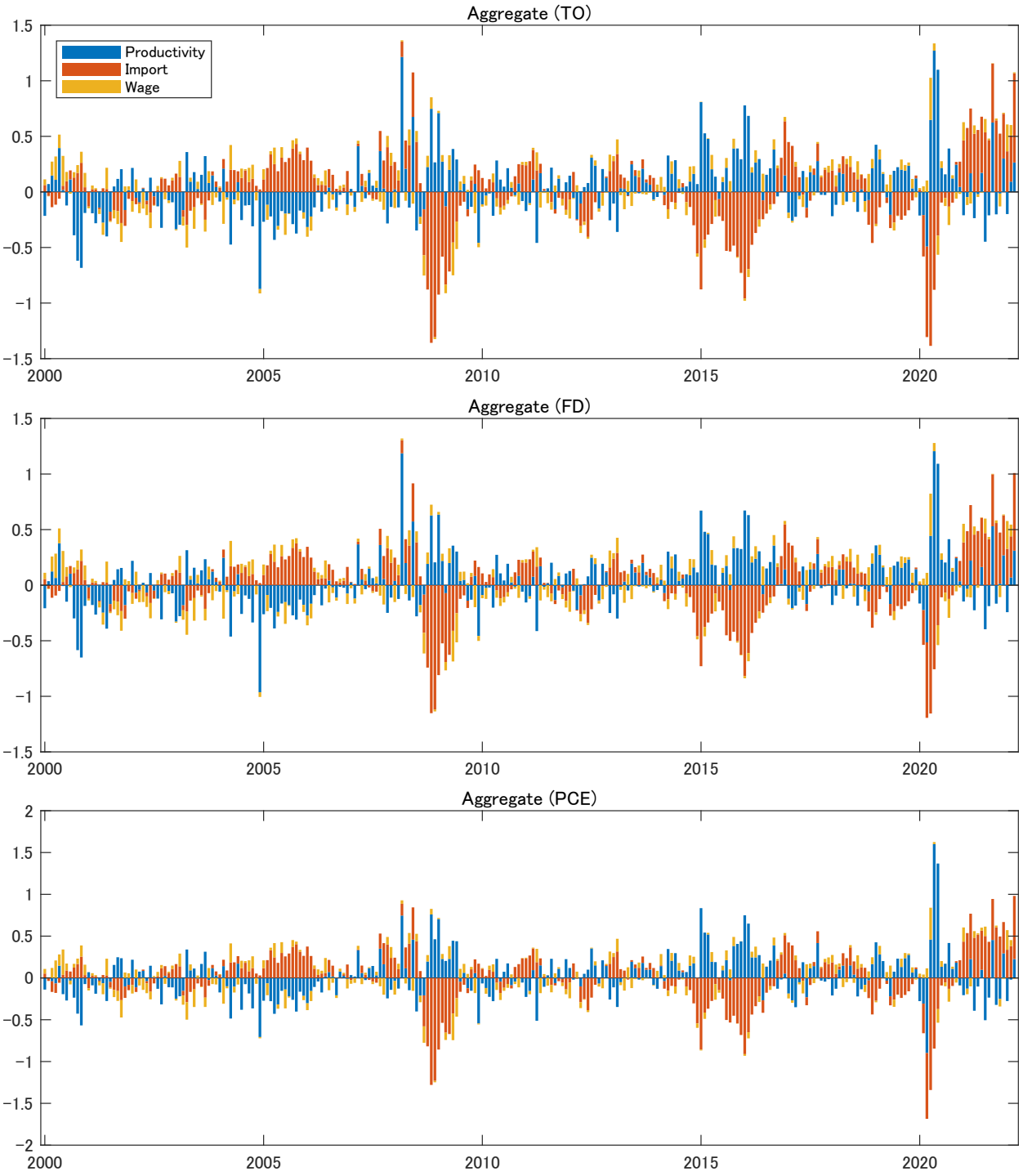


Figure A10: Historical decomposition of aggregate inflation: Japan

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.