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What Drives Trend Inflation in Japan? : A Trend-Cycle BVAR Decomposition Approach

Ryuichiro Hirano*
ryuuichirou.hirano@boj.or.jp

Yutaro Takano**
yuutarou.takano@boj.or.jp

Kosuke Takatomi*
kousuke.takatomi@boj.or.jp

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Bank of Japan
2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo 103-0021, Japan

* Monetary Affairs Department
** Monetary Affairs Department (currently Personnel and Corporate Affairs Department)

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Ryuichiro Hirano† Yutaro Takano‡ Kosuke Takatomi§

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Abstract

This paper estimates Japan's trend inflation and its determinants using a trend-cycle BVAR decomposition. The estimation results indicate that trend inflation in Japan remained subdued as the public had gradually lowered their medium- to long-term inflation expectations following the collapse of the asset price bubble in the early 1990s. The analysis further reveals that subdued real income growth, relative to the labor productivity and labor supply growth, also exerted downward pressure on trend inflation during the period from the 2000s to the early 2010s, when trend inflation was particularly restrained. These findings suggest that monitoring medium- to long-term inflation expectations and trends in structural factors of the economy is important for assessing its long-run inflation trend.

JEL Classification Code: C22, E24, E31, E52, E58
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† Monetary Affairs Department, Bank of Japan (ryuuichirou.hirano@boj.or.jp)

‡ Monetary Affairs Department (currently Personnel and Corporate Affairs Department), Bank of Japan (yuutarou.takano@boj.or.jp)

§ Monetary Affairs Department, Bank of Japan (kousuke.takatomi@boj.or.jp)

1 Introduction

Inflation dynamics are determined by two main factors based on the Phillips curve framework. The first is the short-run business cycle fluctuations. The second is the long-run level to which inflation converges after the impact of short-run business cycle fluctuations dissipate. This long-run level of inflation is often referred to "trend inflation" (Ascari and Sbordone, 2014). Analyzing trend inflation offers critical insights for both central bank practitioners and academic researchers. This is particularly relevant in the case of Japan, where inflation has remained subdued for an extended period, making the study of trend inflation and its determinants a pivotal area of research.

This paper investigates the factors driving Japan's prolonged low trend inflation by employing a trend-cycle BVAR decomposition methodology. This approach allows us to decompose inflation into its underlying trend and cyclical components. Our analysis builds on the framework developed by Ascari and Fosso (2024), who applied a similar method to examine trend inflation in the United States. We quantitatively assess the contributions of various factors to the persistently low trend inflation in Japan.

Previous studies have pointed out several potential factors behind the subdued trend in Japan's inflation since the late 1990s. One key explanation highlights the role of medium- to long-term inflation expectations, which remained persistently depressed over the period (Fuhrer, 2012; Kaihatsu, Nakano and Yamamoto, 2024). At the end of the 1990s, Japan's economy encountered the effective lower bound on short-term nominal interest rates, which severely constrained conventional monetary policy tools. Under these conditions, insufficient increases in inflation expectations are argued to have contributed to the persistence of low inflation.

In parallel, other studies have focused on the structural determinants of the "natural level of output" and their role in Japan's prolonged low inflation. These studies suggest that a slowdown in the growth of key determinants of natural output, particularly labor supply and labor productivity, has contributed significantly to persistent low inflation. Japan's working-age population has been in decline since the mid-1990s due to population aging. Additionally, the collapse of the asset price bubble in the early 1990s led firms to adopt more cautious risk-taking behavior, which constrained fixed investment and suppressed labor productivity growth. Against this background, some studies argue that these structural real factors have weakened aggregate demand, thereby reinforcing the persistence of low inflation (Saito et al., 2012; Shirakawa, 2012; Nishizaki, Sekine and Ueno, 2014; Fukunaga et al., 2024). Other studies further point to subdued growth in real income, relative to labor productivity, as another factor contributing to low inflation (Aoki, Hogen and Takatomi, 2023; Fukunaga, Hogen and Ueno, 2024; Bank of Japan, 2024b).

This paper quantitatively analyzes the degree to which these structural real factors have contributed to the dynamics of Japan's trend inflation. Additionally, we extend our estimation framework to the United States, enabling an international comparison of the characteristics of Japan's trend inflation.

The main contributions of this paper are twofold. First, it identifies the structural factors driving Japan's trend inflation and quantifies their respective impact. To the best of our knowledge, no existing research has attempted to decompose Japan's trend inflation. We decompose trend inflation into its underlying structural factors, using the trend-cycle BVAR decomposition method proposed by Ascari and Fosso (2024), which builds on the VAR with common trends framework developed by Del Negro et al. (2017). This estimation framework allows for the simultaneous extraction of trend components of multiple macroeconomic variables. It further enables the identification and quantification of structural factors by imposing theoretically driven parameter restrictions on the equations linking the trend components to these factors.

Second, we extend the estimation framework proposed by Ascari and Fosso (2024) to quantify the impact of medium- to long-term trends in the determinants of the natural output on trend inflation through the demand channel. While Ascari and Fosso (2024) focus on the impact of medium- to long-term trends in labor supply and labor productivity on trend inflation via changes in aggregate supply, previous studies have highlighted that these trends can also influence households' income and spending behavior, thereby affecting trend inflation. To address this, we expand the scope of their framework by modifying the set of macroeconomic variables and imposing alternative parameter restrictions to capture the effects through both supply and demand channels.

The main findings of this paper are as follows. First, the analysis reveals that Japan's trend inflation declined gradually following the collapse of the asset price bubble in the early 1990s. During this period, medium- to long-term inflation expectations also decreased. Our results align with this development. Second, we find that trend inflation since the end of the 1990s had been suppressed through both the demand channel and the inflation expectations channel. At the end of the 1990s, Japan faced a situation in which short-term nominal interest rates reached the effective lower bound and conventional monetary policy tools were constrained. Under these conditions, the trend growth of real income was lower than that of labor productivity and labor supply. Our findings suggest that these factors may have exerted significant downward pressure on trend inflation. Third, trend inflation since the early 2010s rose to some extent. During this period, the Bank of Japan (BOJ) introduced the price stability target of 2 percent and large-scale monetary easing. These measures coincided with a rise in inflation expectations and a gradual recovery in the trend growth of real income. Together, these factors appear to have contributed to raising trend inflation through both the expectations channel and the demand channel. Meanwhile, our results for the United States indicate that U.S. trend inflation has remained stable near 2 percent, in sharp contrast to Japan. This finding is consistent with the existing literature (e.g., Reis, 2020). Overall, these results suggest that it is important to consider both inflation expectations and trends in structural real factors of the economy – such as labor supply, labor productivity and labor share of income – when evaluating inflation trends.

The remaining structure of this paper is as follows. Section 2 reviews the literature and explains its relationship with this paper. Section 3 describes the model, estimation method and data. Section 4 reports estimation results. Section 5 summarizes the analysis, its implications, and remaining challenges.

2 Related literature

This paper is related to two strands of the literature: (1) the estimation of trend inflation, and (2) the analysis of factors influencing medium- to long-term inflation dynamics. This section provides a review of these studies and highlights their relevance to our research.

Estimation of trend inflation

Trend inflation is inherently unobservable, leading to the development of various estimation methodologies in the existing literature.

One widely used approach to estimate trend inflation involves vector autoregressive (VAR) models. These models extract the trend component of inflation by identifying structural shocks under specific assumptions about the relationships among macroeconomic variables (e.g., Quah and Vahey, 1995).[1] Recent studies have further advanced this approach by proposing estimation methods based on time-varying parameter VAR (TVP-VAR) models (e.g., Rudd, 2020).[2]

Other studies have proposed estimation methods based on theoretical models. For instance, some studies estimate the intercept of the Phillips curve as a time-varying parameter and interpret it as the measure of trend inflation (Kozicki and Tinsley, 2012; Kaihatsu and Nakajima, 2018; Okimoto, 2019; Nakajima, 2023). Alternatively, other studies construct dynamic stochastic general equilibrium (DSGE) models and use them to estimate trend inflation (Ireland, 2007; Kato, Maih and Nishiyama, 2022).

[1] Quah and Vahey (1995) assume a supply shock has a persistent positive effect on real GDP, while a demand shock has no long-run effect. Based on this assumption, they identify structural shocks and extract the long-run component of inflation.

[2] Rudd (2020) estimates a time-varying parameter VAR model and defines trend inflation as the long-run level to which actual inflation converges at each point in time.

A growing body of literature has also employed unobserved component (UC) models to estimate trend inflation. UC models assume that an observed economic variable consists of two components – a stationary cycle component and a non-stationary trend component – and separate them using the state-space model approach.[3] Stock and Watson (2007) is a seminal study that applies this method to U.S. data for analyzing trend inflation.

UC model approaches can be categorized into two types, based on the number of observed variables used in estimation. The first is the univariate approach, which relies solely on inflation data. The second is the multivariate approach, which incorporates multiple data series, such as inflation rates for various items and other macroeconomic variables. Early studies primarily employed the univariate approach. Over time, however, researchers extended this framework to a multivariate setting to enhance the accuracy of trend inflation estimates and to better analyze the mechanisms driving its fluctuations (e.g., Stock and Watson, 2016; Ascari and Fosso, 2024).[4]

The trend-cycle BVAR decomposition method employed in this paper is one of the multivariate UC models. Similar to the approach of Ascari and Fosso (2024), this approach enables us to estimate trend inflation and decompose it into its driving factors. In the estimation process, we account for stochastic volatility in the innovations of both the trend and cyclical equations. This heteroscedasticity assumption enables us to extract components that are robust to temporary shocks.

Potential impact factors on medium- to long-term inflation trends

Basic macroeconomic models that assume full-information rational expectations (FIRE) predict that inflation converges to the level of inflation expectations in the long run. However, empirical studies on the formation of inflation expectations have shown that the FIRE assumption does not always hold (e.g., Coibion, Gorodnichenko and Kamdar, 2018). Against this backdrop, previous research has explored the possibility that factors beyond inflation expectations can

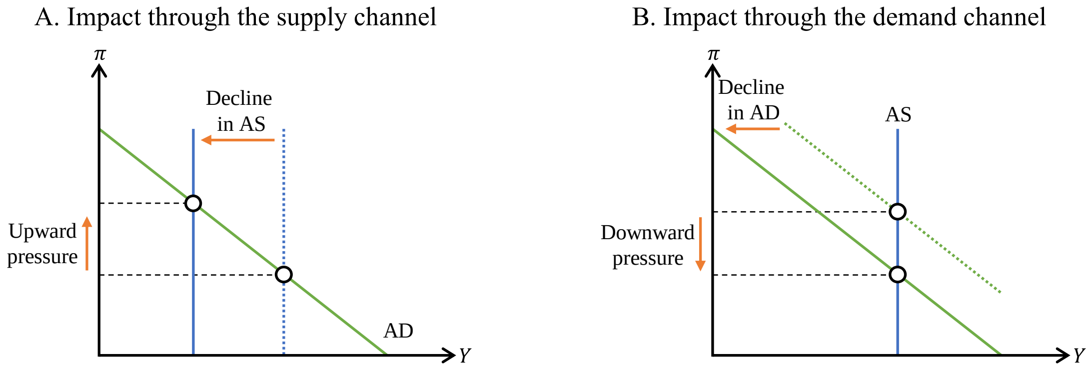
[3] Structural models based on the Phillips curve framework define trend inflation as the level of inflation when the output gap converges to zero, whereas UC models identify it using the time-series characteristics of observed input data.

[4] Several central banks publish estimates of trend inflation using UC models. For example, the Federal Reserve Bank of New York (FRB NY) releases the Multivariate Core Trend Inflation measure on its website. Following Stock and Watson (2016), they estimate this measure using Personal Consumption Expenditure (PCE) inflation data across multiple items, in a multivariate UC model. In Japan, Ueno (2024) estimates the trend component of service price inflation using data on wage and price inflation within a multivariate UC model. Meanwhile, Bank of Japan (2024a) presents several alternative estimates of trend inflation: (1) a TVP-VAR model following Rudd (2020); (2) an approach that estimates the time-varying intercept of the Phillips curve following Nakajima (2023); and (3) a structural model drawing on Bernanke and Blanchard (2025) and Nakamura et al. (2024). In addition, Takahashi (2016) estimates trend inflation as a weighted average of two components: an adaptive expectations component, extracted from actual inflation data; and a forward-looking expectations component, derived from his original model.

also influence the medium- to long-term trend of inflation.

These studies focus on the natural level of output – the long-run level of output to which the economy converges after short-run business cycle fluctuations. Specifically, they discuss how its determinants, such as labor supply and labor productivity, affect the medium- to long-term trend of inflation. In this context, two main channels have been suggested through which changes in the natural level of output may influence inflation trends.

Figure 1. Impact of shifts in labor supply and labor productivity on trend inflation



Note: The figures are constructed by the authors, based on the discussion on pp.412-413 in Mankiw (2022) and pp.114-115 in Dornbusch, Fischer and Startz (2008). π on the y-axis in each figure denotes trend inflation, and Y denotes natural output growth. The AS curve is vertical in a long-run environment.

First, some studies underscore the supply channel (Figure 1.A). A decline in the growth of labor supply or labor productivity reduces the growth of the natural level of output. This, in turn, implies a slowdown in the growth of long-run aggregate supply (LRAS), which may exert upward pressure on medium- to long-term inflation. Some studies argue that population aging in advanced economies and China has slowed labor supply growth, which has subsequently reduced LRAS growth, contributing to upward pressure on inflation (Goodhart and Pradhan, 2020). Second, other studies focus on the demand channel (Figure 1.B). A decline in the growth of labor supply and labor productivity slows natural output growth, which may, in turn, constrain the growth of households' real income. This mechanism, as suggested in prior research, could dampen the growth of long-run aggregate demand (LRAD), thereby exerting downward pressure on medium- to long-term inflation (Saito et al., 2012).[5] In summary, factors such as

[5] Other studies highlight alternative mechanisms through which the demand channel influences inflation. For example, Summers (2014) and Eggertsson, Mehrotra and Robbins (2019) argue that a decline in population growth lowers the natural rate of interest. Under these circumstances, nominal interest rates are more likely to be constrained by the effective lower bound, and the economy may face demand shortages. They note that this mechanism puts downward pressure on inflation. Katagiri (2021) also analyses the impact of demographics on inflation, focusing on the natural rate of interest. Fujita and Fujiwara (2023) examine the possibility that the exit of high-productivity skilled workers from the labor market lowers potential growth and the natural interest rate and, in turn, affects the effectiveness of monetary policy on inflation. Katagiri, Konishi and Ueda (2020) discuss the impact of population aging on inflation from a political economy perspective. Bobeica et al. (2017) report that population aging lowers aggregate saving rates, which can raise inflation.

labor supply and labor productivity affect the natural level of output. Changes in these factors may influence medium- to long-term inflation through both the supply and demand channels, with potentially offsetting effects.

Looking at the empirical literature, there is still no consensus on which channel – supply or demand – plays the dominant role in influencing medium- to long-term inflation trends. For instance, some studies emphasize the impact through the supply channel. Juselius and Takats (2021) examine the impact of population aging on labor supply. Using a multi-country panel dataset covering 22 economies, they estimate a Phillips curve that incorporates the population shares of different age groups as explanatory variables. Their findings reveal a negative relationship between the working-age population ratio and inflation. Similarly, Aksoy et al. (2019) report comparable results based on a panel VAR analysis of 21 OECD economies. Dew-Becker and Gordon (2005) focus specifically on the medium- to long-term effects of productivity changes on inflation. Utilizing long-term U.S. macroeconomic time-series data, they estimate a Phillips curve that includes productivity growth as a key explanatory variable to capture its influence through the supply channel. They find a negative long-run relationship between inflation and productivity growth. Another strand of the literature explores the long-term implications of globalization, particularly regarding firms' sourcing of intermediate inputs. These studies suggest that globalization could influence medium- to long-term inflation through the supply channel by affecting productivity and, consequently, natural output growth. For example, Ascari and Fosso (2024), using a trend-cycle BVAR decomposition with U.S. data, estimate trend inflation and decompose its driving factors. They report that low-cost imported intermediate goods may have contributed to reducing U.S. trend inflation to some extent.

On the other hand, some empirical studies suggest that the impact on trend inflation through the demand channel cannot be overlooked. For example, Bobeica et al. (2017) analyze the relationship between demographics and inflation by applying a vector error correction model (VECM) to a multi-country panel dataset for the euro area. They find a positive relationship between the growth of the working-age population and inflation, indicating that the demand channel also plays a role in shaping inflation trends. Regarding productivity growth, while most studies conclude that downward pressure on inflation through the supply channel is stronger, some suggest that part of this pressure is counterbalanced by upward pressure through the demand channel (Dew-Becker and Gordon, 2005; Basu, Fernald and Kimball, 2006; Kurmann and Sims, 2021). Moreover, the long-term effects of globalization on inflation remain debated, with some studies suggesting an ambiguous overall impact (Forbes, 2019; Kamber and Wong, 2020).

Studies on Japan further indicate that the demand channel's role may not be negligible. For example, Lee, Lee and Miyamoto (2024) analyze the relationship between demographics and inflation using regional-level panel data. They find that the relationship is not necessarily statistically significant, which suggests that the upward pressure on inflation through the supply channel, due to the decline in the working-age population, may be partly offset by downward pressure through the demand channel.[6] Saito et al. (2012) examine the long-run impact of productivity on inflation using a DSGE model.[7] They find that the contribution of technology (productivity) shocks to inflation diminished from the 1990s, following the collapse of the asset price bubble, through the 2000s. They argue that subdued growth expectations among agents may have put downward pressure on inflation through the demand channel. Miyao (2006) also shows, based on a VAR model analysis, that a slowdown in productivity growth has a negative impact on inflation.

The relative importance of the supply and demand channels may also depend on the trend in the labor share of income. If the growth of real wages is subdued relative to that of labor productivity – implying an increase in wage markdowns – the downward pressure on inflation through the supply channel is likely to become stronger. In fact, Stansbury and Summers (2020) argue that the declining trend in workers' wage bargaining power in the U.S. might be a contributing factor to the phenomenon of secular stagnation in inflation. In Japan, Bank of Japan (2024b) suggests that stronger downward pressure on wages has contributed to the prolonged low inflation, drawing on the analysis of wage markdowns by Aoki, Hogen and Takatomi (2023).

This paper identifies the factors that the literature has highlighted as important drivers of trend inflation and quantifies their impact, building on Ascari and Fosso (2024). As indicated in the literature, the determinants of the natural level of output – labor supply and labor productivity – can affect trend inflation through both the supply and demand channels. In this regard, we extend the estimation framework in Ascari and Fosso (2024) to capture impact through both channels.[8]

[6] In addition, Yoon, Kim and Lee (2018) conduct a panel analysis on demographic variables and inflation using data from multiple economies, including Japan. They report a positive correlation between population growth and inflation, and a negative correlation between the share of those aged 65 and over and inflation. They suggest that the positive correlation may reflect that the increase in aggregate demand due to population growth outpaced the increase in aggregate supply. In contrast, the negative correlation may be explained by differences in the propensity to consume between the working-age and the dependent-age populations.

[7] See Fueki et al. (2016) for details.

[8] While this paper analyzes the impact of changes in labor productivity on trend inflation, the recent literature focuses on its reverse mechanism. Some studies argue that a mild increase in the general price level may contribute to more efficient resource allocation (e.g., Adam and Weber 2019, 2023; Santoro and Viviano, 2022; Miyakawa et al., 2022; Inokuma, Katagiri and Sudo, 2024). Also, Katagiri et al. (2024) note that a decline in trend inflation can affect the economy, such as through a slowdown in firms' production.

3 Estimation methodology and data

3.1 Model

As discussed in Section 2, trend inflation is influenced by various factors, including inflation expectations and shifts in the long-run aggregate supply (LRAS) and aggregate demand (LRAD) curves, driven by changes in the natural level of output. To identify these factors, it is crucial to estimate trend inflation by incorporating not only consumer price inflation but also a broader set of economic variables. For this purpose, we employ the trend-cycle BVAR decomposition method proposed by Ascari and Fosso (2024), which uses a multivariate unobserved components model to estimate and decompose trend inflation.

The estimation framework is structured as follows. First, we assume that each observed variable, including consumer price inflation, consists of the following two components: a stationary cycle component, and a non-stationary trend component. This relationship is formalized through observation equations. Second, the stationary cycle component is modeled as a VAR (p) process, while the non-stationary trend component is assumed to be driven by structural factors that follow a unit root process. These dynamics are described by state equations. Third, structural factors are identified by imposing parameter restrictions that define the relationship between the trends in observed variables and the structural factors associated with shifts in the LRAS and LRAD curves, as discussed in Section 2. Details of the model settings are presented below.

Observation equation

We assume that observed values of economic variables (observation variables; Y_t) consists of two directly unobservable state variables: the cycle component ($\tilde{Y}_t$) and the trend component ($\bar{Y}_t$). This relationship is formalized in Equation (1), which represents the observation equation. In this framework, n denotes the total number of observation variables included in the model.

$$\underset{(n\times 1)}{Y_t} = \underset{(n\times 1)}{\tilde{Y}_t} + \underset{(n\times 1)}{\bar{Y}_t} \tag{1}$$

State equation: cycle component

We assume that the cycle component ($\tilde{Y}_t$) follows a stationary VAR (p) process. This relationship is expressed in Equation (2), which serves as the state equation for the cycle component. $\tilde{H}_t$ represents the diagonal elements of the variance-covariance matrix associated with the cycle component. Additionally, $\tilde{F}$ denotes a lower triangular matrix with 1s along its diagonal.

$$\underset{(n\times1)}{\tilde{Y}_t} = \underset{(n\times n)(n\times1)}{\Phi_1\tilde{Y}_{t-1}} + \cdots + \underset{(n\times n)(n\times1)}{\Phi_p\tilde{Y}_{t-p}} + \underset{(n\times n)(n\times n)(n\times1)}{\tilde{F}\tilde{H}_t\tilde{\varepsilon}_t} \tag{2}$$

State equation: trend component

The trend component ($\bar{Y}_t$) is the product of the following two parts: the structural factor ($\bar{\tau}_t$), which consists of $q(\leq n)$ directly unobservable and slow-moving elements, and the factor loading matrix (Λ), which determines the relationship between the structural factor and the trend component. We assume that the structural factor ($\bar{\tau}_t$) follows a stochastic trend characterized by a unit root process, as supported by the literature (e.g., Smets and Wouters, 2003; Cogley and Sargent, 2005; Ireland, 2007; Stock and Watson, 2007; Cogley and Sbordone, 2008; Cogley, Primiceri and Sargent, 2010). The dynamics of the trend component are governed by state equations (3) and (4). In this context, $\bar{H}_t$ represents the diagonal elements of the variance-covariance matrix for the trend component.

$$\underset{(n\times1)}{\bar{Y}_t} = \underset{(n\times q)}{\Lambda} \cdot \underset{(q\times1)}{\bar{\tau}_t} \tag{3}$$

$$\underset{(q\times1)}{\bar{\tau}_t} = \underset{(q\times1)}{\bar{\tau}_{t-1}} + \underset{(q\times q)}{\bar{H}_t} \cdot \underset{(q\times1)}{\bar{\varepsilon}_t} \tag{4}$$

Structural factors in the model

As discussed in Section 2, trend inflation can be decomposed into the following three determinants: (1) changes in natural output – i.e., shifts in the long-run aggregate supply (LRAS) curve; (2) changes in real income and expenditure – i.e., shifts in the long-run aggregate demand (LRAD) curve; and (3) a residual component not explained by the above two factors.

Changes in natural output – shifts in the LRAS curve – can be further decomposed into two factors: changes in labor supply, and changes in labor productivity. Furthermore, changes in labor productivity can be broken down into two components: the component resulting from changes in import costs, and the component that cannot be attributed to import costs.

Based on these understandings, we assume the following three structural factors that may influence long-run aggregate supply: the labor supply factor (ξ_t); the import costs factor (η_t), which affects trend inflation through the labor productivity channel; and the remaining labor productivity factor (α_t), which represents the component of labor productivity after accounting for the import costs factor. Furthermore, we assume the real income factor (ζ_t), which represents shifts in income and expenditure, corresponding to changes in long-run aggregate demand. Finally, we define the remaining component of estimated trend inflation, which cannot be explained by the above factors, as the price-specific factor (π_t^*). This residual factor may partly capture the effects of changes in inflation expectations.

Relationship between structural factors and trend components

To identify the aforementioned five structural factors, we use the following six economic variables as observation variables: employment growth (e_t); import price inflation (imp_t); labor productivity growth (per employee, a_t); real GDP growth (y_t); real wage growth (w_t); and consumer price inflation (π_t). Furthermore, this paper assumes the following relationship between the structural factors ($\bar{\tau}_t$) and the trends in the observation variables ($\bar{Y}_t$), as expressed in Equation (3)' ($\lambda_{kl} > 0$).[9]

$$\overbrace{\begin{bmatrix} \bar{\pi}_t \\ \bar{y}_t \\ \bar{e}_t \\ \bar{a}_t \\ \overline{imp}_t \\ \bar{w}_t \end{bmatrix}}^{\bar{Y}_t} = \overbrace{\begin{bmatrix} -\lambda_{11} & \lambda_{12} & -\lambda_{13} & \lambda_{14} & 1 \\ \lambda_{21} & -\lambda_{22} & \lambda_{23} & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & -\lambda_{42} & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}}^{\Lambda} \cdot \overbrace{\begin{bmatrix} \xi_t \\ \eta_t \\ \alpha_t \\ \zeta_t \\ \pi_t^* \end{bmatrix}}^{\bar{\tau}_t} \tag{3)'$$

<u>The labor supply factor (ξ_t)</u> is determined by the employment trend ($\bar{e}_t$). An increase in the labor supply factor raises the real GDP trend ($\bar{y}_t$) and shifts the LRAS curve to the right. Consequently, this exerts downward pressure on trend inflation.

<u>The import costs factor (η_t)</u> is determined by the import price trend ($\overline{imp}_t$). An increase in the import price reduces the labor productivity trend (per employee, $\bar{a}_t$) and, in turn, the real GDP trend ($\bar{y}_t$), causing a leftward shift in the LRAS curve. As a result, this puts upward pressure on trend inflation.

<u>The remaining labor productivity factor (α_t)</u> represents the remaining component of the labor productivity trend ($\bar{a}_t$) that is not explained by the import costs factor (η_t). Therefore, it can be considered a specific factor for labor productivity per employee. An increase in the remaining labor productivity factor boosts the real GDP trend ($\bar{y}_t$), leading to a rightward shift in the LRAS curve. This, in turn, places downward pressure on trend inflation.

<u>The real income factor (ζ_t)</u> is determined by the real income trend ($\bar{w}_t$). An increase in the real income factor shifts the LRAD curve to the right. Consequently, this exerts upward pressure on

[9] In the baseline estimation, we assume that the relationships between trends in observed variables and structural factors are unchanged over the sample period. To confirm the robustness of this assumption, we also estimate the model where those relationships are time-varying, and we find that the estimation results are almost the same as those in the baseline estimation. For details, see Appendix C.

trend inflation.

The price-specific factor (π_t^*) represents the residual component of the consumer price inflation trend ($\bar{\pi}_t$) that is not explained by other factors. It can, therefore, be considered the specific component of consumer price inflation. An increase in the price-specific factor exerts upward pressure on trend inflation. As outlined above, this factor is likely to partially reflect changes in medium- to long-term inflation expectations.

Variance-covariance matrices for trend and cycle components

The diagonal elements of the variance-covariance matrices for the trend component ($\bar{H}_t$) and the cycle component ($\tilde{H}_t$) are assumed to follow stochastic volatility models. Specifically, the (i,i) element and the (j,j) element of each matrix is determined by latent variables that follow AR(1) processes, denoted by $\bar{h}_{i,t}$ and $\tilde{h}_{j,t}$, respectively.[10]

3.2 Estimation methodology

We estimate the model using a combination of the Gibbs sampling method and the Metropolis-Hastings algorithm, following approaches commonly employed in studies utilizing unobserved components (UC) models (e.g., Del Negro et al., 2017; Johannsen and Mertens, 2021; Ascari and Fosso, 2024; Maffei-Faccioli, 2025). Prior distributions for parameters and initial values for state variables are set based on the literature.[11] For the estimation, we employ 10 mutually independent chains, each with 10,000 iterations. The first 9,000 draws from each chain are discarded as burn-in. From the remaining 1,000 draws per chain, we aggregate a total of 10,000 samples from the posterior distribution and use their medians as the representative estimates. Additionally, the number of lags (p) is set to two, based on the Bayesian Information Criterion (BIC).

In the state-space model analysis, both filtered and smoothed estimates of the state variables are obtained. Filtered estimates are calculated using the information available up to each point in time, whereas smoothed estimates are derived using the full sample of data. Due to this distinction, smoothed estimates are prone to substantial revisions when updated estimations are conducted. Accordingly, this paper presents filtered estimates, aligning with the approach of Nakajima (2023). Meanwhile, the estimates of trend inflation presented in the next section are computed as the sum of the contributions from structural factors, ensuring consistency between trend inflation and its underlying determinants.

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[10] For details, see Appendix A.

[11] For details on prior distributions and initial values for state variables, see Appendix A.

3.3 Data

This paper estimates trend inflation for Japan and the United States, utilizing country-specific data for each analysis. Previous studies have suggested that trend inflation in Japan appears to be relatively less anchored to the inflation target compared to that in the United States (see, for example, Bems et al., 2021, for a discussion of this issue). To investigate this further, we examine whether this tendency is supported by the results of our estimation. The details of the data used in this paper, along with their sources, are provided in the following table.[12] The sample period spans from 1986Q1 to 2024Q3.

Table. Data details

Variables	Japan	United States
Consumer price	Consumer price index (less fresh food and energy)	Personal consumption expenditure price index (excluding food and energy)
Output	Real GDP	Real GDP
Employee	Workers (labor force survey)	Employees (establishment survey)
Labor productivity	Real GDP per worker	Real GDP per employee
Import price	Import price index (excluding petroleum, coal and natural gas)	Import price index (excluding energy)
Real income	Real wage (per worker, monthly labor survey)× workers (labor force survey)	Real wage (per employee)× employees (establishment survey)

Note: 1. Each figure is a log-differenced value (seasonally-adjusted annual rate).
2. Data sources are as follows. Japan: Bank of Japan; Cabinet Office; Ministry of Health, Labour and Welfare; Ministry of Internal Affairs and Communication. United States: Bureau of Economic Analysis (BEA); Burau of Labor Statistics (BLS).
3. Figures for the consumer price index in Japan exclude the impact of consumption tax hikes.
4. Figures for the import price indices in both countries indicate the products with the share of imports in the total supply to the domestic market (nominal imports / nominal total supply to the domestic market), in order to take into account structural shifts in trade during the sample period. The calculation procedure for each country is as follows. Japan: 1) Calculate annual values for the share of imports, using the annual estimates of the System of National Accounts (SNA, Cabinet Office). 2) Construct quarterly series by assuming that the value in each quarter of each year is equal to the corresponding annual estimate. 3) Smooth that quarterly series using the Hodrick-Prescott filter (λ=1600). United States: Apply the same method as in the case of Japan to the annual estimates for the share of import in the total supply to the domestic market in the United States, released by the Organization for Economic Co-operation and Development (OECD).
5. Figures obtained from the monthly labor survey in Japan are those from establishments with 30 or more employee.
6. Figures for employees and real wages in the United States are for production and nonsupervisory employees (total private). Wages are deflated using the CPI-U (all items).

4 Estimation results

This section presents the estimates of trend inflation for Japan and the United States. We also

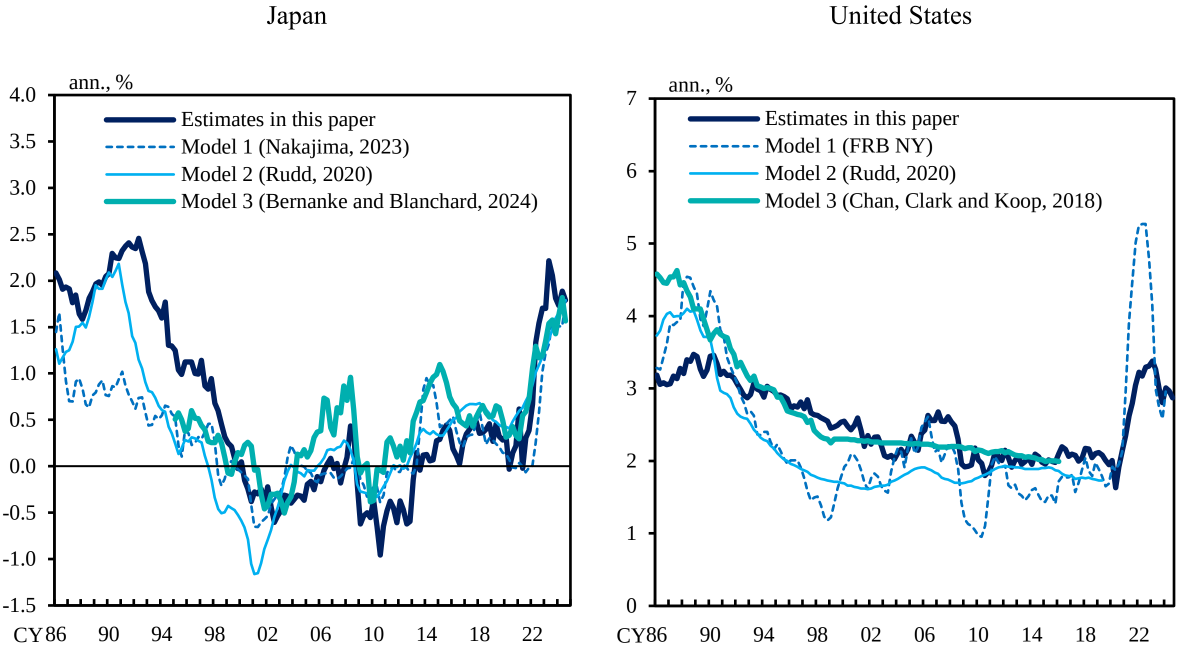
[12] We use the consumer price index (all items less food and energy) for Japan and the personal consumption expenditure deflator (all items less food and energy) for the United States, based on the insights presented in Stock and Watson (2016). They point out that using core price indices, – i.e., indices that exclude items known a priori to be highly volatile items – improves the stability of estimation and enhances the ability of trend inflation to forecast future inflation outcomes.

provide their historical decompositions, highlighting key features and differences between the two countries.

4.1 Trend inflation in Japan and the United States: comparison with other estimates presented in existing studies

Figure 2 compares trend inflation estimates for Japan and the United States, as derived from this paper, with those reported in other studies. The historical developments of trend inflation in Japan estimated in this paper closely align with findings from three prior studies. Trend inflation in Japan declined following the collapse of the asset price bubble in the early 1990s and continued to fall through the early 2000s. Subsequently, Japan experienced a prolonged period of negative trend inflation until the early 2010s, although it occasionally turned positive. Since the Bank of Japan (BOJ) introduced its price stability target of 2 percent and implemented the large-scale Quantitative and Qualitative Monetary Easing (QQE) program, trend inflation has turned positive but has remained below the target. In the 2020s, trend inflation has increased and is currently around 2 percent.[13]

Figure 2. Trend inflation



Note: The estimates for the United States are plotted until 2024Q1 for Model 1, 2019Q2 for Model 2, and 2016Q1 for Model3, respectively. Values for "Model 1 (FRB NY)" in the right-hand figure represent the "Multivariate Core Trend Inflation" estimated by Federal Reserve Bank of New York (available at https://www.newyorkfed.org/research/policy/mct).

The developments of trend inflation in the United States estimated in this paper closely

[13] The most recent estimates are subject to change as the sample is extended or updated, and therefore should be interpreted with some latitude.

resemble those reported in three other studies. Trend inflation in the United States gradually declined throughout the 1990s. Thereafter, consistent with findings in other studies (e.g., Reis, 2020), it remained stable at around 2 percent from the 2000s through the 2010s. In the 2020s, as similarly observed in other studies, trend inflation rose significantly and has recently approached the upper end of the 2 percent range.

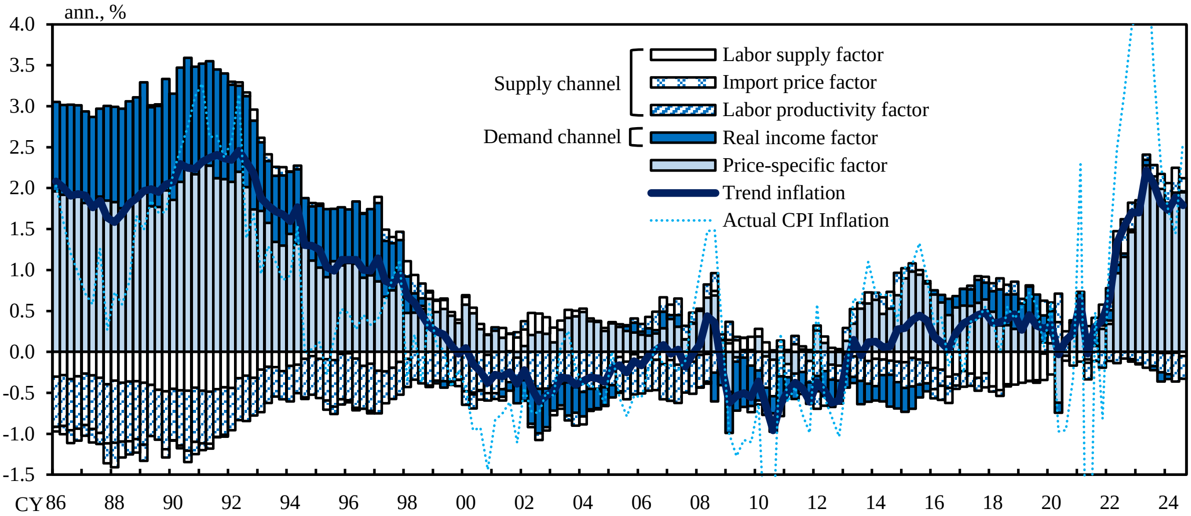
4.2 Historical decompositions of trend inflation

This section begins by presenting an overview of the historical decomposition results of trend inflation in Japan. We then analyze the factors influencing trend inflation in Japan over time, drawing on insights from previous studies. Finally, we compare the results for Japan with those for the United States, highlighting the differences between the two countries.

Time-series developments of trend inflation in Japan

Figure 3 illustrates the decomposition of trend inflation in Japan into the factors described in Section 3.1. In the following discussion, we analyze the key features of the results by dividing the sample into several sub-periods.

Figure 3. Decomposition of trend inflation in Japan

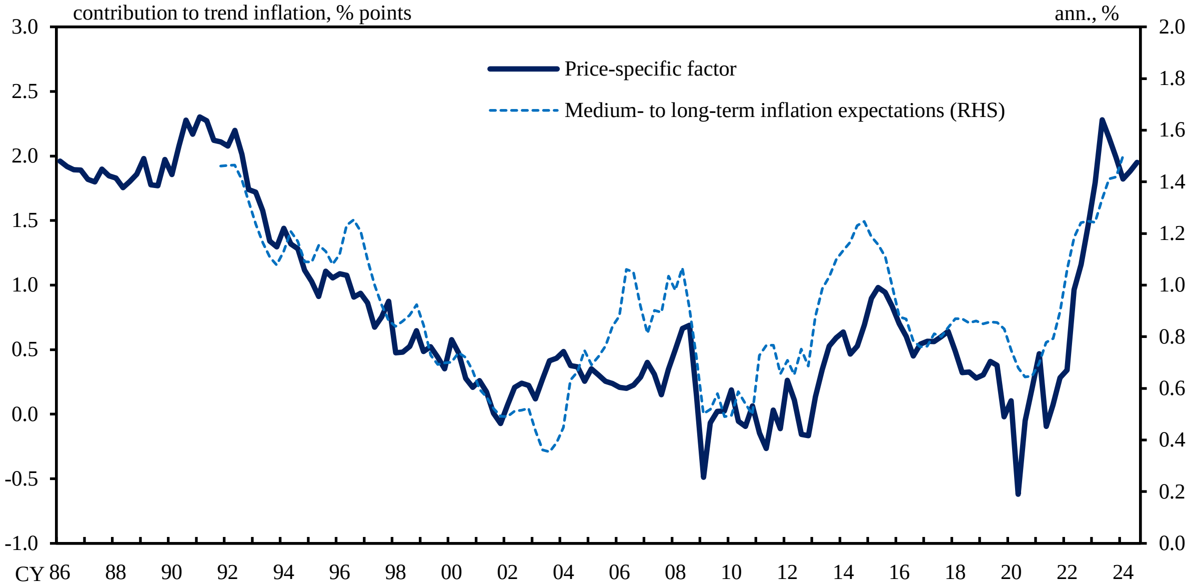


Note: Figures for the import costs factor indicate the impact of changes in import costs on trend inflation in response to shifts in labor productivity and thereby the AS curve. The "labor productivity factor" denotes the component of labor productivity that is unexplained by the import costs factor.

From the late 1980s through the early 1990s, trend inflation remained stable at around 2 percent. The decomposition results indicate that trend inflation faced downward pressure through the supply channel, driven by increases in natural output due to labor force expansion and growth in labor productivity. Simultaneously, increases in natural output contributed to higher real income, which exerted upward pressure on trend inflation through the demand channel. These opposing forces – the downward pressure from the supply channel and the upward pressure from the demand channel – largely offset each other. As a result, trend inflation remained anchored at approximately 2 percent, consistent with the contribution from the price-specific factor.

However, this trend shifted from the early 1990s through the early 2000s. During this period, trend inflation gradually declined as the positive contribution from the price-specific factor diminished. The price-specific factor, which represents the portion of trend inflation not explained by other structural factors, may partly reflect the influence of medium- to long-term inflation expectations. Notably, the contribution of the price-specific factor and the trajectory of medium- to long-term inflation expectations exhibit similar trends (Figure 4). During this period, agents revised their inflation expectations downward, and this decline in expectations likely contributed to the observed decline in trend inflation.

Figure 4. Developments in the contribution of the price-specific factor and inflation expectations



Note: Medium- to long-term inflation expectations presented in the figure are the common component of expectations for firms, households, and experts, extracted by principal component analysis. For details, see Osada and Nakazawa (2024).
Sources: Bank of Japan; Bloomberg; Consensus Economics inc.,"Consensus Forecasts"; QUICK, "QUICK Monthly Market Survey <Bonds>."

Developments in other factors during this period reveal that the downward pressure on trend inflation through the supply channel – represented by the labor supply factor and the remaining labor productivity factor in the figure – diminished. Examining the economic environment of this period, labor force growth gradually slowed due to population aging. At the same time, firms restrained investment in response to the collapse of the asset price bubble in the early 1990s.[14] Corporate activities, including capital accumulation and R&D investment, were

[14] The decline in the growth rate of labor productivity has been attributed not only to the direct impact of reduced corporate investment following the collapse of asset price bubbles, but also to indirect effects channeled through

subdued, which, in turn, led to a slowdown in labor productivity growth. On the demand side, growth in the real income factor also weakened, alongside declines in labor supply and labor productivity growth. Under these circumstances, trend inflation declined as the contribution of the price-specific factor decreased.

From the early 2000s through the early 2010s, trend inflation hovered around zero or was negative overall, although it temporarily turned positive at times. The decomposition results show that the contribution of the price-specific factor remained muted for an extended period beginning in the early 2000s. As suggested by Watanabe (2022, 2024) and Aoki, Ichiue and Okuda (2019), when households' expectations become entrenched in the belief that prices will not rise in the future, they are less willing to accept price increases. This reinforces firms' tendency to keep prices unchanged, further entrenching the behavior and mindset based on the assumption that prices would not increase easily. This mechanism contributed to the prolonged period of low inflation expectations observed during this time.

A further characteristic of this period, unlike in the 1990s, is that the impact through the supply channel (the combined contributions of labor supply and labor productivity) were no longer offset by that through the demand channel (the contribution of real income). Instead, trend inflation appears to have been suppressed because real income growth was weaker than that of labor supply and labor productivity. Following the collapse of the asset price bubble in the early 1990s, competition among firms intensified. As noted by Aoki, Hoghen and Takatomi (2023), firms responded by restraining wages relative to productivity in order to secure profits. Workers, for their part, seemed to prioritize regular employment over wage increases (Bank of Japan, 2024b). Consequently, the labor share of income in Japan has gradually declined since the 2000s, albeit with some fluctuations.[15] The analysis presented in this paper suggests that this long-term reallocation of income away from households may have played a role in dampening trend inflation.

Since 2013, trend inflation – which had previously remained in negative territory – turned positive, largely aligning with the price-specific factor. In January 2013, the BOJ introduced the price stability target of 2 percent, followed in April by the implementation of a large-scale monetary easing program known as Quantitative and Qualitative Monetary Easing (QQE). During this period, medium- to long-term inflation expectations also increased, and this rise in

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the banking sector. Examples of these indirect effects include resource misallocation driven by evergreening loans in the early 1990s and more severe credit constraints such as credit rationing and loan recalls during the late 1990s to early 2000s, which further suppressed investment. A comprehensive discussion on the decline in labor productivity growth in Japan since the 1990s can be found in Miyagawa (2006) and Kameda (2009). Recent developments in this area are analyzed by Yagi, Furukawa and Nakashima (2023).

[15] For an overview of the background to the declining trend in the labor share of income in Japan since the 2000s, see Haneda, Kwon and Ijiri (2000), for example.

expectations may have contributed to the improvement in trend inflation.

However, the rise in trend inflation stalled around the mid-2010s. The decomposition results suggest that this stagnation was primarily due to the positive contribution of the price-specific factor reaching a plateau. During this period, crude oil prices declined significantly, and inflation expectations also fell. These developments in inflation expectations are likely to have influenced the dynamics of trend inflation.

Toward the late 2010s, notable changes emerged in factors beyond the price-specific factor. The labor supply factor exerted downward pressure on trend inflation as labor force participation rose markedly, particularly among women and the elderly. At the same time, this increased participation contributed to growth in aggregate real income. Under these circumstances, trend inflation appears to have reverted to a pattern similar to that observed in the 1990s, with its movements largely aligning with the price-specific factor.

More recently, trend inflation has begun to rise since around 2022, when actual inflation rates exceeded 2 percent, and it remains close to 2 percent at present. This development also corresponds to movements in medium- to long-term inflation expectations. Some studies have noted that agents in Japan tend to form inflation expectations in a more adaptive manner compared to those in other advanced economies (Ehrmann, 2015; Nishino et al., 2016). Additionally, a recent study on household expectations formation suggests that actual inflation at any given time is more readily incorporated into inflation expectations, particularly under conditions of significant inflation fluctuation (Fujii, Nakano and Takatomi, 2025). These features of expectations formation in Japan may have contributed to the upward shift in inflation expectations, which, in turn, appears to be reflected in the trajectory of trend inflation.[16]

Comparison with results for the United States

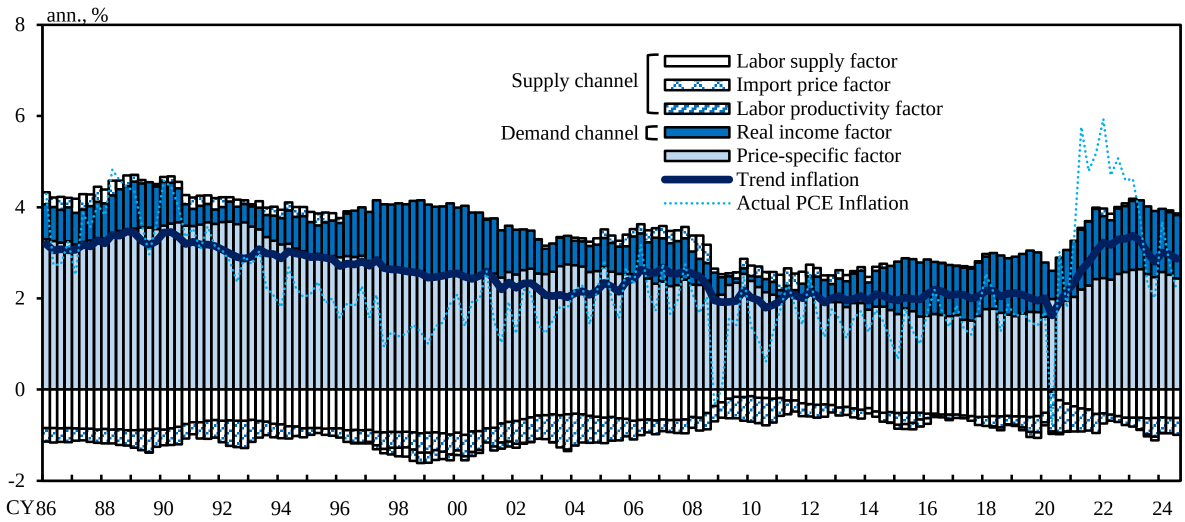
Figure 5 presents the results of the decomposition of trend inflation in the United States. Overall, downward pressure through the supply channel, represented by the labor supply and labor productivity factors, and upward pressure through the demand channel, represented by the real income factor, have tended to offset each other. Unlike in Japan, the sustained growth in the labor force population in the United States, driven partly by immigration, suggests that potential output has continued to expand at a steady pace and has been distributed as income. Under these conditions, trend inflation appears to move largely in line with the price-specific factor, which is thought to reflect developments in inflation expectations. This stands in contrast to the experience of Japan during the 2000s and 2010s.

[16] The most recent estimates are subject to change as the sample is extended or updated, and therefore should be interpreted with some latitude.

In particular, from the late 1990s to around 2000, the downward pressure on trend inflation through the supply channel and the upward pressure through the demand channel appear to have offset each other, stabilizing trend inflation at approximately 2 percent.[17] This contrasts with the situation in Japan, where the price-specific factor has exhibited significantly larger fluctuations.

In the 2020s, trend inflation in the United States has risen, mirroring similar developments in Japan. This increase is driven primarily by the growing positive contribution of the price-specific factor, which aligns closely with the trajectory of medium- to long-term inflation expectations.[18] Additionally, the positive contribution of the real income factor has expanded, reflecting a recent rise in personnel costs. These shifts are likely to have contributed to the increase in trend inflation.

Figure 5. Decomposition of trend inflation in the United States



Note: Figures for the import costs factor indicate the impact of changes in import costs on trend inflation in response to shifts in labor productivity and thereby the AS curve. The "labor productivity factor" denotes the component of labor productivity that is unexplained by the import costs factor.

5 Conclusion

This paper estimated and decomposed trend inflation in Japan using a trend-cycle BVAR decomposition method. We analyzed the factors behind the decline in Japan's inflation since the late 1990s and its prolonged low levels, with a focus on structural factors such as inflation expectations, demographics, and productivity. Additionally, we applied this methodology to

[17] Previous studies suggest that one of the reasons why trend inflation and medium- to long-term inflation expectations became anchored in the United States is the set of steps the Federal Reserve has taken since the 1990s to increase the transparency of monetary policy. For details, see Daly (2022).

[18] For example, according to the survey conducted by University of Michigan, households' medium- to long-term inflation expectations (5 years ahead) stood at 2.4% in 2019 and subsequently rose to 3.0% by 2024.

U.S. data, allowing for a comparative analysis between the two countries.

Key findings of this study are summarized as follows. First, following the collapse of the asset price bubble in the early 1990s, Japan's trend inflation gradually declined. During this period, inflation expectations also weakened, consistent with the estimation results presented in this paper. Second, from the 2000s through the early 2010s, subdued growth in real income – relative to labor supply and labor productivity – seems to have exerted downward pressure on trend inflation through the demand channel. Third, beginning in the early 2010s, trend inflation turned positive, driven by developments in the price-specific factor. This shift aligns with an increase in medium- to long-term inflation expectations in the context of the BOJ's introduction of a 2 percent price stability target and large-scale monetary easing. Fourth, in the 2020s, trend inflation has risen to approximately 2 percent. Collectively, these findings highlight the importance of monitoring structural real factors – such as labor supply, labor productivity, and the labor share of income – in addition to inflation expectations when evaluating inflation trends.

While this analysis provides valuable insights, it also underscores areas requiring further exploration. One of the critical analytical issues is understanding the determinants of the price-specific factor, which is a major driver of trend inflation. As demonstrated in Section 3, the price-specific factor exhibits a similar pattern to medium- to long-term expected inflation rates, suggesting a potential linkage to the mechanism through which inflation expectations are formed. Examining how the characteristics of expectation formation among economic agents in Japan influence the price-specific factor remains an important subject for future analysis.

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Appendix A: Estimation assumptions

This appendix provides a detailed description of the model, including the initial distributions of the state variables, the prior distributions of the parameters, and the estimation algorithm.

A.1 Model

The model utilized in this paper is formulated as follows.

Observation equation

$$Y_t = CX_t + Ru_t \tag{A.1}$$

Where
$$C = \begin{bmatrix} \Lambda & I & 0 \end{bmatrix}$$

$$X_t = \begin{bmatrix} \bar{\tau}_t \\ \tilde{Y}_t \\ \vdots \\ \tilde{Y}_{t-p+1} \end{bmatrix}$$

State equation

$$X_t = AX_{t-1} + H_t \varepsilon_t \tag{A.2}$$

Where

$$A = \begin{bmatrix} I & 0 & 0 & \dots & 0 & 0 \\ 0 & \Phi_1 & \Phi_1 & \dots & \Phi_{p-1} & \Phi_p \\ 0 & I & 0 & \dots & 0 & 0 \\ 0 & 0 & I & & & \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & I & 0 \end{bmatrix}$$

$$H_t = \begin{bmatrix} \bar{H}_t & 0 \\ 0 & \tilde{F}\tilde{H}_t \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix}$$

$$\bar{H}_t = \begin{bmatrix} \exp(\bar{h}_{1,t}/2) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \exp(\bar{h}_{q,t}/2) \end{bmatrix}$$

$$\tilde{H}_t = \begin{bmatrix} \exp(\tilde{h}_{1,t}/2) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \exp(\tilde{h}_{n,t}/2) \end{bmatrix}$$

$$\tilde{F} = \begin{bmatrix} 1 & & \cdots & & 0 \\ f_{2,1} & 1 & & & \\ f_{3,1} & f_{3,2} & \ddots & & \vdots \\ \vdots & \vdots & & 1 & 0 \\ f_{n,1} & f_{n,2} & \cdots & f_{n,n-1} & 1 \end{bmatrix}$$

Stochastic volatilities for the trend and cycle components

$$\bar{h}_{i,t} - \bar{\mu}_i = \bar{\psi}_i(\bar{h}_{i,t-1} - \bar{\mu}_i) + \bar{\gamma}_i \bar{v}_{i,t} \quad (A.3)$$

$$\tilde{h}_{j,t} - \tilde{\mu}_j = \tilde{\psi}_j(\tilde{h}_{j,t-1} - \tilde{\mu}_j) + \tilde{\gamma}_j \tilde{v}_{j,t} \quad (A.4)$$

A.2 Initial distributions of state variables

This paper specifies the initial distributions of state variables as follows. The index *0* of each variable means the initial values.

Table A1. Initial distributions of state variables

	Variables	Initial distributions
$\bar{\tau}_0$	Structural factors	$\mathcal{N}(\mu_{\bar{\tau}}, \Sigma_{\bar{\tau}})$
$\tilde{Y}_0$	Cycle component	$\mathcal{N}(0, \Sigma_{\tilde{Y}})$
$\bar{h}_{i,0}$	Volatility of the structural factor i	$\mathcal{N}(\mu_{\bar{h}_i}, \sigma^2_{\bar{h}_i})$
$\tilde{h}_{j,0}$	Volatility of the cycle component j	$\mathcal{N}(\mu_{\tilde{h}_j}, \sigma^2_{\tilde{h}_j})$

$\mu_{\bar{\tau}}$ is constructed using the initial matrix of the factor loadings (Λ_0) and the first 10-year (1986/Q1 - 1995/Q4) sample averages of the observation variables ($\bar{Y}_0$). $\Sigma_{\bar{\tau}}$ is constructed using the initial values of the volatilities of the structural factor ($\bar{h}_{i,0}$). $\Sigma_{\tilde{Y}}$ is constructed using the initial values of the volatilities of the cycle component ($\tilde{h}_{j,0}$) and the initial values of the parameters (mentioned later). $\mu_{\bar{h}_i}$ and $\sigma^2_{\bar{h}_i}$ are constructed using the unconditional mean and volatility of values obtained from Equation (A.3), with the parameters set to initial values (mentioned later). $\mu_{\tilde{h}_j}$and $\sigma^2_{\tilde{h}_j}$ are constructed in the same manner, using Equation (A.4).

A.3 Prior distributions of parameters

The prior distributions of parameters in the factor loading matrix are as follows. Elements of the factor loading matrix (Λ) are assumed to follow the initial distributions formed as truncated normal distributions subject to the sign restrictions presented in Section 3.1. $\mathcal{TN}(\mu, \sigma^2; a, b)$ denotes the truncated normal distribution with the mean μ and the variance σ^2 and is defined in the interval $[a, b]$. We use different values for these parameters of the truncated normal distributions between Japan and the United States.

Table A2. Prior distributions of parameters (factor loading matrix)

	Relationships between structural factors and trends			Prior distributions	
				Japan	United States
$-\lambda_{11}$	ξ_t	$\rightarrow$	$\bar{\pi}_t$	$\mathcal{TN}(-1,1;-\infty,0)$	$\mathcal{TN}(-0.5,0.5;-\infty,0)$
λ_{12}	η_t			$\mathcal{TN}(1,1;0,\infty)$	$\mathcal{TN}(0.5,0.5;0,\infty)$
$-\lambda_{13}$	α_t			$\mathcal{TN}(-1,1;-\infty,0)$	$\mathcal{TN}(-1,0.5;-\infty,0)$
λ_{14}	ζ_t			$\mathcal{TN}(1,1;0,\infty)$	$\mathcal{TN}(1,0.5;0,\infty)$
λ_{21}	ξ_t	$\rightarrow$	$\bar{y}_t$	$\mathcal{TN}(1,1;0,\infty)$	$\mathcal{TN}(1,0.5;0,\infty)$
$-\lambda_{22}$	η_t			$\mathcal{TN}(-1,1;-\infty,0)$	$\mathcal{TN}(-1,0.5;-\infty,0)$;
λ_{23}	α_t			$\mathcal{TN}(1,1;0,\infty)$	$\mathcal{TN}(1,0.5;0,\infty)$
$-\lambda_{42}$	η_t	$\rightarrow$	$\bar{a}_t$	$\mathcal{TN}(-1,1;-\infty,0)$	$\mathcal{TN}(-1,0.5;-\infty,0)$

The prior distributions of other parameters are as follows. We use different values for some of them between Japan and the United States.

Table A3. Prior distributions of other parameters

	Parameters	Prior distributions
$vec(\Phi)$	Parameters in the VAR model for the cycle component	$\mathcal{N}(vec(\underline{\Phi}),\Sigma_{\tilde{Y}}\otimes\Omega)I(vec(\Phi))$
$\tilde{f}_{l,m}$	Element located at (l,m) in the matrix $\tilde{F}$	$\mathcal{N}(\hat{f}_{l,m},\sigma_f^2)$
$\bar{\mu}_i$	Mean of the volatility of the structural factor i	$\mathcal{N}(\bar{\mu}_{i,0},0.01^2)$
$\tilde{\mu}_j$	Mean of the volatility of the cycle component j	$\mathcal{N}(\tilde{\mu}_{j,0},0.01^2)$
$\bar{\gamma}_i$	Variance of the shocks to the structural factor i	$\mathcal{IG}(30,3.3)$
$\tilde{\gamma}_j$	Variance of the shocks to the cycle component j	$\mathcal{IG}(30,3.3)$

The parameters in the VAR model for the cycle component (Φ) are assumed to follow the standard Minnesota prior, with a hyperparameter value of 0.2. $I(vec(\Phi))$ denotes the indicator function that takes the value of 1 if the VAR model is stationary, and 0 otherwise. $\hat{f}_{l,m}$ is constructed using the (l,m) element of a matrix derived by standardizing the variance-covariance matrix of the observation variables, such that its diagonal elements are all equal to one. In the estimation, the value of σ_f^2 is set to 0.02^2 for Japan and 0.01^2 for the United States. The values of $\{\bar{\mu}_{i,0}\}_{i=1}^q$ are set to $\log([5,5,5,2.5,5]\times 10^{-2})$ for Japan and $\log([1.25,1.25,1.25,0.56,1.25]\times 10^{-2})$ for the United States, based on the literature. The values of $\{\tilde{\mu}_{j,0}\}_{j=1}^n$ are constructed using the variances of the observation variables. The values of autoregressive coefficients of the stochastic volatilities $\{\bar{\psi}_i\}_{i=1}^q$ and $\{\tilde{\psi}_j\}_{j=1}^n$ are fixed at 0.7.

A.4 Estimation algorithm

We need to estimate the state variables $s_t = [\bar{\tau}_t \quad \tilde{Y}_t]$ and $h_t = \left[\{\bar{h}_{i,t}\}_{i=1}^{q} \quad \{\tilde{h}_{j,t}\}_{j=1}^{n}\right]$ and the parameters $\theta = [\Lambda \quad \Phi \quad \tilde{F}]$ and $\delta = \left[\{\bar{\mu}_i\}_{i=1}^{q} \quad \{\tilde{\mu}_j\}_{j=1}^{n} \quad \{\bar{\gamma}_i\}_{i=1}^{q} \quad \{\tilde{\gamma}_j\}_{j=1}^{n}\right]$, but it is difficult to directly sample these variables from posterior distributions at the same time. Accordingly, this paper employs the MCMC method, which combines the Gibbs sampler and the Metropolis-Hastings (MH) algorithm, to draw samples. Specifically, samples are drawn sequentially by iterating the following steps.

Step 1. Sampling the factor loading matrix Λ and the state variables s_t

In this step, we conduct sampling for the factor loading matrix Λ and the state variables s_t, using the posterior distribution $p(\Lambda, s_t | h_t, \theta_{-\Lambda}, \delta, Y_t)$. First, we compute the likelihood using the Kalman filter, given the values of the observation variables (Y_t) and parameters other than Λ (i.e., $\theta_{-\Lambda}$, δ). Second, we obtain the posterior distribution of the factor loading matrix by multiplying the likelihood and the prior distribution of the factor loading matrix. Third, we draw a sample (Λ^*) from the obtained posterior distribution of the factor loading matrix. Finally, based on the simulation smoother proposed by Durbin and Koopman (2002), we draw a sample (s_t^*) from the obtained posterior distribution of the state variables, given the sampled factor loading matrix (Λ^*).

Step 2. Sampling the parameters $\theta_{-\Lambda}$

In this step, we conduct sampling for the parameters $\theta_{-\Lambda}$, using the posterior distribution $p(\theta_{-\Lambda} | \Lambda^*, s_t^*, h_t, \delta, Y_t)$. First, we derive the Gaussian posterior distribution of the parameters in the VAR model for the cycle component, since the prior distribution of the VAR coefficients is assumed to be Gaussian. Second, we draw a sample (Φ^*) from the obtained posterior distribution of the VAR coefficients. To ensure the stationarity of the VAR process, a rejection sampling step is applied (Cogley and Sargent, 2005; Clark, 2011). Third, we derive the Gaussian posterior distribution of $\tilde{F}$, given a set of the VAR coefficients (Φ^*). This is also based on a conjugate prior setup, as in the case of the VAR coefficients. Finally, we draw a sample $\tilde{F}^*$ (Cogley and Sargent, 2005).

Step 3. Sampling the stochastic volatilities h_t and the parameters δ

In this step, we conduct sampling for the state variables: h_t for the stochastic volatilities and the remaining parameters: δ, using the posterior distribution $p(h_t, \delta | s_t^*, \theta^*, Y_t)$. First, given the state variables of s_t^* and the parameters θ^*, we denote $\bar{\tau}_t^* - \bar{\tau}_{t-1}^*$ by $\bar{e}_t$ and ${\tilde{F}^{*}}^{-1}(\tilde{Y}_t^* - \Phi_1^*\tilde{Y}_{t-1}^* - \cdots - \Phi_p^*\tilde{Y}_{p-1}^*)$ by $\tilde{e}_t$, respectively. Second, we can express the ith element of H and the jth element of H in Equation (A.2) as follows: $\exp(\tilde{h}_{j,t}/2)\,\tilde{\varepsilon}_{j,t} = \tilde{e}_{j,t}$ and $\exp(\bar{h}_{i,t}/$

2) $\bar{\varepsilon}_{i,t} = \bar{e}_{i,t}$. Third, we derive the logarithms of their squared values. Then, the model of the stochastic volatilities is represented as the following state space model. Although we show the estimation procedure for the trend component volatilities as an example, the procedure for the cycle component is the same as for the trend component.

Observation equation

$$\log(\bar{e}_{i,t}^2) = \bar{h}_{i,t} + \log(\bar{\varepsilon}_{i,t}^2) \tag{A.5}$$

State equation

$$\bar{h}_{i,t} - \bar{\mu}_i = \bar{\psi}_i(\bar{h}_{i,t-1} - \bar{\mu}_i) + \bar{\gamma}_i \bar{v}_{i,t} \tag{A.6}$$

$\log(\bar{\varepsilon}_{i,t}^2)$ is not Gaussian, and thereby Equations (A.5) and (A.6) are non-Gaussian linear models. In response, we applied the method to approximate Equation (A.5) by a Gaussian distribution, using a mixture sampler (Kim, Shephard and Chib 1998; Omori et al. 2007).[19] Then, we first draw a sample of the latent variable $z_{i,t}$, which indicates the index of the mixture component. Second, we approximate $\log(\bar{\varepsilon}_{i,t}^2)$ by a Gaussian distribution and then compute the likelihood, using the Kalman filter. Third, samples of $\bar{\gamma}_i^*$ and $\bar{\mu}_i^*$ are drawn sequentially Finally, based on the simulation smoother proposed by Durbin and Koopman (2002), we draw a sample of the state variable $\bar{h}_{i,t}^*$ from its posterior distribution.

[19] A multi-move sampler is also known to be an efficient estimation method, as an alternative to a mixture sampler (Shephard and Pitt, 1997; Watanabe and Omori, 2004). For an overview of this topic, see Omori and Watanabe (2008).

Appendix B: Estimated posterior distributions of factor loadings

Estimated posterior distributions of factor loadings are as follows.

Table A4. Posterior distributions of parameters (Japan)

Relationships between structural factors and trends				Prior distributions	Posterior distributions		
					Means	Medians	90% credible intervals
$-\lambda_{11}$	ξ_t	$\rightarrow$	$\bar{\pi}_t$	$\mathcal{TN}(-1,1;-\infty,0)$	-0.34	-0.28	(-0.84, -0.03)
λ_{12}	η_t			$\mathcal{TN}(1,1;0,\infty)$	0.48	0.40	(0.04, 1.18)
$-\lambda_{13}$	α_t			$\mathcal{TN}(-1,1;-\infty,0)$	-0.38	-0.34	(-0.87, -0.04)
λ_{14}	ζ_t			$\mathcal{TN}(1,1;0,\infty)$	0.48	0.45	(0.09, 0.96)
λ_{21}	ξ_t	$\rightarrow$	$\bar{y}_t$	$\mathcal{TN}(1,1;0,\infty)$	1.02	1.01	(0.31, 1.76)
$-\lambda_{22}$	η_t			$\mathcal{TN}(-1,1;-\infty,0)$	-2.34	-2.34	(-3.65, -1.00)
λ_{23}	α_t			$\mathcal{TN}(1,1;0,\infty)$	1.03	1.01	(0.52, 1.61)
$-\lambda_{42}$	ζ_t	$\rightarrow$	$\bar{a}_t$	$\mathcal{TN}(-1,1;-\infty,0)$	-2.22	-2.18	(-3.55, -0.99)

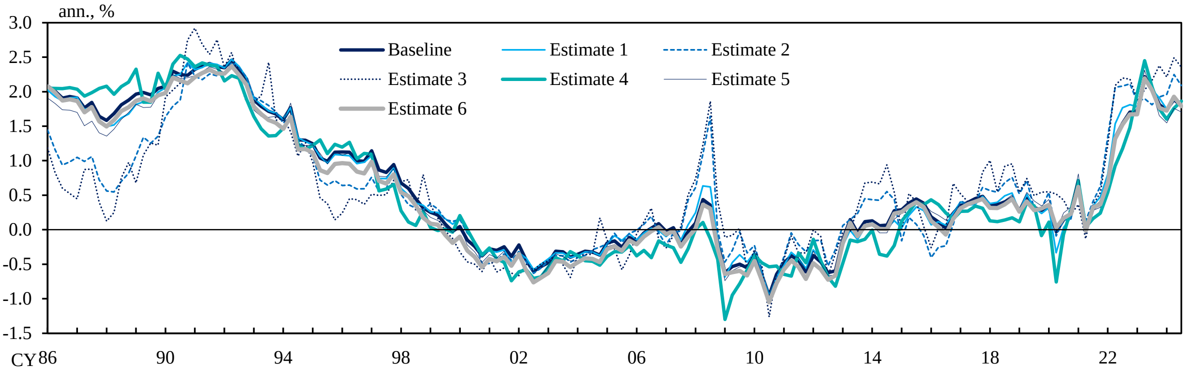
Table A5. Posterior distributions of parameters (United States)

Relationships between structural factors and trends				Prior distributions	Posterior distributions		
					Means	Medians	90% credible intervals
$-\lambda_{11}$	ξ_t	$\rightarrow$	$\bar{\pi}_t$	$\mathcal{TN}(-0.5,0.5;-\infty,0)$	-0.43	-0.37	(-0.96, -0.04)
λ_{12}	η_t			$\mathcal{TN}(0.5,0.5;0,\infty)$	1.17	1.15	(0.40, 1.99)
$-\lambda_{13}$	α_t			$\mathcal{TN}(-1,0.5;-\infty,0)$	-0.41	-0.28	(-1.32, -0.02)
λ_{14}	ζ_t			$\mathcal{TN}(1,0.5;0,\infty)$	0.62	0.56	(0.08, 1.47)
λ_{21}	ξ_t	$\rightarrow$	$\bar{y}_t$	$\mathcal{TN}(1,0.5;0,\infty)$	1.18	1.17	(0.65, 1.73)
$-\lambda_{22}$	η_t			$\mathcal{TN}(-1,0.5;-\infty,0)$	-1.02	-1.01	(-1.77, -0.25)
λ_{23}	α_t			$\mathcal{TN}(1,0.5;0,\infty)$	0.73	0.72	(0.21, 1.31)
$-\lambda_{42}$	ζ_t	$\rightarrow$	$\bar{a}_t$	$\mathcal{TN}(-1,0.5;-\infty,0)$	-1.20	-1.17	(-2.10, -0.35)

Appendix C: Robustness checks on the trend inflation estimates

This appendix evaluates the robustness of the trend inflation estimates presented in the main text (hereafter referred to as the baseline estimates). Specifically, we examine three alternative scenarios: (1) employing alternative price indices for the observation variables; (2) modifying the identification strategy for the structural factors; and (3) allowing for time variation in the model parameters.

Figure A1. Trend inflation in Japan: results of the robustness checks



(1) Using alternative price indices for the observation variables

In the baseline estimation, we employ the Consumer Price Index (CPI, all items less fresh food and energy) as the observation variable for consumer price inflation, and the Import Price Index (IPI, all commodities excluding petroleum, coal, and natural gas) as the observation variable for import price inflation, as described in Section 3.3. For this robustness check, we estimate trend inflation using alternative combinations of price indices: Estimate 1: the IPI (all commodities) and the CPI (all items); Estimate 2: the IPI (all commodities) and the CPI (all items less fresh food); and Estimate 3: the IPI (all commodities) and the CPI (all items less fresh food and energy). The estimation results suggest that the alternative estimates of trend inflation broadly align with the baseline estimates. While some differences are observed depending on whether energy is excluded from the indices, the overall patterns remain largely consistent.

(2) Modifying the identification strategy for the structural factors

In the baseline estimates, the import costs factor (η_t) is modeled to influence both trend inflation and the labor productivity trend, reflecting the downward impact of rising prices for imported intermediate goods on potential output per worker. As part of a robustness check, we analyze the dynamics of trend inflation under a more simplified specification (Estimate 4), where import price inflation is excluded from the observation variables, and the import costs factor is omitted from the structural factors. Moreover, the baseline model assumes that shifts in the LRAD curve affect trend inflation due to the assumption of a completely vertical LRAS curve. As an additional robustness check, we examine a scenario in which the AS curve is not necessarily vertical, allowing the real income factor – assumed in the baseline model to capture the impact of an LRAD curve shift on trend inflation – to influence not only trend inflation but also output (Estimate 5). The estimation results indicate that the alternative trend inflation estimates are broadly consistent with the baseline results.

(3) Allowing for time variation in the model parameters

In the baseline estimates, the relationships between trends in the observation variables and the structural factors (as represented in Equation (3)') are assumed to remain constant throughout the sample period. However, these relationships may vary over time. To address this possibility, we analyze the dynamics of trend inflation using a specification in which each parameter in Equation (3)' is assumed to be time-varying and modeled as following a unit root process (Estimate 6). The estimation results suggest that the alternative trend inflation estimates are broadly consistent with the baseline estimates.