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Abstract

We compare Japanese and US inflation dynamics during the post-Global Financial Crisis period by utilizing Bayesian VAR-GMM to estimate several specifications of the New Keynesian Phillips curve. With the estimation method, we derive expectations in the Phillips curve from a VAR and analyze the formation of inflation expectations explicitly. We select the specification with variable elasticity of demand for Japan and that with sticky information for the US, using quasi-marginal likelihood. The selected specifications show that the persistence of inflation expectations formation is higher and trend inflation is lower in Japan than in the US. These findings account for persistently weak inflation developments in Japan: in the presence of firms' cautious price-setting behavior that reflects the purchasing attitude of consumers who are sensitive to price increases, inflation remains low and induces, through the highly persistent formation of inflation expectations, low expected future inflation and hence low trend inflation, which in turn put downward pressure on present inflation through the Phillips curve.

JEL Classification: E31, C11, C26, C52

Keywords: New Keynesian Phillips curve; Inflation expectations formation; Variable elasticity of demand; VAR-GMM; Bayesian method

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1 Introduction

Inflation has recently gained renewed attention in advanced economies. Prior to the COVID-19 pandemic, inflation developments in the economies had been weak since the onset of the Global Financial Crisis. However, amid the pandemic, the PCE inflation rate in the US has risen above the Federal Reserve's longer-run inflation goal of two percent, and the inflation rate of the HICP in the euro area has also exceeded the European Central Bank's recently revised medium-term inflation target of two percent. In Japan, where prices have not easily increased for a prolonged period, the inflation rate of the CPI excluding fresh foods has been slightly positive and below the Bank of Japan's price stability target of two percent. These observations raise the question as to why inflation developments in Japan have been persistently weak relative to other advanced economies.

In this paper we compare Japanese and US inflation dynamics during the post-Global Financial Crisis period by utilizing Bayesian VAR-GMM to estimate several specifications of the New Keynesian Phillips curve (NKPC). With the estimation method, we derive expectational variables in the NKPC from a VAR and can thus explicitly analyze the formation of inflation expectations, through which expected future inflation converges to trend inflation in the long run. The specifications of the NKPC we estimate are based on Coibion and Gorodnichenko (2011), which is derived from a staggered price model of Calvo (1983) where each period a fraction of prices remains unchanged in line with micro evidence, so that the level of trend inflation affects inflation dynamics.[1] In this baseline NKPC, we introduce intrinsic inflation inertia, since inflation data exhibit persistence in both Japan and the US. Specifically, we consider three sources of inertia that have been proposed in the existing literature: the rule-of-thumb price setters of Galí and Gertler (1999), sticky information suggested by Dupor et al. (2010), and variable (price) elasticity of demand by Kurozumi and Van Zandweghe (2019).[2] For each country, we estimate the baseline NKPC and its three

[1]This feature contrasts with that of the textbook NKPC (e.g., Woodford, 2003). In the textbook NKPC, trend inflation plays little role in inflation dynamics, since either zero trend inflation or price indexation to trend inflation is assumed.

[2]In the literature there is another source of intrinsic inflation inertia of the NKPC, the upward-sloping hazard function proposed by Sheedy (2010). Our paper does not employ this source due to the lack of tractability. We also do not consider the price indexation to lagged inflation used in previous studies, including Cogley and Sbordone (2008), since it implies that all prices change in every period, which contradicts the micro evidence.

variants with intrinsic inflation inertia, and compare them using quasi-marginal likelihood (QML) as advocated by Inoue and Shintani (2018).[3]

The main findings of the paper are twofold. First, we select the specification of the NKPC with variable elasticity of demand for Japan and that with sticky information for the US, using QML. The variable elasticity implies that relative demand for each good becomes more price-elastic for an increase in the relative price of the good and less price-elastic for a decrease in the relative price, which induces firms to keep their prices near those of their competitors. Thus, the selected specification describes well the fact that in Japan firms adopt cautious price-setting behavior stemming from the purchasing attitude of consumers who are more sensitive to price increases but less sensitive to price decreases.[4] The specification selected for the US is consistent with the result of Dupor et al. (2010), who show that their estimation data support their specification of the NKPC with sticky information over its counterpart with rule-of-thumb price setters, although they implicitly assume either zero trend inflation or price indexation to trend inflation and do not consider the counterpart with variable elasticity of demand.[5]

Second, the selected specifications of the NKPC for Japan and the US show that the persistence of inflation expectations formation is higher in Japan. This result is in line with the finding of previous studies that the formation of inflation expectations is largely adaptive in Japan.[6] Moreover, the selected specifications demonstrate that trend inflation in Japan is lower than the US counterpart of about two percent and that inflation inertia of the NKPC is higher in the US. We then consider that the higher persistence of inflation expectations

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[3]We also estimate a canonical hybrid form of the NKPC and show that, in terms of QML, it underperforms all the specifications of the NKPC considered in the paper.

[4]From the results of surveys in Japan and the US, Watanabe (2022) points out that consumers are more sensitive to price increases and less sensitive to price decreases in Japan relative to the US. The Cabinet Office (2013) survey of firms in Japan also shows that they keep sales prices until their competitors raise prices. Moreover, Koga et al. (2019) report micro evidence on firms' price-setting behavior that supports the presence of variable elasticity of demand, using a large set of firm-level panel data from the Bank of Japan's *Tankan* survey, the short-term economic survey of enterprises in Japan.

[5]As proposed by Mankiw and Reis (2002), sticky information is due to the presence of costs of information acquisition and reoptimization. For the importance of these costs in the US, see, e.g., Zbaracki et al. (2004), who show that managerial costs, including information gathering and decision-making costs, are much higher than menu costs, using data from a large US industrial manufacturer.

[6]See the Bank of Japan (2016, 2021), Nishino et al. (2016), and Maruyama and Suganuma (2019). Ehrmann (2015) shows that inflation expectations are more dependent on lagged inflation in Japan than in inflation-targeting countries under persistently low inflation.

formation and lower trend inflation are important factors behind persistently weak inflation developments in Japan relative to the US and that the persistence measured in US inflation data may be ascribable to the higher inflation inertia of the NKPC.

These two main findings account for persistently weak inflation developments in Japan during the post-Global Financial Crisis period. In the presence of firms' cautious price-setting behavior that reflects the purchasing attitude of consumers who are sensitive to price increases, inflation remains low and induces, through the highly persistent formation of inflation expectations, low expected future inflation and hence low trend inflation, which in turn put downward pressure on present inflation through the NKPC. On the other hand, in the US, the weak output gap stemming from the Great Recession continues to put downward pressure on inflation, and this adverse effect on inflation remains for some time due to the relatively high inflation inertia of the NKPC that arises from sticky information. However, its spillover effect on expected future inflation is limited because of the low persistence of inflation expectations formation, which keeps trend inflation near two percent and thus present and expected future inflation evolve around two percent.[7]

In the literature, there have been a considerable number of studies that estimate the NKPC with Japanese and US data. Most of the previous studies, however, derive the NKPC from models that assume either zero trend inflation or price indexation to trend inflation.[8] In such models, all prices change in every period, which contradicts the micro evidence, and trend inflation plays little role in inflation dynamics. A few notable exceptions are Cogley and Sbordone (2008), Gemma et al. (2017), and Hirose et al. (2020, 2021). Cogley and Sbordone (2008) derive the NKPC with time-varying trend inflation and estimate it using US data up to 2003. In estimating the NKPC, they employ the two-step procedure proposed by Sbordone (2002) in which a VAR is first estimated to derive expectational variables in the NKPC and then the minimum distance estimation is conducted to infer the NKPC parameters. Gemma et al. (2017) use Bayesian GMM to estimate the NKPC with Japanese and US data and

[7]We consider that trend inflation plays the role of the "norm" advocated by Okun (1981), since it determines a standard or level of present and expected future inflation. The NKPC describes inflation dynamics in terms of deviations of present and expected future inflation (as well as past inflation if any) from trend inflation or the inflation norm. Therefore, the NKPC—which explicitly takes trend inflation into account—emphasizes the importance of not only inflation expectations but also the inflation norm in inflation dynamics.

[8]See, e.g., Galí and Gertler (1999), Galí et al. (2005), Dupor et al. (2010), and Guerrieri et al. (2010) for empirical research on the NKPC for the US and Tsuruga and Muto (2008) for the Japanese counterpart.

compare the estimated NKPC for Japan between before and during the deflation period starting from 1998 as well as that for the US between during and after the Great Inflation period. In contrast with the limited-information estimation methods employed in these studies, Hirose et al. (2020, 2021) adopt a full-information Bayesian method to estimate the NKPC as well as other equilibrium conditions for households and the monetary authority using US data, and compare the estimated whole model between the Great Inflation and the Great Moderation periods. Our paper estimates several specifications of the NKPC during the post-Global Financial Crisis period using the limited-information approach of Bayesian VAR-GMM and compares the selected specifications for Japan and the US to investigate the factors behind persistently weak inflation developments in Japan relative to the US.[9]

The remainder of the paper proceeds as follows. Section 2 presents several specifications of the NKPC. Section 3 explains our method and data for estimating them. Section 4 shows our empirical results. Section 5 concludes.

2 New Keynesian Phillips Curve

In this section we present several specifications of the NKPC estimated later. They are based on the NKPC of Coibion and Gorodnichenko (2011), which is derived from a staggered price model of Calvo (1983) where each period a fraction of prices remains unchanged. Moreover, we consider three sources of intrinsic inertia of inflation in the NKPC: the rule-of-thumb price setters of Galí and Gertler (1999), sticky information suggested by Dupor et al. (2010), and variable elasticity of demand by Kurozumi and Van Zandweghe (2019). For each of the three sources, we derive the NKPC with intrinsic inflation inertia in what follows.

2.1 Baseline specification

We begin by presenting the baseline specification of the NKPC. Under the assumption

$$\alpha \max\left(\beta\pi^{\theta}, \pi^{\theta-1}\right) < 1, \tag{1}$$

[9]Moreover, to implement the Bayesian VAR-GMM estimation of the NKPC, we utilize a Block Metropolis-Hastings algorithm to simultaneously estimate the NKPC parameters and its associated VAR coefficients. For the algorithm, see, e.g., Herbst and Schorfheide (2015).

the baseline NKPC can be derived as

$$\hat{\pi}_t = \beta\pi^{1+\theta} E_t\hat{\pi}_{t+1} + \kappa_{x,b}\,\hat{x}_t + \kappa_{\phi,b}\,(\theta-1)\sum_{j=1}^{\infty}(\alpha\beta\pi^{\theta-1})^j E_t\hat{\pi}_{t+j}, \tag{2}$$

where $\hat{\pi}_t \equiv \log\pi_t - \log\pi$, π_t is the gross inflation rate, π is the gross trend inflation rate, $\hat{x}_t$ is the output gap, $\beta \in (0,1)$ is the subjective discount factor, $\theta > 1$ is the elasticity of substitution between goods, $\alpha \in (0,1)$ is the probability of no price change, and the slope coefficient $\kappa_{x,b}$ and the other composite coefficient $\kappa_{\phi,b}$ are given by[10]

$$\kappa_{x,b} \equiv \frac{2(1-\alpha\pi^{\theta-1})(1-\alpha\beta\pi^{2\theta})}{\alpha\pi^{\theta-1}(1+\theta)}, \quad \kappa_{\phi,b} \equiv \frac{(\pi^{1+\theta}-1)(1-\alpha\pi^{\theta-1})}{\alpha\pi^{\theta-1}(1+\theta)}.$$

Therefore, all coefficients (on the output gap and expected future inflation rates) in this NKPC depend on trend inflation, so that its level has influence on inflation dynamics.

When the trend inflation rate is zero (i.e., $\pi = 1$), the baseline NKPC (2) is reduced to the textbook form $\hat{\pi}_t = \beta E_t\hat{\pi}_{t+1} + \kappa_{x,b}\,\hat{x}_t$ as in Woodford (2003).

2.2 Specification with rule-of-thumb price setters

Next, we present three variants of the baseline NKPC that are augmented with intrinsic inflation inertia. The first variant is derived from the model embedded with the rule-of-thumb price setters of Galí and Gertler (1999) under the assumption (1). The NKPC then takes the form

$$\hat{\pi}_t = \rho_{\pi,r}\,\hat{\pi}_{t-1} + \frac{\alpha\beta\pi^{2\theta}}{\alpha\pi^{\theta-1}+\tilde{\omega}_r} E_t\hat{\pi}_{t+1} + \kappa_{x,r}\,\hat{x}_t + \kappa_{\phi,r}\,(\theta-1)\sum_{j=1}^{\infty}(\alpha\beta\pi^{\theta-1})^j E_t\hat{\pi}_{t+j}, \tag{3}$$

where the inflation inertia coefficient $\rho_{\pi,r}$ and the slope coefficient $\kappa_{x,r}$ are given by

$$\rho_{\pi,r} \equiv \frac{\omega_r}{\alpha\pi^{\theta-1}+\tilde{\omega}_r}, \quad \kappa_{x,r} \equiv \frac{2(1-\alpha\pi^{\theta-1})(1-\alpha\beta\pi^{2\theta})(1-\omega_r)}{(\alpha\pi^{\theta-1}+\tilde{\omega}_r)(1+\theta)},$$

$\omega_r \in [0,1)$ is the fraction of rule-of-thumb price setters among firms, and the remaining composite coefficients $\kappa_{\phi,r}$ and $\tilde{\omega}_r$ are given in Appendix A. This NKPC is called the ROT-

[10] In the baseline NKPC and its three variants with inflation inertia, we assume a unit elasticity of labor supply to explicitly derive them, in particular the specification with variable elasticity of demand.

NKPC in the present paper and can be reduced to the baseline NKPC (2) in the absence of rule-of-thumb price setters, i.e., $\omega_r = 0$.

2.3 Specification with sticky information

The second variant is derived under the assumption (1) from the model that alternatively introduces the sticky information of Mankiw and Reis (2002) as a source of intrinsic inflation inertia along the lines of Dupor et al. (2010). The NKPC then takes the form

$$\begin{aligned}
\hat{\pi}_t = \rho_{\pi,s}\,\hat{\pi}_{t-1} &+ \frac{\alpha\beta\pi^{2\theta}}{\alpha\pi^{\theta-1}+\tilde{\omega}_s}\,E_t\hat{\pi}_{t+1} + \kappa_{x,s}\,\hat{x}_t + \kappa_{\phi,s}\,(\theta-1)\sum_{j=1}^{\infty}(\alpha\beta\pi^{\theta-1})^j E_t\hat{\pi}_{t+j} \\
&- \kappa_\omega \sum_{j=1}^{\infty}(\alpha\beta\pi^{2\theta})^j\left[\theta E_t\hat{\pi}_{t+j} + (1-\alpha\beta\pi^{2\theta})E_t\hat{x}_{t+j}\right] + \kappa_\omega \sum_{j=1}^{\infty}\omega_s^{j-1}\Big\{\omega_{s1}E_{t-j}\hat{x}_t - E_{t-j}\hat{x}_{t-1} \\
&- \sum_{k=1}^{\infty}(\alpha\beta\pi^{2\theta})^{k-1}\left[\theta(\omega_{s1}E_{t-j}\hat{\pi}_{t+k} - E_{t-j}\hat{\pi}_{t+k-1}) + (1-\alpha\beta\pi^{2\theta})(\omega_{s1}E_{t-j}\hat{x}_{t+k} - E_{t-j}\hat{x}_{t+k-1})\right] \\
&+ \frac{(\theta-1)(1-\alpha\beta\pi^{\theta-1})}{2(1-\alpha\beta\pi^{2\theta})}\sum_{k=1}^{\infty}(\alpha\beta\pi^{\theta-1})^{k-1}(\omega_{s1}E_{t-j}\hat{\pi}_{t+k} - E_{t-j}\hat{\pi}_{t+k-1})\Big\},
\end{aligned} \tag{4}$$

where the inflation inertia coefficient $\rho_{\pi,s}$ and the slope coefficient $\kappa_{x,s}$ are given by

$$\rho_{\pi,s} \equiv \frac{\omega_s\alpha\pi^{\theta-1}}{\alpha\pi^{\theta-1}+\tilde{\omega}_s}, \quad \kappa_{x,s} \equiv \frac{2(1-\alpha\pi^{\theta-1})(1-\alpha\beta\pi^{2\theta})(1-\omega_s)(1+\omega_{s1})}{(\alpha\pi^{\theta-1}+\tilde{\omega}_s)(1+\theta)},$$

$\omega_s \in [0,1)$ is the probability of no information update, and the remaining composite coefficients $\kappa_{\phi,s}$, κ_ω, $\tilde{\omega}_s$, and ω_{s1} are given in Appendix A. This NKPC is referred to as the SI-NKPC in the present paper and can be reduced to the baseline NKPC (2) in the absence of information rigidity, i.e., $\omega_s = 0$.

2.4 Specification with variable elasticity of demand

The third variant is derived along the lines of Kurozumi and Van Zandweghe (2019) from the model incorporated with a non-CES goods aggregator of the sort proposed by Kimball (1995) under the assumption

$$\alpha \max\left(\beta\pi^{2\gamma}, \beta\pi^{\gamma}, \pi^{\gamma-1}, \pi^{-1}\right) < 1, \tag{5}$$

where $\gamma \equiv \theta(1+\epsilon)$ and ϵ is the parameter that governs the curvature of demand curves. The case of $\epsilon < 0$ is of particular interest in this paper because it gives rise to a variable elasticity of demand that makes relative demand for each good more price-elastic for an increase in the relative price of the good and less price-elastic for a decrease in the relative price. The NKPC then takes the form

$$
\begin{aligned}
\hat{\pi}_t = {} & \rho_{\pi,v} \sum_{j=1}^{\infty} \rho_d^{j-1} \hat{\pi}_{t-j} + \frac{\beta \pi^{1+\gamma}(1+\kappa_{\epsilon d})}{1-\kappa_{\epsilon d}\omega_o} E_t \hat{\pi}_{t+1} + \frac{\kappa_{x,v}}{1-\kappa_{\epsilon d}\omega_o} \hat{x}_t \\
& + \frac{\kappa_{\phi,v}}{1-\kappa_{\epsilon d}\omega_o} \left\{ \gamma \left[1 + \frac{\kappa_{\varepsilon d}(1-\alpha\beta\pi^{\gamma-1})}{1-\rho_d \alpha \beta \pi^{\gamma-1}} \right] - 1 \right\} \sum_{j=1}^{\infty} (\alpha\beta\pi^{\gamma-1})^j E_t \hat{\pi}_{t+j} \\
& + \frac{\kappa_{\epsilon\zeta}}{1-\kappa_{\epsilon d}\omega_o} \sum_{j=1}^{\infty} (\alpha\beta\pi^{\gamma})^j \left\{ \gamma \left[1 + \frac{\kappa_{\varepsilon d}(1-\alpha\beta\pi^{\gamma})}{1-\rho_d\alpha\beta\pi^{\gamma}} \right] E_t \hat{\pi}_{t+j} + 2(1-\alpha\beta\pi^{\gamma}) E_t \hat{x}_{t+j} \right\} \\
& + \frac{\kappa_{\epsilon\psi}}{1-\kappa_{\epsilon d}\omega_o} \sum_{j=1}^{\infty} (\alpha\beta\pi^{-1})^j E_t \hat{\pi}_{t+j},
\end{aligned} \tag{6}
$$

where the inflation inertia coefficient $\rho_{\pi,v}$ and the slope-related coefficient $\kappa_{x,v}$ are given by

$$
\rho_{\pi,v} \equiv \frac{\kappa_{\epsilon d}(1+\rho_d \omega_o)}{1-\kappa_{\epsilon d}\omega_o}, \quad \kappa_{x,v} \equiv \frac{2(1-\alpha\pi^{\gamma-1})(1-\alpha\beta\pi^{2\gamma})(1+\epsilon_1)}{\alpha\pi^{\gamma-1}\{(1+\epsilon_3)[1-\epsilon_2\gamma/(\gamma-1-\epsilon_2)]+\gamma\}},
$$

and the remaining composite coefficients $\kappa_{\phi,v}$, $\kappa_{\epsilon\zeta}$, $\kappa_{\epsilon\psi}$, $\kappa_{\epsilon d}$, ρ_d, ω_o, ϵ_1, ϵ_2, and ϵ_3 are given in Appendix A. This NKPC is called the VED-NKPC in the present paper and can be reduced to the baseline NKPC (2) in the case of constant elasticity of demand, i.e., $\epsilon = 0$.

3 Estimation Method and Data

In this section we explain our method and data for estimating the NKPC presented above.

3.1 Bayesian VAR-GMM

We utilize Bayesian VAR-GMM to estimate the NKPC. This limited-information estimation method is substantially different from those used in the empirical literature on the NKPC mainly in the following three respects.[11] First, in the GMM estimation, expectational vari-

[11] We adopt the limited-information estimation method because this method leaves other equations in the model unspecified and it is therefore much less subject to misspecification issues than full-information

ables in the NKPC are derived from a VAR, instead of being replaced with their realizations as in previous studies, including Galí and Gertler (1999) and Galí et al. (2005). This estimation method is referred to as VAR-GMM by Mavroeidis et al. (2014) and is adopted by Guerrieri et al. (2010) to estimate an open-economy version of the NKPC. With VAR-GMM, we can explicitly analyze the formation of inflation expectations (e.g., the persistence) and estimate each specification of the NKPC up to the latest period, in particular those with multiperiod expectations.[12] Moreover, as in Guerrieri et al. (2010), the NKPC parameters and the VAR coefficients can be estimated in one step, which contrasts with the two-step procedure employed in previous studies, such as Sbordone (2002), Cogley and Sbordone (2008), and Dupor et al. (2010), that first estimate a VAR and then infer the NKPC parameters, given expectations derived from the solely estimated VAR.

Second, we apply Bayesian methods to the VAR-GMM estimation. This application is similar to that of Inoue and Shintani (2018) and Gemma et al. (2017), who adopt Bayesian methods in the classical GMM estimation. As reviewed by Mavroeidis et al. (2014), the literature has extensively discussed the weak identification issue in the estimation of the NKPC. Kleibergen and Mavroeidis (2014) demonstrate that this issue can be mitigated using Bayesian methods. Moreover, we utilize a Block Metropolis-Hastings algorithm (see, e.g., Herbst and Schorfheide, 2015) to estimate the NKPC parameters and the VAR coefficients simultaneously.

Third, we use quasi-marginal likelihood (QML) for model selection, that is, not only selection of the NKPC from all the specifications presented above but also selection of the lag length in the VAR for each specification. As shown by Inoue and Shintani (2018), a model with a higher QML is regarded as a better one, and this model selection procedure is valid even when some model parameters are weakly identified or set identified.[13]

Next, we describe our Bayesian VAR-GMM estimation of the NKPC. In each specification of the NKPC there are only the two variables, the inflation rate $\hat{\pi}_t$ and the output gap $\hat{x}_t$,

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estimation methods.

[12]For example, when we estimate the baseline NKPC (2)—which contains the infinite-horizon inflation expectations $\sum_{j=1}^{\infty}(\alpha\beta\pi^{\theta-1})^j E_t\hat{\pi}_{t+j}$—using GMM as in previous studies, such as Galí and Gertler (1999) and Galí et al. (2005), we need to truncate the expectations at a finite horizon to replace them with their realizations, so we cannot estimate the NKPC up to the latest period.

[13]With QML, Inoue and Shintani (2018) compare some specifications of the NKPC with price indexation, and Gemma et al. (2017) compare the NKPC both with the indexation and without it.

and thus we assume that expectational variables in the NKPC are derived from a finite-order VAR

$$Y_t \equiv [\hat{\pi}_t, \hat{x}_t, \hat{\pi}_{t-1}, \hat{x}_{t-1}, \ldots, \hat{\pi}_{t-n+1}, \hat{x}_{t-n+1}]' = A\, Y_{t-1} + \varepsilon_t,$$

where n denotes the lag length in the VAR. Under this assumption, we derive, for example, the one-step-ahead inflation forecast as $E_t \hat{\pi}_{t+1} = e_\pi' E_t Y_{t+1} = e_\pi' A\, Y_t$, where e_π is the selection vector for inflation. This implies that expected future inflation converges to trend inflation in the long run, i.e., $E_t \hat{\pi}_{t+j} = e_\pi' A^j Y_t \to 0$ (i.e., $E_t \pi_{t+j} \to \pi$) as $j \to \infty$. By replacing expectational variables with their corresponding VAR forecasts, we can obtain the representation of the NKPC for estimation; for instance, the baseline NKPC (2) can be rewritten as

$$\hat{\pi}_t = \beta \pi^{1+\theta} e_\pi' A_b Y_t + \kappa_{x,b}\, \hat{x}_t + \kappa_{\phi,b}(\theta - 1)\, e_\pi' A_{b1} (I - A_{b1})^{-1} Y_t, \tag{7}$$

where A_b is the VAR coefficient matrix in the baseline NKPC and $A_{b1} = \alpha \beta \pi^{\theta-1} A_b$. The representations of the other specifications for estimation are shown in Appendix B.1

Let $\varphi \equiv [\vartheta', vec(A)']'$ denote a vector that combines the NKPC parameters ϑ and its associated VAR coefficients $vec(A)$, and let $g_t(\varphi)$ be a vector of moment functions that satisfies $E(g_t(\varphi)) = 0$ at a true value of $\varphi = \varphi_0$. Define the moment functions $g_t(\varphi)$ as

$$g_t(\varphi) = \begin{bmatrix} h_t(\varphi) Z_t \\ (Y_t - A\, Y_{t-1}) Y_{t-1} \\ \log \pi_{l,t} - \log \pi \end{bmatrix}, \tag{8}$$

where $h_t(\varphi)$ is the NKPC's residual function, Z_t is the vector of instruments including a constant of unity, and $\pi_{l,t}$ denotes the gross rate of long-term expected future inflation. The function $h_t(\varphi)$ is defined as, for example,

$$h_t(\varphi) = \hat{\pi}_t - \left[\beta \pi^{1+\theta} e_\pi' A_b Y_t + \kappa_{x,b}\, \hat{x}_t + \kappa_{\varphi,b}(\theta - 1)\, e_\pi' A_{b1} (I - A_{b1})^{-1} Y_t \right]$$

for the baseline NKPC (7). The top and middle parts of the moment functions $g_t(\varphi)$ in (8) imply the orthogonality conditions for the NKPC and the VAR, respectively. The bottom part reflects our estimation's assumption that $\log \pi = E(\log \pi_{l,t})$, which stems from the aforementioned assumption on inflation expectations formation, through which expected future inflation converges to trend inflation in the long run.

We employ the efficient two-step GMM estimator, as in previous studies, such as Galí and Gertler (1999), Galí et al. (2005), and Guerrieri et al. (2010). The estimator chooses $\varphi \in \Phi$ so as to maximize the objective function $q(\varphi) = -(1/2)\, g(\varphi)'\, W\, g(\varphi)$, where $g(\varphi) = (1/\sqrt{T}) \sum_{t=1}^{T} g_t(\varphi)$ and W is the optimal weight matrix based on the HAC estimator of Newey and West (1987). It is calculated as $W = [\Gamma_j(\tilde{\varphi}) + \sum_{j=1}^{J}(j/J)(\Gamma_j(\tilde{\varphi}) + \Gamma_j(\tilde{\varphi})')]^{-1}$, where $\Gamma_j(\tilde{\varphi}) = [1/(T-j)] \sum_{t=j+1}^{T} g_t(\tilde{\varphi}) g_{t-j}(\tilde{\varphi})'$, $\tilde{\varphi}$ is the arbitrary consistent estimator, and the lag length J is selected by the automatic bandwidth selection method of Andrews (1991).

Following Chernozhukov and Hong (2003), we apply Bayesian methods to the VAR-GMM estimation. The quasi-posterior distribution for φ is defined as

$$\frac{\exp(q(\varphi))p(\varphi)}{\int_{\Phi} \exp(q(\varphi))p(\varphi)d\varphi},$$

where $p(\varphi)$ is the prior distribution for φ. To obtain the quasi-posterior distribution, we use the Markov Chain Monte Carlo (MCMC) method. Specifically, we utilize the Block Metropolis-Hastings algorithm with two blocks for the NKPC parameters and the VAR coefficients to estimate them simultaneously without time-consuming computation of a large Hessian matrix of the quasi-posterior probability density for the moment functions (8) and its computational error.[14] To obtain initial values for MCMC draws, we generate $10,000$ draws from the prior distribution of the NKPC parameters and numerically maximize the quasi-posterior probability density to find the mode, given values of coefficients in the solely estimated VAR. We then use the Block Metropolis-Hastings algorithm to generate $210,000$ MCMC draws that meet assumption (1) or (5), and discard the first $10,000$ draws as a burn-in to obtain the quasi-posterior distribution. We check the convergence of the NKPC parameters and the VAR coefficients using the convergence diagnostic of Geweke (1992).

In conducting model selection, we follow Inoue and Shintani (2018) to use the QML defined as

$$\int_{\Phi} \exp(q(\varphi))p(\varphi)d\varphi. \tag{9}$$

[14]See Appendix B.2 for details of the Block Metropolis-Hastings algorithm in the Bayesian VAR-GMM estimation of the NKPC.

With the modified harmonic mean method of Geweke (1999), we compute the QML for each specification of the NKPC with each lag length of the VAR.[15] Then, a specification of the NKPC with a lag length of the VAR that has a higher QML is selected as a better model.

3.2 Data

To estimate the NKPC with Bayesian VAR-GMM, we use four quarterly time series: the inflation rate, the output gap, long-term inflation expectations, and the wage inflation rate. Following Galí et al. (2005), we employ four lags of the inflation rate and two lags of the output gap and the wage inflation rate as instruments in Z_t.

The four series for Japan are the inflation rate of the CPI excluding fresh foods, the output gap estimated by the Bank of Japan, the long-term inflation expectations by the method of Maruyama and Suganuma (2019), and the wage inflation rate based on the total cash earnings of establishments with five or more employees. Those for the US are the PCE inflation rate, the output gap estimated by the Congressional Budget Office, the Index of Common Inflation Expectations by the method of Ahn and Fulton (2020), and the wage inflation rate based on hourly compensation in the nonfarm business sector.

The sample period is from 2010:Q1 through 2019:Q4. We choose this period both because we aim to compare Japanese and US inflation dynamics during the post-Global Financial Crisis period and because the data fluctuates erratically during the COVID-19 pandemic.

3.3 Fixed parameters and prior distributions

In estimating each specification of the NKPC, we fix the values of two parameters to avoid identification issues. For both Japan and the US, we set the subjective discount factor β at 0.9975 and the elasticity of substitution between goods θ at 7.88, which implies a static markup of about 15 percent and is equal to the estimate of Rotemberg and Woodford (1997). All the remaining parameters in the NKPC and coefficients in the VAR are estimated.

[15] In this paper we report the Geweke (1999) modified harmonic mean estimator of QML with the value of the truncation parameter τ set at 0.5. We confirmed the robustness of the model selection results with respect to the modified harmonic mean method, by using an alternative value of the truncation parameter of $\tau = 0.9$ in the Geweke (1999) estimator and employing an alternative estimator of Sims et al. (2008) with the value of the truncation parameter q set equal to 0.5 and 0.9, as in Herbst and Schorfheide (2015).

Table 1 presents the prior distributions for the parameters in each specification of the NKPC. The prior for the annualized trend inflation rate $\overline{\pi}\,(\equiv 400\log\pi)$ is centered around 2, which is equal to both the Bank of Japan's price stability target and the Federal Reserve's longer-run inflation goal. The prior distribution for the probability of no price change α is set to be the beta distribution with mean 0.5 and standard deviation 0.1. The same beta distribution is also chosen for the prior distributions of the fraction of rule-of-thumb price setters ω_r in the ROT-NKPC (3) and the probability of no information update ω_s in the SI-NKPC (4). As for the parameter governing the curvature of demand curves ϵ in the VED-NKPC (6), the prior for $-\epsilon$ is set to be the gamma distribution with mean 3 and standard deviation 1, following Hirose et al. (2021).

Table 1: Prior distributions for the NKPC parameters

Parameter		Distribution	Mean	Std. dev.
$\overline{\pi}$	annualized trend inflation rate	normal	2	1.5
α	probability of no price change	beta	0.5	0.1
ω_r	fraction of rule-of-thumb price setters	beta	0.5	0.1
ω_s	probability of no information update	beta	0.5	0.1
$-\epsilon$	parameter governing the curvature of demand curves	gamma	3	1

Note: $\overline{\pi}\equiv 400\log\pi$.

For the VAR coefficients, we employ the Minnesota prior in which the covariance matrix of the VAR error term is replaced with the OLS estimate, following Canova (2007). The hyper-parameters of the Minnesota prior are set in the same manner as that of Villemot and Pfeifer (2017).

Using the prior mean of parameters presented in Table 1, we examine the features of the three specifications of the NKPC with intrinsic inflation inertia. Table 2 shows the prior mean of each specification's inflation inertia and slope and whether they increase or decrease when the values of its parameters rise from the prior mean. In this table, we represent the degrees of inflation inertia in the ROT-NKPC (3) and the SI-NKPC (4) as the inflation inertia coefficients $\rho_{\pi,r}$ and $\rho_{\pi,s}$, respectively, and the degree in the VED-NKPC (6) as the sum of the coefficients on lagged inflation rates given by $\rho_{\pi,v}/(1-\rho_d)$. The slope of the NKPC is identical to the slope coefficient in each specification, i.e., $\kappa_{x,r}$, $\kappa_{x,s}$, and $\kappa_{x,v}/(1-\kappa_{\epsilon d}\omega_o)$. As displayed in the third column of the table, the prior mean of inflation inertia is the highest and that of slope is the smallest in the ROT-NKPC. In contrast, the prior mean of inflation inertia is the lowest and that of slope is the largest in the VED-NKPC. The degrees of inflation inertia and slope in the SI-NKPC are intermediate between those in the ROT-NKPC and the VED-NKPC. Then, a rise in the degree of each source of the NKPC's inflation inertia (i.e., ω_r, ω_s, and $-\epsilon$) from its prior mean increases the inflation inertia and decreases the slope, as seen in the fourth column. Moreover, the last two columns show that the qualitative effects of trend inflation π and the probability of no price change α on the inflation inertia are the same between the SI-NKPC and the VED-NKPC but are different from those in the ROT-NKPC, whereas the qualitative effects on the slope are identical between the ROT-NKPC and the SI-NKPC but are distinct from those in the VED-NKPC. Thus, we consider that these differences help the estimation data identify the three specifications with intrinsic inflation inertia.

Table 2: Features of the NKPC's inflation inertia and slope in each specification with intrinsic inflation inertia

NKPC specification		Prior mean	$\omega_r/\omega_s/-\epsilon$	π	α
ROT-NKPC	inflation inertia	0.49	+	−	−
	slope	0.024	−	−	−
SI-NKPC	inflation inertia	0.29	+	+	+
	slope	0.035	−	−	−
VED-NKPC	inflation inertia	0.06	+	+	+
	slope	0.083	−	+	−

Notes: For each specification of the NKPC with intrinsic inflation inertia, the table shows the prior mean of its inflation inertia and slope and whether they increase (+) or decrease (−) when the values of its parameters rise from the prior mean presented in Table 1. The degrees of inflation inertia in the ROT-NKPC (3) and the SI-NKPC (4) are represented as the inflation inertia coefficients $\rho_{\pi,r}$ and $\rho_{\pi,s}$, respectively, while the degree in the VED-NKPC (6) is represented as the sum of the coefficients on lagged inflation rates given by $\rho_{\pi,v}/(1-\rho_d)$. The slope of the NKPC is identical to the slope coefficient in each specification, i.e., $\kappa_{x,r}$, $\kappa_{x,s}$, and $\kappa_{x,v}/(1-\kappa_{\epsilon d}\omega_o)$.

4 Empirical Results

In this section, we present results on model selection and then compare the selected specifications of the NKPC for Japan and the US.

4.1 Model selection

For both Japan and the US, we conduct model selection using QML. Specifically, we select not only the lag length of the VAR within each specification of the NKPC but also the best specification among all those considered. In addition to the specifications presented in Section 2, we also pick up, for comparison, a canonical hybrid form of the NKPC

$$\hat{\pi}_t = \rho_{\pi,c}\,\hat{\pi}_{t-1} + (1-\rho_{\pi,c})E_t\hat{\pi}_{t+1} + \kappa_{x,c}\,\hat{x}_t, \tag{10}$$

where $\rho_{\pi,c} \in [0,1]$ and $\kappa_{x,c}$ are the inflation inertia and slope coefficients, respectively.[16] To estimate the canonical NKPC with Bayesian VAR-GMM, we set the priors for $\rho_{\pi,c}$ and $\kappa_{x,c}$ to be the beta distribution with mean 0.5 and standard deviation 0.1, and the normal distribution with mean 0.025 and standard deviation 0.025, respectively.

We begin by presenting the result of the model selection for Japan. Table 3 reports the value of log QML for each specification of the NKPC with VAR lag length of $n = 1, 2, 3, 4$, estimated with the Japanese data. In this table we detect three main findings. First, within each specification of the NKPC, a VAR lag length of $n = 1$ is selected in terms of QML.[17] On each line of the table, which corresponds to each specification of the NKPC, the value of log QML is the largest in the case of a VAR lag length of $n = 1$. Second, structurally introducing intrinsic inertia of inflation improves the NKPC's empirical performance. The three specifications with inflation inertia—the ROT-NKPC, the SI-NKPC, and the VED-NKPC—have larger values of log QML than the baseline NKPC, where inflation inertia is absent. In addition, the value of log QML is the smallest in the canonical NKPC, where inflation inertia is embedded in an ad hoc manner. Third, the VED-NKPC with a VAR lag length of $n = 1$ is the best specification for Japan. It has the largest value of log QML among all the specifications considered.

The VED-NKPC describes well the fact that in Japan firms adopt cautious price-setting behavior stemming from the purchasing attitude of consumers who are more sensitive to price increases and less sensitive to price decreases. As pointed out by Kurozumi and Van

[16] This hybrid form has often been employed in the empirical literature on the NKPC, including Mavroeidis et al. (2014).

[17] A VAR lag length of $n = 1$ is also selected when the VAR is solely estimated with trend inflation set at the sample average of the data on long-term inflation expectations.

Table 3: Model selection results for Japan

NKPC specification	VAR lag length $n = 1$	$n = 2$	$n = 3$	$n = 4$
Baseline NKPC	-22.97	-35.29	-42.70	-51.36
ROT-NKPC	-22.50	-37.78	-41.98	-49.61
SI-NKPC	-18.77	-33.64	-40.57	-46.78
VED-NKPC	-16.83	-25.71	-43.60	-50.41
Canonical NKPC	-26.62	-40.81	-42.10	-48.64

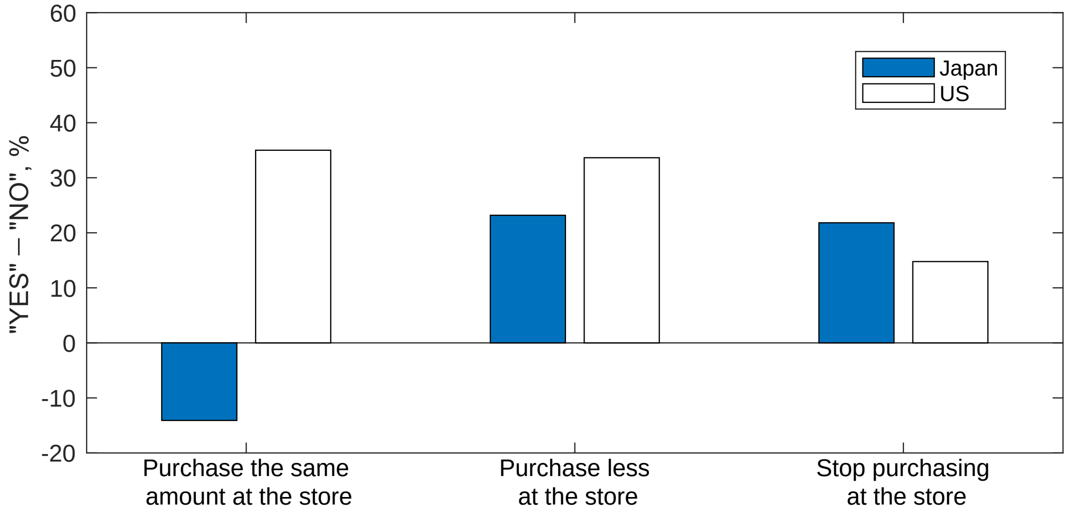
Note: The table reports the value of log QML for each specification of the NKPC with VAR lag length of $n = 1, 2, 3, 4$, estimated with the Japanese data.

Zandweghe (2019), the variable elasticity of demand implies that relative demand for each good becomes more price-elastic for an increase in the relative price of the good and less price-elastic for a decrease in the relative price. This feature of variable elasticity is consistent with the results of questionnaire surveys presented in Watanabe (2022). The surveys ask consumers in Japan and the US as to whether and how they purchase a good when its price rises or declines by 10 percent at a usual store, as shown in Figure 1. Specifically, regarding the question of whether they purchase the same amount of the good at the store given a 10 percent price rise, the fraction of respondent consumers who answer NO exceeds that of respondents answering YES by about 15 percent points in Japan, whereas the fraction of respondents answering YES is larger by about 35 percent points in the US. This suggests that consumers in Japan are more sensitive to price rises than those in the US. In addition, regarding the question of whether they purchase the good more at the store given a 10 percent price decline, the fraction of respondents in Japan who answer NO slightly exceeds that of respondents answering YES, while the fraction of respondents in the US answering YES is greater by about 20 percent points. This implies that consumers in Japan are less sensitive to price declines than those in the US. Thus, the variable elasticity of demand captures well the purchasing attitude of consumers in Japan.

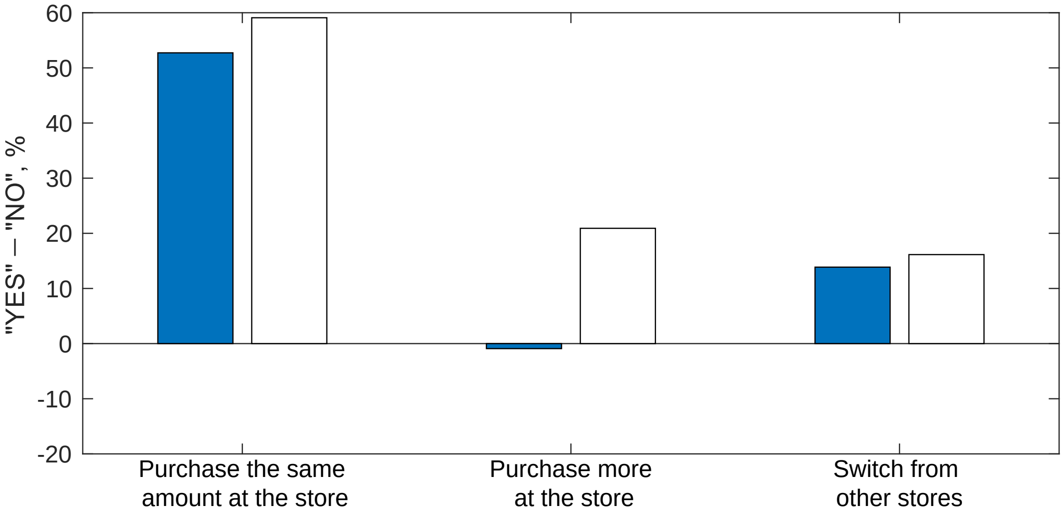
Moreover, the variable elasticity of demand induces firms to keep their prices near those of their competitors. This arises because firms face the elasticity of demand that increases for price rises and decreases for price declines. This feature—which is often called strategic complementarity in firms' price-setting—is consistent with the result of a questionnaire survey presented in the Cabinet Office (2013). Figure 2 illustrates the survey results for

Figure 1: Response of consumers to price rises or declines

(a) 10% price rise



(b) 10% price decline



Source: Watanabe (2022)

the reasons why firms in Japan do not pass on cost increases to sales prices. Near half of the respondent firms answer that they keep sales prices until their competitors raise prices. In addition, about one third of the respondents point to their fear of a fall in sales volume caused by raising prices. Koga et al. (2019) use a large set of firm-level panel data from the Bank of Japan's *Tankan* survey, the short-term economic survey of enterprises in Japan, and report micro evidence on firms' price-setting behavior that supports the presence of variable elasticity of demand. They show that firms in Japan set their prices depending on those of their competitors and that the degree of such strategic complementarity in price-setting is stronger for price decreases than for price increases. These features of consumers and firms in Japan suggest that the VED-NKPC describes well firms' cautious price-setting behavior that reflects the purchasing attitude of consumers in Japan.

Figure 2: Reasons for not passing on cost increases to sales prices

Source: Cabinet Office (2013)

Next, we present the results for model selection for the US. Table 4 reports the value of log QML for each specification of the NKPC with a VAR lag length of $n = 1, 2, 3, 4$, estimated with the US data. As is the case with Japan, a VAR lag length of $n = 1$ is selected within each specification of the NKPC, since the value of log QML is largest when $n = 1$.[18] For the

[18]Moreover, a VAR lag length of $n = 1$ is also selected when the VAR is solely estimated with trend inflation set at the sample average of the data on long-term inflation expectations.

US, however, the SI-NKPC with a VAR lag length of $n = 1$ is the best specification among all those considered.[19]

Table 4: Model selection results for the US

NKPC specification	VAR lag length $n = 1$	$n = 2$	$n = 3$	$n = 4$
Baseline NKPC	-26.37	-34.80	-42.57	-49.56
ROT-NKPC	-28.08	-38.88	-41.86	-49.51
SI-NKPC	-16.54	-27.82	-41.10	-48.88
VED-NKPC	-24.21	-31.18	-40.71	-48.21
Canonical NKPC	-30.89	-37.80	-41.48	-49.48

Note: The table reports the value of log QML for each specification of the NKPC with a VAR lag length of $n = 1, 2, 3, 4$, estimated with the US data.

The model selection results for the US are consistent with Dupor et al. (2010). These authors point out that the data used in their estimation support their specification of the NKPC with sticky information over its counterpart with rule-of-thumb price setters, although they implicitly assume either zero trend inflation or price indexation to trend inflation and do not consider the counterpart with variable elasticity of demand.

As proposed by Mankiw and Reis (2002), sticky information emphasizes the role of firms' costs of information acquisition and reoptimization. The importance of these costs in the US is demonstrated by Zbaracki et al. (2004), who show that managerial costs, including information gathering and decision-making costs, are much higher than menu costs, using data from a large US industrial manufacturer.

4.2 Comparison of Japanese and US inflation dynamics

We have shown that the best specifications for Japan and the US are the VED-NKPC and the SI-NKPC with respective VAR lag lengths of one. We compare these selected specifications to address the question of why inflation developments in Japan have been persistently weak relative to the US.

We begin by comparing the estimates of the NKPC parameters and the VAR coefficients in the selected specifications between Japan and the US. Table 5 reports the quasi-posterior

[19] As is the case with Japan, the model selection results for the US show that the canonical NKPC (10) underperforms all the other specifications considered.

mean and 90 percent highest quasi-posterior density interval for each of the parameters and coefficients in the VED-NKPC for Japan and the SI-NKPC for the US. In this table, two main findings are detected. First, the annualized trend inflation rate $\overline{\pi}$ in Japan is lower than the US counterpart of about two percent, as shown on the third line of the table.

Second, and more importantly, the persistence in the formation of inflation expectations is higher in Japan than in the US. On the sixth line of the table, the estimate of the autoregressive coefficient $A_{\pi\pi}$ in the (selected first-order) VAR's inflation equation for Japan is larger than that for the US. This result is in line with the findings of previous studies. The Bank of Japan (2016, 2021), Nishino et al. (2016), and Maruyama and Suganuma (2019) indicate that the formation of inflation expectations is largely adaptive in Japan, and Ehrmann (2015) shows that inflation expectations are more dependent on lagged inflation in Japan than in inflation-targeting countries under persistently low inflation.

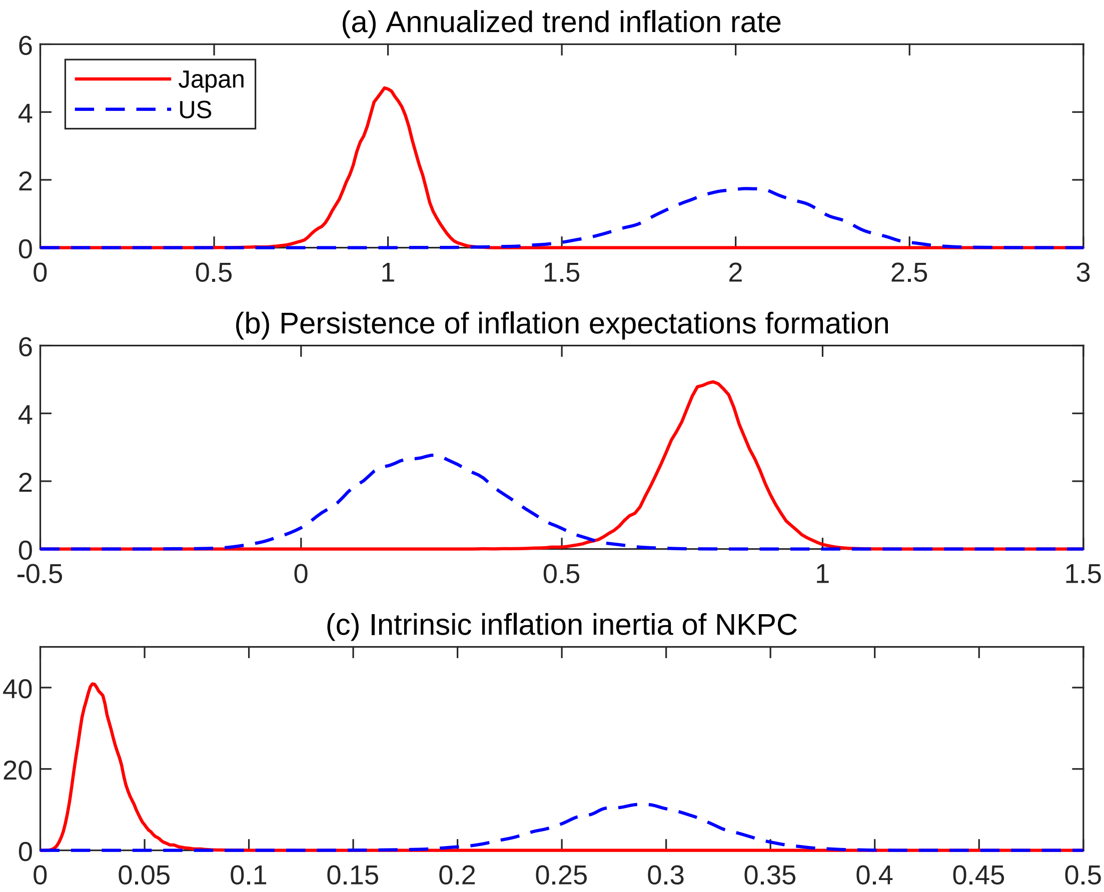
Table 5: Quasi-posterior estimates of NKPC parameters and VAR coefficients in selected specifications for Japan and the US

Japan: VED-NKPC			US: SI-NKPC		
	Mean	90% interval		Mean	90% interval
$\overline{\pi}$	0.99	$[0.84, 1.13]$	$\overline{\pi}$	2.01	$[1.63, 2.38]$
α	0.54	$[0.43, 0.66]$	α	0.53	$[0.38, 0.68]$
$-\epsilon$	3.03	$[1.45, 4.56]$	ω_s	0.49	$[0.33, 0.65]$
$A_{\pi\pi}$	0.78	$[0.64, 0.92]$	$A_{\pi\pi}$	0.24	$[0.02, 0.49]$
$A_{\pi x}$	0.03	$[-0.00, 0.06]$	$A_{\pi x}$	0.03	$[0.01, 0.05]$
$A_{x\pi}$	-0.10	$[-0.31, 0.11]$	$A_{x\pi}$	0.02	$[-0.42, 0.47]$
A_{xx}	0.87	$[0.84, 0.90]$	A_{xx}	0.95	$[0.92, 0.99]$

Note: The table reports the quasi-posterior mean and 90 percent highest quasi-posterior density interval for each of the parameters and coefficients in the selected specifications for Japan and the US, which are the VED-NKPC and the SI-NKPC with respective VAR lag lengths of one.

These two findings are also illustrated in Figure 3. This figure displays the quasi-posterior distributions of key components in the VED-NKPC for Japan and the SI-NKPC for the US. In each panel, the solid red and the dashed blue lines display the distributions for Japan and the US, respectively. Panel (a) plots the distributions of the annualized trend inflation rate $\overline{\pi}$. The distribution of the trend inflation rate in Japan is centered around the quasi-posterior mean of about one percent and lower than the US counterpart that is more dispersed around the mean of about two percent. Panel (b) depicts the distributions of the autoregressive coefficient $A_{\pi\pi}$ in the VAR's inflation equation. The distribution for Japan is more concentrated around the quasi-posterior mean than that for the US, and the two distributions are almost disjoint, so that, even in terms of quasi-posterior distributions, we confirm that the persistence of inflation expectations formation is higher in Japan.

Figure 3: Quasi-posterior distributions of key components of VED-NKPC for Japan and SI-NKPC for the US



Notes: For Japan and the US, panels (a) and (b) display the quasi-posterior distributions of the annualized trend inflation rate $\overline{\pi}$ and the autoregressive coefficient $A_{\pi\pi}$ in the VAR's inflation equation, respectively. Panel (c) plots the quasi-posterior distributions for intrinsic inflation inertia $\rho_{\pi,v}/(1-\rho_d)$ in the VED-NKPC for Japan and $\rho_{\pi,s}$ in the SI-NKPC for the US.

Panel (c) exhibits the distributions for inflation inertia of the NKPC. The distribution of the inflation inertia of the VED-NKPC for Japan (i.e., $\rho_{\pi,v}/(1-\rho_d)$) is concentrated around the quasi-posterior mean 0.03 and lower than that of the inflation inertia of the SI-NKPC for the US (i.e., $\rho_{\pi,s}$), which is more dispersed around the mean 0.28. The higher inflation inertia of the NKPC in the US is in contrast with the higher persistence of inflation expectations formation in Japan. We consider that lower trend inflation and the higher persistence of inflation expectations formation are important factors behind persistently weak inflation developments in Japan relative to the US and that the persistence measured in US inflation data may be ascribable to the higher inflation inertia of the NKPC.[20]

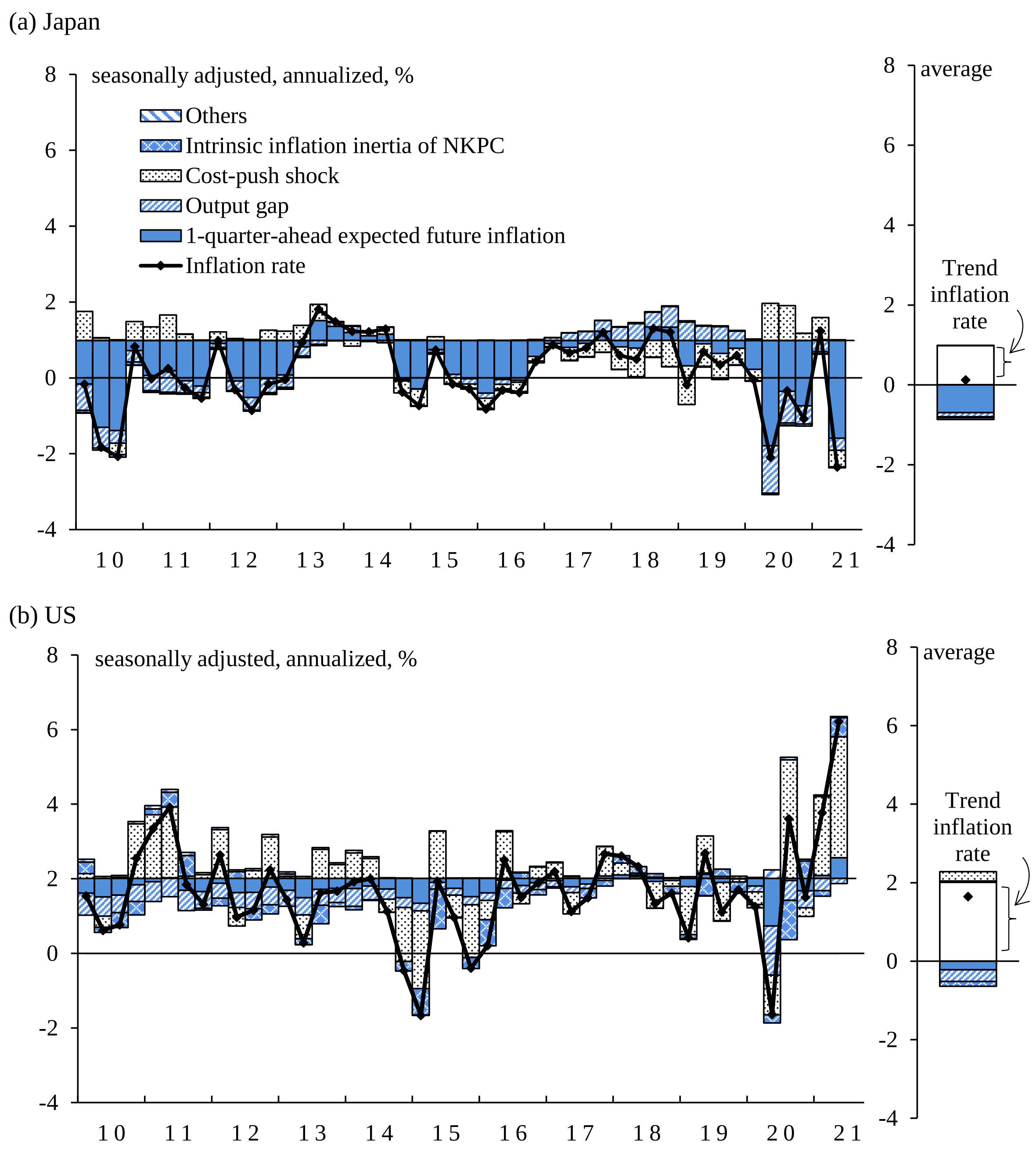
The three panels in Figure 3 provide an account for why the VED-NKPC and the SI-NKPC are selected respectively for Japan and the US. In Japan, the quasi-posterior mean of trend inflation, which is mostly determined by the data on long-term inflation expectations, is about one percent. This level of trend inflation is higher than the sample average of the inflation data that is slightly positive, which gives rise to the relatively high persistence of inflation expectations formation from the estimated VAR. This relatively high persistence explains much of the high persistence measured in the inflation data, so the inflation inertia of the NKPC should be relatively low. Therefore, the VED-NKPC is selected for Japan because it can generate low inflation inertia as shown in Table 2. As for the US, both the quasi-posterior mean of trend inflation and the sample average of the inflation data are about two percent, which leads to the relatively low persistence of inflation expectations formation from the estimated VAR and as a consequence, the inflation inertia of the NKPC should not be low. Then, as the persistence measured in the inflation data is not high, the SI-NKPC is selected for the US because it can yield a moderate degree of inflation inertia, which is intermediate between those generated by the VED-NKPC and the ROT-NKPC.

Last, we utilize the historical decompositions of actual inflation based on the selected specifications of the NKPC to examine inflation developments in Japan and the US during the post-Global Financial Crisis period. The historical decompositions are displayed in Figure 4.

Panel (a) illustrates the decomposition of the inflation rate of the CPI excluding fresh foods in Japan during the post-Global Financial Crisis period. In this panel we detect two main findings. First, the persistently weak inflation developments are caused mainly by low trend inflation and the factor of one-quarter-ahead expected future inflation. This finding reflects the above estimation result that the trend inflation rate is lower and the persistence

[20]The results on the estimates of the NKPC parameters and the VAR coefficients in the selected specification for each country are qualitatively robust with respect to the sample within the post-Global Financial Crisis period, because we confirm that the qualitatively same results are obtained by estimating the selected specifications with a rolling window of 10 years starting from 2008:Q4.

Figure 4: Decompositions of actual inflation in Japan and the US during post-Global Financial Crisis period based on selected specifications of NKPC



Notes: Panel (a) shows the historical decomposition of the inflation rate of the CPI excluding fresh foods in Japan based on the VED-NKPC and panel (b) displays that of the PCE inflation rate in the US based on the SI-NKPC. These decompositions are calculated using the quasi-posterior mean of the NKPC parameters and the VAR coefficients in the selected specifications.

of inflation expectations formation is higher in Japan relative to the US. A negative output gap or an adverse cost-push shock induces low inflation and thus generates, through the highly persistent formation of inflation expectations, low expected future inflation and hence low trend inflation, which in turn put downward pressure on present inflation through the NKPC.

Second, the cost-push shock factor—which is identified as the NKPC's residuals—makes a smaller contribution to actual inflation in Japan relative to the US, as explained later. This finding reflects the aforementioned model selection result that the VED-NKPC, that is, the specification with variable elasticity of demand is the best for Japan. Even when a cost-push shock occurs, firms in Japan that face variable elasticity hardly pass on the shock to their prices, so that the contribution of the shock factor to actual inflation is smaller in Japan.

The findings we have obtained above account for the persistently weak inflation developments in Japan. In the presence of firms' cautious price-setting behavior that reflects the purchasing attitude of consumers who are sensitive to price increases, inflation remains low and induces, through the highly persistent formation of inflation expectations, low expected future inflation and hence low trend inflation, which in turn put downward pressure on present inflation through the NKPC.

Panel (b) shows the historical decomposition of the PCE inflation rate in the US. In this panel, two main findings are also detected. First, inflation developments are pushed downward by the output gap factor. The weak output gap stemming from the Great Recession and the COVID-19 pandemic put downward pressure on inflation, and the relatively high inflation inertia of the NKPC arising from sticky information sustains the downward effect on inflation for some time.

Second, the cost-push shock factor mainly drives fluctuations in the inflation rate around its trend rate of about two percent.

In summary, for developments in US inflation during the post-Global Financial Crisis period, the weak output gap stemming from the Great Recession continues to put downward pressure on inflation, and this adverse effect on inflation remains for some time due to the relatively high inflation inertia of the NKPC that arises from sticky information. Yet its spillover effect on expected future inflation is limited because of the low persistence of inflation expectations formation, which keeps trend inflation near two percent and thus present and expected future inflation evolve around two percent.

5 Concluding Remarks

In this paper, we have compared Japanese and US inflation dynamics during the post-Global Financial Crisis period by utilizing Bayesian VAR-GMM to estimate several specifications of the NKPC. With the estimation method, we derive expectational variables in the NKPC from a VAR and can thus explicitly analyze the formation of inflation expectations, through which expected future inflation converges to trend inflation in the long run. We have selected the specification with variable elasticity of demand for Japan and that with sticky information for the US, using QML. The selected specifications have shown that the persistence of inflation expectations formation is relatively high in Japan, in line with the results of previous studies showing that inflation expectations formation is largely adaptive in Japan. Moreover, trend inflation in Japan is lower than the US counterpart of about two percent. These findings account for the persistently weak inflation developments in Japan. In the presence of firms' cautious price-setting behavior that reflects the purchasing attitude of consumers who are sensitive to price increases, inflation remains low and induces, through the highly persistent formation of inflation expectations, low expected future inflation and hence low trend inflation, which in turn put downward pressure on present inflation through the NKPC.

This paper focuses on the persistence of inflation expectations formation and the level of trend inflation as the factors behind persistently weak inflation developments in Japan relative to the US. Yet, in addition to these, we can point to the labor market and the pass-through of import prices. To this end, elaborating the labor market specification in the NKPC and extending the NKPC to an open economy are left as a possible agenda for future research.

Appendix

A Details of NKPC

This appendix presents the remaining details of the three variants of the NKPC with intrinsic inflation inertia. In the ROT-NKPC (3), the composite coefficients $\kappa_{\phi,r}$ and $\tilde{\omega}_r$ are given by

$$\kappa_{\phi,r} \equiv \frac{(\pi^{1+\theta}-1)(1-\alpha\pi^{\theta-1})(1-\omega_r)}{(\alpha\pi^{\theta-1}+\tilde{\omega}_r)(1+\theta)}, \quad \tilde{\omega}_r \equiv \omega_r[1-\alpha\pi^{\theta-1}(1-\beta\pi^{1+\theta})].$$

In the SI-NKPC (4), the composite coefficients $\kappa_{\phi,s}$, κ_ω, $\tilde{\omega}_s$, and ω_{s1} are given by

$$\kappa_{\phi,s} \equiv \frac{\{\pi^{1+\theta}[1+\omega_s(1-\alpha\beta\pi^{\theta-1})]-1\}(1-\alpha\pi^{\theta-1})(1-\omega_s)}{(\alpha\pi^{\theta-1}+\tilde{\omega}_s)(1+\theta)},$$
$$\kappa_\omega \equiv \frac{2\omega_s(1-\omega_s)(1-\alpha\pi^{\theta-1})(1-\alpha\beta\pi^{2\theta})}{(\alpha\pi^{\theta-1}+\tilde{\omega}_s)(1+\theta)}, \quad \tilde{\omega}_s \equiv \omega_s[1-\alpha\pi^{\theta-1}(1-\alpha\beta\pi^{2\theta})], \quad \omega_{s1} \equiv \omega_s\alpha\beta\pi^{2\theta}.$$

In the VED-NKPC (6), the composite coefficients $\kappa_{\phi,v}$, $\kappa_{\epsilon\zeta}$, $\kappa_{\epsilon\psi}$, $\kappa_{\epsilon d}$, ρ_d, ω_o, ϵ_1, ϵ_2, and ϵ_3 are given by

$$\kappa_{\phi,v} \equiv \frac{(\pi^{1+\gamma}-1)(1-\alpha\pi^{\gamma-1})(1+\epsilon_3)}{\alpha\pi^{\gamma-1}\{(1+\epsilon_3)[1-\epsilon_2(1+\gamma)/(\gamma-1)]+\gamma[1-\epsilon_2/(\gamma-1)]\}},$$
$$\kappa_{\epsilon\zeta} \equiv -\frac{\epsilon_3(\pi^\gamma-1)(1-\alpha\pi^{\gamma-1})}{\alpha\pi^{\gamma-1}\{(1+\epsilon_3)[1-\epsilon_2\gamma/(\gamma-1-\epsilon_2)]+\gamma\}},$$
$$\kappa_{\epsilon\psi} \equiv \frac{\epsilon_2(\pi^{1+2\gamma}-1)(1-\alpha\pi^{\gamma-1})(1+\epsilon_3)}{\alpha\pi^{\gamma-1}\{(1+\epsilon_3)[\gamma-1-\epsilon_2(1+\gamma)]+\gamma(\gamma-1-\epsilon_2)\}},$$
$$\kappa_{\epsilon d} \equiv -\frac{\epsilon_1\alpha\pi^{-1}(\pi^\gamma-1)}{(1+\epsilon_1)(1-\alpha\pi^{-1})}, \quad \rho_d \equiv \frac{\alpha\pi^{-1}(1+\epsilon_1\pi^\gamma)}{1+\epsilon_1},$$
$$\omega_o \equiv \kappa_d + \rho_d\beta\pi^{1+\gamma} + \gamma\rho_d\alpha\beta\pi^{\gamma-1}\left[\frac{\kappa_{\phi,v}(1-\alpha\beta\pi^{\gamma-1})}{1-\rho_d\alpha\beta\pi^{\gamma-1}} + \frac{\kappa_{\epsilon\zeta}\pi(1-\alpha\beta\pi^\gamma)}{1-\rho_d\alpha\beta\pi^\gamma}\right],$$
$$\epsilon_1 \equiv \epsilon\left(\frac{1-\alpha\pi^{\gamma-1}}{1-\alpha}\right)^{\frac{\gamma}{1-\gamma}}, \quad \epsilon_2 \equiv \epsilon_1\frac{1-\alpha\beta\pi^{\gamma-1}}{1-\alpha\beta\pi^{-1}}, \quad \epsilon_3 \equiv \epsilon_1\frac{1-\alpha\beta\pi^{2\gamma}}{1-\alpha\beta\pi^\gamma},$$

where

$$\kappa_d \equiv \gamma\left[\frac{\kappa_{x,v}}{2}\left(1+\frac{1}{1+\epsilon_1}\right)-\tilde{\kappa}\right] - \alpha\beta\pi^{2\gamma} - \frac{1}{\alpha\pi^{\gamma-1}},$$
$$\tilde{\kappa} \equiv \frac{(1-\alpha\pi^{\gamma-1})(1-\alpha\beta\pi^{\gamma-1})(1+\epsilon_3)}{\alpha\pi^{\gamma-1}\{(1+\epsilon_3)[1-\epsilon_2(1+\gamma)/(\gamma-1)]+\gamma[1-\epsilon_2/(\gamma-1)]\}}.$$

B Details of Bayesian VAR-GMM Estimation of NKPC

In this appendix we explain the details of the Bayesian VAR-GMM estimation of the NKPC.

B.1 Representations of NKPC for estimation

We begin by presenting the remaining representations of the NKPC for estimation. The ROT-NKPC (3) can be rewritten as

$$\hat{\pi}_t = \rho_{\pi,r}\,\hat{\pi}_{t-1} + \frac{\alpha\beta\pi^{2\theta}}{\alpha\pi^{\theta-1}+\tilde{\omega}_r}\,e_\pi' A_r Y_t + \kappa_{x,r}\,\hat{x}_t + \kappa_{\phi,r}(\theta-1)\,e_\pi' A_{r1}(I-A_{r1})^{-1}Y_t,$$

where A_r is the VAR coefficient matrix in the ROT-NKPC and $A_{r1} = \alpha\beta\pi^{\theta-1}A_r$.

The SI-NKPC (4) can be rewritten as

$$\begin{aligned}
\hat{\pi}_t = {} & \rho_{\pi,s}\,\hat{\pi}_{t-1} + \frac{\alpha\beta\pi^{2\theta}}{\alpha\pi^{\theta-1}+\tilde{\omega}_s}\,e_\pi' A_s Y_t + \kappa_{x,s}\,\hat{x}_t + \kappa_{\phi,s}(\theta-1)\,e_\pi' A_{s1}(I-A_{s1})^{-1}Y_t \\
& - \kappa_\omega\big[\theta e_\pi' + (1-\alpha\beta\pi^{2\theta})e_x'\big]A_{s2}(I-A_{s2})^{-1}Y_t \\
& + \kappa_\omega\Big\{e_x'(A_{s3}-I) - \big[\theta e_\pi' + (1-\alpha\beta\pi^{2\theta})e_x'\big]A_s(A_{s3}-I)(I-A_{s2})^{-1} \\
& + \frac{(\theta-1)(1-\alpha\beta\pi^{\theta-1})}{2(1-\alpha\beta\pi^{2\theta})}\,e_\pi' A_s(A_{s3}-I)(I-A_{s1})^{-1}\Big\}\sum_{j=1}^{\infty}(\omega_s A_s)^{j-1}Y_{t-j},
\end{aligned} \tag{A1}$$

where A_s is the VAR coefficient matrix in the SI-NKPC, $A_{s1} \equiv \alpha\beta\pi^{\theta-1}A_s$, $A_{s2} \equiv \alpha\beta\pi^{2\theta}A_s$, $A_{s3} \equiv \omega_{s1}A_s$, and e_x is the selection vector for the output gap.

The VED-NKPC (6) can be represented as

$$\begin{aligned}
\hat{\pi}_t = {} & \rho_{\pi,v}\sum_{j=1}^{\infty}\rho_d^{j-1}\hat{\pi}_{t-j} + \frac{\beta\pi^{1+\gamma}(1+\kappa_{\epsilon d})}{1-\kappa_{\epsilon d}\omega_o}\,e_\pi' A_v Y_t + \frac{\kappa_{x,v}}{1-\kappa_{\epsilon d}\omega_o}\,\hat{x}_t \\
& + \frac{\kappa_{\phi,v}}{1-\kappa_{\epsilon d}\omega_o}\left\{\gamma\left[1+\frac{\kappa_{\varepsilon d}(1-\alpha\beta\pi^{\gamma-1})}{1-\rho_d\alpha\beta\pi^{\gamma-1}}\right]-1\right\}e_\pi' A_{v1}(I-A_{v1})^{-1}Y_t \\
& + \frac{\kappa_{\epsilon\zeta}}{1-\kappa_{\epsilon d}\omega_o}\left\{\gamma\left[1+\frac{\kappa_{\varepsilon d}(1-\alpha\beta\pi^{\gamma})}{1-\rho_d\alpha\beta\pi^{\gamma}}\right]e_\pi' + 2(1-\alpha\beta\pi^{\gamma})e_x'\right\}A_{v2}(I-A_{v2})^{-1}Y_t \\
& + \frac{\kappa_{\epsilon\psi}}{1-\kappa_{\epsilon d}\omega_o}\,e_\pi' A_{v3}(I-A_{v3})^{-1}Y_t,
\end{aligned} \tag{A2}$$

where A_v is the VAR coefficient matrix in the VED-NKPC, $A_{v1} = \alpha\beta\pi^{\gamma-1}A_v$, $A_{v2} = \alpha\beta\pi^{\gamma}A_v$, and $A_{v3} = \alpha\beta\pi^{-1}A_v$.

The SI-NKPC (A1) and the VED-NKPC (A2) contain infinite backward summation. We approximate the summation with the truncated sum of 16 lags, following Gemma et al. (2017). We also experimented with 12 or 20 lags, without the results being qualitatively affected.

B.2 Block Metropolis-Hastings algorithm in Bayesian VAR-GMM estimation of NKPC

In this appendix we explain the procedure of the Block Metropolis-Hastings algorithm in the Bayesian VAR-GMM estimation of the NKPC. Specifically, we apply the algorithm to obtain the quasi-posterior distribution of the NKPC parameters ϑ and the VAR coefficients $vec(A)$. The algorithm is a natural application of the standard Block Metropolis-Hastings algorithm described in Herbst and Schorfheide (2015) but with clear-cut parameter blocks in light of the fundamental property of VAR-GMM. We set two blocks, one for the VAR coefficients and the other for the NKPC parameters. The algorithm consists of the following steps:

1. Estimate a VAR solely to obtain the quasi-posterior mean A_{-1} and the quasi-posterior variance Σ_{-1}. Initialize $vec(A_0)$ at $vec(A_{-1})$.

2. Initialize ϑ_0 at their quasi-posterior mode $\hat{\vartheta}$, fixing $vec(A)$ at $vec(A_{-1})$. This requires numerical maximization of their log quasi-posterior probability density.

3. Apply the Block Metropolis-Hastings algorithm. First, draw candidate values $vec(\tilde{A})$ of the VAR coefficients from a Gaussian proposal distribution with mean $vec(A_{j-1})$ and variance $c_1^2\Sigma_{-1}$, where $vec(A_{j-1})$ is the previous draw of $vec(A)$ and c_1 is the scaling parameter chosen to obtain an acceptance rate of approximately 25 percent.

   Set
   $$A_j = \begin{cases} \tilde{A} & \text{with probability } \alpha_{1,j} \\ A_{j-1} & \text{with probability } 1 - \alpha_{1,j}, \end{cases}$$
   where
   $$\alpha_{1,j} = \min\left\{1, \frac{p(\vartheta_{j-1}, vec(\tilde{A})|Y)}{p(\vartheta_{j-1}, vec(A_{j-1})|Y)}\right\}.$$

4. Then, draw candidate values $\tilde{\vartheta}$ of the NKPC parameters from a Gaussian proposal distribution with mean ϑ_{j-1} and variance $c_2^2\hat{\Sigma}$, where ϑ_{j-1} is the previous draw of ϑ, $\hat{\Sigma}$ is the negative of the inverse Hessian of the log quasi-posterior probability density of ϑ evaluated at $\hat{\vartheta}$, calculated as

$$\hat{\Sigma} = -\left(\left.\frac{\partial^2 \log(p(\vartheta, vec(A_{-1})|Y))}{\partial\vartheta\partial\vartheta'}\right|_{\vartheta=\hat{\vartheta}}\right)^{-1}$$

and c_2 is the scaling parameter chosen to obtain an acceptance rate of approximately 25 percent.

Set

$$\vartheta_j = \begin{cases} \tilde{\vartheta} & \text{with probability } \alpha_{2,j} \\ \vartheta_{j-1} & \text{with probability } 1-\alpha_{2,j}, \end{cases}$$

where

$$\alpha_{2,j} = \min\left\{1, \frac{p(\tilde{\vartheta}, vec(A_j)|Y)}{p(\vartheta_{j-1}, vec(A_j)|Y)}\right\}.$$

5. Increment j to $j+1$ and return to step 3.

6. Repeat from step 3 to step 5. Discard a certain number of first draws as a burn-in and use the remaining draws to obtain the quasi-posterior distribution of the NKPC parameters and the VAR coefficients.

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