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Trend Inflation and Evolving Inflation Dynamics: A Bayesian GMM Analysis*

Yasufumi Gemma† Takushi Kurozumi‡ Mototsugu Shintani§

Abstract

Inflation dynamics are investigated by estimating a generalized version of the New Keynesian Phillips curve (NKPC) of Galí and Gertler (1999) using Bayesian GMM. US macroeconomic data suggests that the generalized NKPC (GNKPC) performs best in terms of quasi-marginal likelihood among those considered both during and after the Great Inflation period. The estimated GNKPC indicates that when trend inflation fell after the Great Inflation period, the probability of price change decreased and the GNKPC flattened, which is in line with findings by previous studies.

JEL Classification: C11, C26, E31

Keywords: Inflation dynamics, Trend inflation, Inflation inertia, Bayesian GMM, Quasi-marginal likelihood

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1 Introduction

The dynamics of inflation have long been the subject of intense investigation in macroeconomics. To describe inflation dynamics, the New Keynesian Phillips curve (NKPC) is often derived by assuming either zero trend inflation or price indexation to trend and lagged inflation.[1] However, these assumptions in the canonical NKPC are at odds with empirical observations. Recent studies thus examine the effect of nonzero trend inflation on the NKPC, particularly without the indexation.[2] The studies have shown that such a generalized NKPC (GNKPC) has substantially distinct features from the canonical NKPC, thereby generating important implications for policy and welfare. This finding raises the question as to which is a more plausible description of inflation dynamics, the GNKPC or the canonical NKPC.

This paper estimates and evaluates the GNKPC using a novel model selection procedure under the framework of limited-information Bayesian estimation. In the empirical literature on NKPCs, two main approaches have been adopted: limited-information (or single-equation) methods and full-information (or system) methods. For example, the GMM estimation of the NKPC in Galí and Gertler (1999) and the minimum distance estimation of the GNKPC in Cogley and Sbordone (2008) can be classified as limited-information methods. On the other hand, NKPCs in the estimated dynamic stochastic general equilibrium (DSGE) models of Christiano et al. (2005) and Smets and Wouters (2007) can be categorized as full-information methods. In a recent paper, Hirose et al. (2020) conduct a full-information Bayesian analysis to compare a GNKPC and an NKPC in an otherwise identical DSGE model, and show that the model with the GNKPC outperforms that with the NKPC in terms of marginal likelihood. However, as Mavroeidis et al. (2014) emphasize in their review of the empirical literature on NKPCs, "By imposing a theoretical model

[1]See, e.g., Woodford (2003), Christiano et al. (2005), and Smets and Wouters (2007).

[2]See, e.g., Alves (2014), Ascari (2004), Ascari and Ropele (2009), Coibion and Gorodnichenko (2011), Coibion et al. (2012), Kurozumi and Van Zandweghe (2016, 2020, 2023), and Shirota (2015). For a review of the literature, see, e.g., Ascari and Sbordone (2014).

on all the variables in the system, full-information methods have the potential to improve estimator precision, but they also introduce the risk of misspecification in other equations, inducing bias or inconsistency of the NKPC parameters of interest (p. 125)." In contrast, the limited-information methods, including the single-equation GMM used by Galí and Gertler (1999), are much less subject to such a misspecification issue. Yet the GMM estimation of NKPCs has been known to suffer from a weak-identification problem, especially when NKPCs are nearly flat, or when the variation of inflation expectations is small as a result of successful monetary policy in anchoring the expectations (Mavroeidis et al., 2014, p. 139). To circumvent the weak-identification issue, our paper estimates the GNKPC with Bayesian GMM and evaluates its empirical performance using the quasi-marginal likelihood (QML) proposed by Inoue and Shintani (2018), who theoretically show that the model selection consistency of QML is robust to the presence of weakly identified parameters.[3]

To reconcile NKPCs with the inflation data that exhibit persistence, previous studies have suggested introducing backward-looking price setting because it generates inflation inertia in NKPCs. Such an empirically plausible version of the NKPC is often called the hybrid NKPC. In a Calvo (1983) staggered price model, Galí and Gertler (1999) incorporate rule of thumb (ROT) price setters, while Woodford (2003) embeds dynamic price indexation (DPI) to lagged inflation. In the ROT specification, the hybrid NKPC is based on the presence of two types of firms, optimizing and ROT firms. In each period, both types of firms set prices using (full) indexation to trend inflation with a certain probability, while with the remaining probability, optimizing firms choose prices optimally and ROT firms adjust prices using a backward-looking ROT. In the DPI specification, the hybrid NKPC arises from the price-setting behavior of firms that adjust prices using (full) DPI to an average of lagged and trend inflation with a certain probability and optimize prices with the remaining probability

[3]This result does not necessarily imply that Bayesian GMM inference is valid for weakly identified parameters. However, Kleibergen and Mavroeidis (2014) point out that Bayesian methods can mitigate the weak-identification issue and be considered as an alternative to the weak-identification robust GMM approach employed by Kleibergen and Mavroeidis (2009).

in each period. Inoue and Shintani (2018) estimate these two types of the hybrid NKPC using Bayesian GMM and show that the Galí-Gertler NKPC outperforms the Woodford NKPC in terms of QML.[4] In light of this empirical result, our paper employs the Galí-Gertler NKPC as the baseline NKPC to be compared with the GNKPC.

As our primary specification of the GNKPC, we consider a generalized version of the Galí-Gertler NKPC in which all types of firms with a certain probability keep prices unchanged instead of setting prices with the indexation. This small change gives rise to two notable features of the resulting GNKPC that are substantially different from those of the Galí-Gertler NKPC. First, the driving force of inflation in the GNKPC includes not only the real marginal cost, which further consists of the real unit labor cost and relative price distortion, but also the expected growth rates of future demand and the expected discount rates on future profits under nonzero trend inflation. Second, and more importantly, the GNKPC slope and inflation-inertia coefficients depend on the level of trend inflation, as well as the probability of price change and the fraction of ROT firms. These two features hold even for a Galí-Gertler GNKPC in which all types of firms with a certain probability set prices using partial indexation to trend inflation, called the Galí-Gertler GNKPC with indexation.

In addition to the Galí-Gertler GNKPC, we also consider a generalized version of the Woodford NKPC in which firms with a certain probability set prices using partial DPI to an average of lagged and trend inflation instead of the full DPI. This Woodford GNKPC also has two features similar to those of the Galí-Gertler GNKPC and includes as a special case a simple variant of the GNKPC of Cogley and Sbordone (2008) in which trend inflation is constant.[5] Moreover, we consider a GNKPC that (theoretically) nests both Galí-Gertler and Woodford GNKPCs.

The main findings of the paper are twofold. First, US macroeconomic data suggests that the Galí-Gertler GNKPC outperforms the baseline (Galí-Gertler) NKPC, the Galí-

[4] The latter NKPC is referred to as the NKPC of Smets and Wouters (2007) in Inoue and Shintani (2018).

[5] The GNKPC of Cogley and Sbordone (2008) features time-varying trend inflation and partial DPI only to lagged inflation.

Gertler GNKPC with indexation, the Woodford and the Cogley-Sbordone GNKPCs, and the GNKPC that nests both Galí-Gertler and Woodford GNKPCs, in terms of QML, both during and after the Great Inflation period. Second, the estimated Galí-Gertler GNKPC indicates that when trend inflation fell after the Great Inflation period, the probability of price change decreased and the GNKPC flattened. Therefore, the Phillips curve Alan Greenspan (and Ben Bernanke) faced is not the same as the one Paul Volcker had faced, as conjectured by Ball et al. (1988).[6]

These findings are comparable to empirical evidence reported in previous studies. Our finding that the Galí-Gertler GNKPC empirically outperforms the Galí-Gertler NKPC coincides with the result of Hirose et al. (2020), which is based on the full-information Bayesian method.[7] Since the Galí-Gertler and the Woodford GNKPCs are generalizations of their NKPC counterparts, our finding that the Galí-Gertler GNKPC outperforms the Woodford GNKPC is analogous to the result of Inoue and Shintani (2018) on the NKPC counterparts. While Cogley and Sbordone (2008) reach the conclusion that there is no need for backward-looking price setting in their GNKPC once drifting trend inflation is incorporated in it, our finding suggests that their conclusion may depend on the specification of backward-looking price setting (i.e., DPI to lagged inflation), in addition to the drifting trend inflation. In our estimated Galí-Gertler GNKPC, the probability of price change decreased after the Great Inflation period, in line with the micro evidence of Nakamura et al. (2018) that the frequency of regular price change declined after that period. The flattening of the estimated GNKPC is consistent with the empirical results of Benati (2007), Ball and Mazumder (2011), and the

[6]The concurrence of the fall in trend inflation, the decrease in the probability of price change, and the flattening of the slope in the estimated GNKPC coincides with the theoretical prediction in the literature on endogenous price stickiness, such as Ball et al. (1988), Levin and Yun (2007), and Kurozumi (2016).

[7]Restricting attention to a post-Great Inflation period, Ascari et al. (2011) estimate three DSGE models with distinct NKPCs: an NKPC with (full) DPI to lagged inflation as in Christiano et al. (2005), a GNKPC with partial DPI to lagged inflation as in Cogley and Sbordone (2008), and a GNKPC with partial price indexation to trend inflation. Their model selection based on marginal likelihood shows that the latter GNKPC performs best, while the NKPC performs worst.

International Monetary Fund (2013), among others.

The remainder of the paper proceeds as follows. Section 2 presents our main specification of the GNKPC. Section 3 explains our method and data for estimating and evaluating it. Section 4 shows the results of the model selection and accounts for the estimation results of the selected model. Section 5 concludes.

2 Generalized New Keynesian Phillips Curve

This section presents a generalized version of the hybrid NKPC of Galí and Gertler (1999).

2.1 Main specification: Galí-Gertler GNKPC

Our main specification of the GNKPC is derived from a Calvo (1983) staggered price model in which there are two types of firms, optimizing firms and rule of thumb (ROT) firms, and $\omega_r \in [0, 1)$ denotes the fraction of ROT firms, as in Galí and Gertler (1999). In each period, both types of firms keep prices unchanged with probability $\lambda \in [0, 1)$, while with the remaining probability, optimizing firms choose prices optimally and ROT firms set prices using a backward-looking ROT. As shown in Appendix, the GNKPC can be obtained as

$$\hat{\pi}_t = \gamma_b \hat{\pi}_{t-1} + \gamma_f E_t \hat{\pi}_{t+1} + \kappa \hat{mc}_t + \kappa_f \sum_{j=1}^{\infty} \rho_f^j \left(E_t \hat{gy}_{t+j} + \theta E_t \hat{\pi}_{t+j} - E_t \hat{r}_{t+j-1} \right) \tag{1}$$

under the assumption

$$\lambda \pi^{\theta} < \min(1, \pi), \tag{2}$$

where hatted variables denote log-deviations from steady-state values, E_t is the expectation operator conditional on information available in period t, π_t is the inflation rate, mc_t is the real marginal cost, gy_t is the output growth rate, r_t is the nominal interest rate, π is the trend inflation rate, and $\theta > 1$ is the elasticity of substitution between individual differentiated goods.[8] The reduced-form coefficients are given by $\gamma_b \equiv \omega_r/\phi$, $\gamma_f \equiv \beta\lambda\pi^{\theta}/\phi$, $\kappa \equiv (1-\lambda\pi^{\theta-1})(1-\beta\lambda\pi^{\theta})(1-\omega_r)/\phi$, $\kappa_f \equiv (\pi-1)(1-\lambda\pi^{\theta-1})(1-\omega_r)/\phi$, $\phi \equiv \lambda\pi^{\theta-1}+\omega_r[1-\lambda\pi^{\theta-1}(1-\beta\pi)]$, and $\rho_f \equiv \beta\lambda\pi^{\theta-1}$, where $\beta \in (0,1)$ is the subjective discount factor.

In the GNKPC (1), two points are worth noting. First, the driving force of inflation in the GNKPC includes not only the real marginal cost mc_t but also the expected growth rates of future demand $E_t[\hat{gy}_{t+j}+(\theta-1)\hat{\pi}_{t+j}]$ and the expected discount rates on future profits $E_t[\hat{r}_{t+j-1}-\hat{\pi}_{t+j}]$ under nonzero trend inflation, i.e., $\pi \neq 1$. Furthermore, the real marginal cost consists of the real unit labor cost ulc_t and the relative price distortion Δ_t:

$$\hat{mc}_t = \hat{ulc}_t - \hat{\Delta}_t, \tag{3}$$

since the distortion has a first-order effect in the GNKPC under nonzero trend inflation. Then, the law of motion of the distortion is given by

$$\hat{\Delta}_t = \rho_\Delta \hat{\Delta}_{t-1} + \kappa_\Delta \hat{\pi}_t = \kappa_\Delta \sum_{j=0}^{\infty} \rho_\Delta^j \hat{\pi}_{t-j}, \tag{4}$$

where $\rho_\Delta \equiv \lambda\pi^{\theta}$ and $\kappa_\Delta \equiv \theta\lambda\pi^{\theta-1}(\pi-1)/(1-\lambda\pi^{\theta-1})$.

Second, both the slope κ and the inflation-inertia coefficient γ_b in the GNKPC depend not only on the probability of no price change λ and the fraction of ROT firms ω_r but also on the level of trend inflation π and the elasticity of substitution θ.[9] Table 1 summarizes how the slope κ and the inflation-inertia coefficient γ_b are related to the model parameters λ, ω_r, π, and θ. As shown on the second line of the table, a flatter slope κ is caused by a

[8]Note that assumption (2) does not depend on the fraction of ROT firms ω_r.

[9]The slope κ and the inflation-inertia coefficient γ_b depend on the subjective discount factor β as well. As β decreases, the slope κ steepens and the inertia coefficient γ_b increases. This property arises because only optimizing firms take into account the discount factor β. A decrease in β makes optimizing firms myopic, so they respond more to the current real marginal cost and less to the expected future one. Their increased sensitivity to the current real marginal cost steepens the slope κ, while their comparative indifference to the expected future one reduces the inflation-expectation coefficient γ_f and increases the inertia coefficient γ_b.

Table 1: Relationships between model parameters and reduced-form coefficients of GNKPC

	λ	ω_r	π	θ (if $\pi > 1$)	θ (if $\pi < 1$)
slope κ	$-$	$-$	$-$	$-$	$+$
inflation inertia γ_b	$-$	$+$	$-$	$-$	$+$

Note: The model parameters λ, ω_r, π, and θ denote the probability of no price change, the fraction of ROT firms, trend inflation, and the elasticity of substitution, respectively.

higher probability λ, a larger fraction ω_r, or higher trend inflation π. It is also generated by a higher elasticity θ if trend inflation is positive (i.e., $\pi > 1$) and by a lower elasticity θ if trend inflation is negative (i.e., $\pi < 1$). These factors, except for a larger fraction ω_r, give rise to a lower inflation-inertia coefficient γ_b, and so does a smaller fraction ω_r, as seen on the last line of the table.

To understand the relationships presented in Table 1, the following log-linearized aggregate price equation is particularly helpful:

$$0 = (1 - \omega_r)(1 - \lambda\pi^{\theta-1})\,\hat{p}_t^o + \omega_r(1 - \lambda\pi^{\theta-1})\,\hat{p}_t^r + \lambda\pi^{\theta-1}\,(-\hat{\pi}_t)\,.$$

This equation shows that the steady-state contributions of optimizing firms ($\hat{p}_t^o$), ROT firms ($\hat{p}_t^r$), and non-adjusting firms ($-\hat{\pi}_t$) to the aggregate price are given by $(1-\omega_r)(1-\lambda\pi^{\theta-1})$, $\omega_r(1-\lambda\pi^{\theta-1})$, and $\lambda\pi^{\theta-1}$, respectively. The slope κ flattens when the contribution of optimizing firms declines, since only these firms respond (directly) to the real marginal cost. The inflation-inertia coefficient γ_b decreases when the contribution of ROT firms declines. Because a higher probability of no price change λ reduces the contributions of both types of firms, it flattens the slope and decreases the inflation-inertia coefficient. A smaller fraction of ROT firms ω_r reduces the contribution of such firms while raising that of optimizing firms, thus decreasing the inertia coefficient and steepening the slope. Higher trend inflation π flattens the slope and decreases the inertia coefficient, since it reduces the contributions of both types of firms. Likewise, under positive trend inflation (i.e., $\pi > 1$), a higher elasticity of substitution θ reduces them and thus generates a flatter slope and a smaller inertia coefficient. If trend inflation is negative (i.e., $\pi < 1$), a higher elasticity raises them, thus inducing a steeper slope and a larger inertia coefficient.

2.2 Galí-Gertler NKPC and GNKPC with indexation

The GNKPC is a simple variant of the hybrid NKPC of Galí and Gertler (1999). Indeed, the NKPC can be obtained only by altering the model so that the prices that are kept unchanged in the aforementioned model setting are instead adjusted using (full) indexation to trend inflation.[10] Then, the parameter λ represents the probability of trend inflation-indexed price setting. Much more importantly, the level of trend inflation no longer influences the NKPC coefficients and there is no first-order effect of the relative price distortion, $\hat{\Delta}_t = 0$. In fact, the NKPC coincides with the GNKPC (1) in which its coefficients are set at their values under zero trend inflation (i.e., $\pi = 1$) and there is no distortion term:

$$\hat{\pi}_t = \gamma_{b1}\hat{\pi}_{t-1} + \gamma_{f1}E_t\hat{\pi}_{t+1} + \kappa_1 u\hat{l}c_t, \tag{5}$$

where γ_{b1}, γ_{f1}, and κ_1 correspond to γ_b, γ_f, and κ at $\pi = 1$, respectively. It is worth noting that the GNKPC (1) and the NKPC (5) coincide only when trend inflation is zero.

We can also consider a GNKPC that nests both GNKPC (1) and NKPC (5). It can be derived by generalizing the above model setting (for the NKPC) using partial indexation to trend inflation with the degree $\omega_i \in [0, 1]$, under the assumption

$$\lambda\pi^{\theta(1-\omega_i)} < \min\left(1, \pi^{1-\omega_i}\right), \tag{6}$$

which generalizes assumption (2). This GNKPC with indexation takes the same form as (1), but with the coefficients $\gamma_b = \omega_r/\phi$, $\gamma_f = \beta\lambda\pi^{\theta(1-\omega_i)}/\phi$, $\kappa = (1 - \lambda\pi^{(\theta-1)(1-\omega_i)})(1 - \beta\lambda\pi^{\theta(1-\omega_i)})(1 - \omega_r)/\phi$, $\kappa_f = (\pi^{1-\omega_i} - 1)(1 - \lambda\pi^{(\theta-1)(1-\omega_i)})(1 - \omega_r)/\phi$, $\phi = \lambda\pi^{(\theta-1)(1-\omega_i)} + \omega_r[1 - \lambda\pi^{(\theta-1)(1-\omega_i)}(1 - \beta\pi^{1-\omega_i})]$, and $\rho_f \equiv \beta\lambda\pi^{(\theta-1)(1-\omega_i)}$. In addition, the law of motion

[10] For the NKPC (5), assumption (2) is redundant.

of the relative price distortion is of the same form as (4), but with $\rho_\Delta \equiv \lambda\pi^{\theta(1-\omega_i)}$ and $\kappa_\Delta = \theta\lambda\pi^{(\theta-1)(1-\omega_i)}(\pi^{1-\omega_i} - 1)/(1 - \lambda\pi^{(\theta-1)(1-\omega_i)})$. The GNKPC with indexation includes the GNKPC (1) and the NKPC (5) as the special cases of $\omega_i = 0$ and $\omega_i = 1$, respectively.

3 Estimation Method and Data

This section explains our method and data for estimating and evaluating the GNKPC and the NKPC presented in the preceding section.

3.1 Bayesian GMM

Early empirical studies on NKPCs have extensively used GMM, which is classified as a limited-information method. Moment conditions in GMM estimation are derived using instruments that are orthogonal to expectation errors obtained from the forward-looking variables of NKPCs being replaced with their realizations. This procedure is used by, for instance, Galí and Gertler (1999) and Galí et al. (2005).[11] An alternative popular limited-information method is the two-step procedure that first derives the forward-looking variables of an NKPC from a VAR and then conducts minimum distance estimation of model parameters using theoretical restrictions on the NKPC. This approach is adopted by, for example, Sbordone (2002) and Cogley and Sbordone (2008).

The most distinctive feature of our paper from previous studies is that we utilize Bayesian GMM in estimating the GNKPC and the NKPC instead of classical GMM. As in the early empirical studies, we use moment conditions with the GNKPC's and the NKPC's forward-looking variables being replaced by their realizations and with instruments orthogonal to their expectation errors. We then conduct Bayesian GMM estimation of the single equation (i.e., the GNKPC or NKPC) based on the moment conditions. A similar approach has been taken by Lubik and Schorfheide (2007) for the estimation of monetary policy rules and by

[11]The procedure is sometimes referred to as the generalized instrumental variables (IV) estimation.

Inoue and Shintani (2018) for the estimation of hybrid NKPCs. Within the framework of Bayesian GMM, the classical GMM estimator can be viewed as a special case with flat priors. The limited-information Bayesian GMM estimation of the GNKPC and the NKPC has at least three advantages over the estimation procedures used in previous studies on NKPCs.

First, the limited-information method is much less subject to misspecification issues than full-information methods, which have been widely used in most of the previous studies on estimated DSGE models with an NKPC or GNKPC, such as Christiano et al. (2005), Smets and Wouters (2007), Ascari et al. (2011), and Hirose et al. (2020). Bayesian GMM leaves unspecified other equations in the model.

Second, Bayesian methods can mitigate the weak-identification issue that has been extensively discussed in the empirical literature on NKPCs, such as Mavroeidis (2005), Nason and Smith (2008), Canova and Sala (2009), Kleibergen and Mavroeidis (2009, 2014), Magnusson and Mavroeidis (2014), and Mavroeidis et al. (2014). As pointed out by Kleibergen and Mavroeidis (2014), Bayesian methods can be considered as an alternative to the weak-identification robust GMM approach employed by Kleibergen and Mavroeidis (2009).

Third, as shown by Inoue and Shintani (2018), the QML model selection criterion leads to consistent model selection. In particular, model selection based on QML is theoretically valid, even if some model parameters are weakly identified or set identified. Inoue and Shintani (2018) use this property to compare alternative specifications of hybrid NKPCs. This framework is useful for our analysis in comparing the performance of the GNKPC and the NKPC presented in the preceding section.[12]

In the econometric literature, our estimator belongs to the class of limited-information quasi-Bayesian estimators. Its asymptotic properties, such as consistency and asymptotic normality, have been established by Kim (2002) and Chernozhukov and Hong (2003). The latter study emphasizes a computational advantage of the Bayesian GMM estimator over the classical one, since the Markov Chain Monte Carlo (MCMC) method can be utilized even if

[12]Christiano et al. (2016) also employ QML in the selection of DSGE models estimated with a minimum distance approach for impulse response functions.

GMM objective functions cannot be expressed in a simple form.

Let ϑ denote an m-dimensional vector of model parameters to be estimated and $g_t(\vartheta)$ be an n-dimensional vector of moment functions that satisfies $E(g_t(\vartheta)) = 0$ at a true value of $\vartheta = \vartheta_0$, where E is the unconditional expectation operator. In our estimation, trend inflation π is assumed to meet the condition $\log \pi = E \log \pi_t$, i.e., $E\hat{\pi}_t = 0$. Thus, $g_t(\vartheta)$ is defined as

$$g_t(\vartheta) = [\, u_t \quad \mathbf{z}_t u_t \quad u_{\pi,t} \,]', \tag{7}$$

where $\mathbf{z}_t$ is an $(n-2)$-dimensional vector of instruments and $u_{\pi,t} = \log \pi_t - \log \pi$. As for ϑ and u_t, in the case of the GNKPC or that with indexation we have $\vartheta = [\pi \ \theta \ \lambda \ \omega_r]'$ or $\vartheta = [\pi \ \theta \ \lambda \ \omega_r \ \omega_i]'$ and

$$u_t = u_{\pi,t} - \gamma_b u_{\pi,t-1} - \gamma_f u_{\pi,t+1} - \kappa \left(\hat{ulc}_t - \kappa_\Delta \sum_{j=0}^{\infty} \rho_\Delta^j u_{\pi,t-j} \right) - \kappa_f \sum_{j=1}^{\infty} \rho_f^j \left(\hat{gy}_{t+j} + \theta u_{\pi,t+j} - \hat{r}_{t+j-1} \right),$$

which can be obtained by combining (1), (3), and (4). To approximate the infinite sums of log-deviations of inflation, output growth, and the nominal interest rate from steady-state values, we use their truncated sums, following Galí et al. (2005).[13,14] In the case of the

[13]For the quarterly model, this paper employs 16 lags of the log-deviation of inflation and 16 leads of the log-deviations of inflation, output growth, and the nominal interest rate. We also experimented with 12 lags and 12 leads, and with 20 lags and 20 leads, and confirmed that the empirical results presented in this paper hold qualitatively.

[14]Taking second quasi-differences of the GNKPC, we can obtain a representation of it with no infinite sums. However, we claim that such a representation of the GNKPC and the NKPC (5) are not comparable. We took second quasi-differences of the NKPC in a similar manner and confirmed that such a representation and the original one (5) of the NKPC lead to different quasi-posterior estimates of model parameters and distinct values of QML. This finding implies that the GNKPC representation with no infinite sums and the NKPC (5) are not comparable. Therefore, in the estimation of the GNKPC, we use a representation with truncated sums, as in Galí et al. (2005).

NKPC (5), we have $\vartheta = [\pi\ \theta\ \lambda\ \omega_r]'$ and

$$u_t = u_{\pi,t} - \gamma_{b1} u_{\pi,t-1} - \gamma_{f1} u_{\pi,t+1} - \kappa_1 u\hat{l}c_t.$$

This paper employs the efficient two-step GMM estimator.[15] This estimator maximizes the objective function $\hat{q}(\vartheta) = -(1/2)g(\vartheta)'\hat{W}\,g(\vartheta)$ with regard to $\vartheta \in \Theta$, where $g(\vartheta) = (1/\sqrt{T})\sum_{t=1}^{T} g_t(\vartheta)$ and $\hat{W}$ is a consistent estimator of an $n \times n$ positive semidefinite optimal weighting matrix based on the HAC estimator of Newey and West (1987). The matrix $\hat{W}$ is calculated as $\hat{W} = [\Gamma_j(\tilde{\vartheta}) + \sum_{j=1}^{J}(j/J)(\Gamma_j(\tilde{\vartheta}) + \Gamma_j(\tilde{\vartheta})')]^{-1}$, where $\Gamma_j(\vartheta) = [1/(T-j)]\sum_{t=j+1}^{T} g_t(\vartheta)g_{t-j}(\vartheta)'$, $\tilde{\vartheta}$ is a first-step consistent estimator of the true value ϑ_0, and the lag length J is set by the automatic bandwidth selection method of Andrews (1991).[16]

Next, Bayesian methods are applied to the GMM estimation. Following Chernozhukov and Hong (2003), the quasi-posterior distribution of ϑ is defined as

$$\frac{\exp(\hat{q}(\vartheta))\,p(\vartheta)}{\int_{\Theta}\exp(\hat{q}(\vartheta))\,p(\vartheta)\,d\vartheta},$$

where $p(\vartheta)$ is the prior distribution for ϑ. The mean and credible interval of the quasi-posterior distribution can be computed using the MCMC method.[17]

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[15]Following most of the previous studies, such as Galí and Gertler (1999) and Galí et al. (2005), our paper uses the two-step GMM estimator rather than the continuous updating GMM estimator proposed by Hansen et al. (1996).

[16]The HAC covariance matrix estimator of the moment functions (7) is employed for two reasons. First, the inflation gap $u_{\pi,t} = \log \pi_t - \log \pi$ in (7) is possibly serially correlated. Second, the use of the HAC estimator makes the resulting estimation valid not only for the exact specifications of the GNKPC and the NKPC but also for the case in which a disturbance (e.g., cost-push shock) is incorporated in them.

[17]In our estimation, $210,000$ MCMC draws that meet assumption (6) were generated, and the first $10,000$ draws were discarded as a burn-in. The random-walk Metropolis–Hastings algorithm was applied to generate draws from the quasi-posterior distribution. The scale factor for the jumping distribution in the algorithm was adjusted so that an acceptance ratio of around 25 percent is obtained.

3.2 Quasi-Bayesian model selection

For the model selection, this paper follows Inoue and Shintani (2018) in using the QML defined as

$$\int_{\Theta} \exp(\hat{q}(\vartheta))\, p(\vartheta)\, d\vartheta.$$

As with the model selection based on marginal likelihood in full-information Bayesian estimation, a model with higher QML is regarded as superior.[18]

The QML is calculated using the modified harmonic mean method. This method computes the QML as the reciprocal of

$$E\left[\frac{w(\vartheta)}{\exp(\hat{q}(\vartheta))\, p(\vartheta)}\right],$$

which is evaluated using MCMC draws, given a weighting function $w(\vartheta)$. This paper considers two alternative choices for the weighting function proposed in the literature. The first choice is suggested by Geweke (1999), who sets $w(\vartheta)$ to be the truncated normal density

$$w(\vartheta) = \frac{\exp[-(1/2)(\vartheta - \bar{\vartheta})'\bar{V}_{\vartheta}^{-1}(\vartheta - \bar{\vartheta})]}{(2\pi)^{m/2}|\bar{V}_{\vartheta}|^{1/2}} \frac{\mathbf{1}\{(\vartheta - \bar{\vartheta})'\bar{V}_{\vartheta}^{-1}(\vartheta - \bar{\vartheta}) \leq \chi^2_{m,\tau}\}}{\tau},$$

where $\bar{\vartheta}$ is the quasi-posterior mean, $\bar{V}_{\vartheta}$ is the quasi-posterior covariance matrix, π in this subsection is the circular constant, $\mathbf{1}\{\cdot\}$ is an indicator function, $\chi^2_{m,\tau}$ is the 100τth percentile of the chi-square distribution with m degrees of freedom, and $\tau \in (0,1)$ is a constant.[19] The second choice is proposed by Sims et al. (2008). They argue that the choice of Geweke (1999) may not work well when the posterior distribution is non-elliptical, and suggest the

[18] Theoretically, the model selection is said to be consistent if the probability of selecting the true model approaches one as the sample size goes to infinity. The consistency of the model selection based on the QML has been shown by Kim (2014) for nested models and by Inoue and Shintani (2018) for nonnested models.

[19] Recall that m denotes the number of model parameters to be estimated.

weighting function given by

$$w(\vartheta) = \frac{\Gamma(m/2)}{2\pi^{m/2}|\hat{V}_\vartheta|^{1/2}} \frac{f(r)}{r^{m-1}} \frac{\mathbf{1}\{\hat{q}(\vartheta) + \log p(\vartheta) > L_{1-q}\}}{\bar{\tau}},$$

where $\hat{V}_\vartheta$ is the second moment matrix centered around the quasi-posterior mode $\hat{\vartheta}$, $f(r) = [vr^{v-1}/(c_{90}^v/0.9 - c_1^v)]\,\mathbf{1}\{c_1 < r < c_{90}/(0.9)^{1/v}\}$, $v = \log(1/9)/\log(c_{10}/c_{90})$, $r = [(\vartheta - \hat{\vartheta})'\hat{V}_\vartheta^{-1}(\vartheta - \hat{\vartheta})]^{1/2}$, c_j is the jth percentile of the distance r, L_{1-q} is the $100(1-q)$th percentile of the log quasi-posterior distribution, $q \in (0,1)$ is a constant, and $\bar{\tau}$ is the quasi-posterior mean of $\mathbf{1}\{\hat{q}(\vartheta) + \log p(\vartheta) > L_{1-q}\}\,\mathbf{1}\{c_1 < r < c_{90}/(0.9)^{1/v}\}$.

The ensuing analysis calculates QML using various values of the truncation parameters, τ in the estimator of Geweke (1999) and q in that of Sims et al. (2008), for robustness. Following Herbst and Schorfheide (2015), this paper chooses $\tau = 0.5$ and 0.9 for the former estimator and $q = 0.5$ and 0.9 for the latter.

3.3 Data

The primary data for the estimation of the GNKPC consists of four U.S. time series on the quarterly frequency: inflation π_t, the real unit labor cost ulc_t, output growth gy_t, and the nominal interest rate r_t. As for instruments $\mathbf{z}_t$ in (7), this paper follows Galí et al. (2005) in choosing four lags of inflation and two lags of wage inflation and the other three variables that appear in the GNKPC, i.e., ulc_t, gy_t, and r_t.

As in Galí and Gertler (1999) and Galí et al. (2005), the data on π_t is the inflation rate of the GDP implicit price deflator, and that on ulc_t is the labor income share in the nonfarm business sector. Those on gy_t and r_t are the per-capita real GDP growth rate and the three-month Treasury bill rate, respectively.[20] The wage inflation data is based on the hourly compensation in the nonfarm business sector. To take into account a possible shift in trend inflation, the estimation is performed separately for the Great Inflation period (1966:Q1–

[20]The empirical results presented in this paper using the GDP and its deflator hold qualitatively even when the PCE and its price index are instead employed.

1982:Q3) and the period thereafter (1982:Q4–2015:Q4), as well as for the full sample period since 1966:Q1.[21]

For the real unit labor cost, output growth, and the nominal interest rate, the time series of their log-deviations from steady-state values $\{\hat{ulc}_t, \hat{gy}_t, \hat{r}_t\}$ are constructed separately for each sample period; they are all demeaned using their respective sample period averages.

3.4 Prior distributions

In each estimation, the subjective discount factor β is fixed at 0.995. All the remaining model parameters are estimated. The prior distributions for the parameters are presented in Table 2.

Table 2: Prior distributions for model parameters to be estimated

Model parameter		Distribution	Mean	Std. dev.	90% interval
$\bar{\pi}$	annualized trend inflation rate	Normal	3.53	1.50	[1.06,6.00]
θ	elasticity of substitution	Gamma	9.32	1.00	[7.74,11.02]
λ	probability of no price change	Beta	0.50	0.10	[0.34,0.66]
ω_r	fraction of ROT firms	Beta	0.50	0.10	[0.34,0.66]
ω_i	degree of indexation to trend inflation	Uniform $[0, 1]$	0.50	0.29	[0.05,0.95]

Notes: $\bar{\pi} \equiv 400 \log \pi$. In the Galí-Gertler NKPC and GNKPC with indexation, λ represents the probability of trend inflation-indexed price setting.

The prior for the annualized trend inflation rate $\bar{\pi}\,(\equiv 400 \log \pi)$ is centered around the full sample period average inflation rate of 3.53 with standard deviation 1.5. That for the elasticity of substitution θ is set to be the gamma distribution with mean 9.32 and standard deviation 1. The value of 9.32 is the estimate of Ascari and Sbordone (2014). For the priors for the probability of no price change (or trend inflation-indexed price setting) λ and the fraction of ROT firms ω_r, the beta distributions are chosen with mean 0.5 and standard deviation 0.1. The prior for the degree of price indexation to trend inflation ω_i is set to be

[21]In estimating the GNKPC with the quarterly data, this paper uses 16 leads of inflation, output growth, and the nominal interest rate, so the second subsample and the full sample periods end in 2015:Q4 by taking into account the COVID-19 pandemic since 2020.

the uniform distribution between 0 and 1, because the GNKPC with indexation includes the GNKPC (1) and the NKPC (5) as the special cases of $\omega_i = 0$ and $\omega_i = 1$, respectively.

4 Empirical Results

This section presents the results of the model selection and accounts for the estimation results of the selected model.

4.1 Comparison of Galí-Gertler GNKPC, NKPC, and GNKPC with indexation

We begin by comparing the empirical performance of the GNKPC (1), the NKPC (5), and the GNKPC with indexation. As noted in the preceding section, the performance is evaluated in terms of QML, which is computed with the two alternative modified harmonic mean estimators proposed by Geweke (1999) and by Sims et al. (2008). For each of the three, Table 3 reports log QML using the truncation parameter values of $\tau = 0.5, 0.9$ for the estimator of Geweke (1999) and $q = 0.5, 0.9$ for that of Sims et al. (2008).

The third to fifth columns of Table 3 show that the GNKPC has higher QML than the NKPC and the GNKPC with indexation in all the three estimation periods for both estimators with both truncation parameter values. This result indicates that the GNKPC describes inflation dynamics better than the NKPC and the GNKPC with indexation both during and after the Great Inflation period as well as the full sample period. Moreover, the absence of the indexation, that is, retaining some unchanged prices in each quarter in line with micro evidence improves the GNKPC's fit to the macroeconomic data. These findings coincide with those of Hirose et al. (2020). They conduct a full-information Bayesian analysis to compare a Galí-Gertler GNKPC and NKPC in an otherwise identical DSGE model, and show that the model with the GNKPC outperforms that with the NKPC during both the Great Inflation and Great Moderation periods in terms of marginal likelihood. As noted in Introduction, recent studies have pointed out that GNKPCs possess substantially distinct

Table 3: QML for Galí-Gertler GNKPC, NKPC, and GNKPC with indexation

		No restriction			No inertia: $\omega_r = 0$	
Period	Estimator	GNKPC	NKPC	GNKPC with indexation	GNKPC	NKPC
Great Inflation (1966:Q1–1982:Q3)	G, 0.5	−7.48	−8.56	−7.85	−8.89	−12.58
	G, 0.9	−7.46	−8.56	−7.80	−8.88	−12.58
	S, 0.5	−4.39	−5.51	−4.72	−5.85	−9.76
	S, 0.9	−5.16	−6.27	−5.42	−6.63	−10.49
Post-Great Inflation (1982:Q4–2015:Q4)	G, 0.5	−16.52	−20.44	−17.64	−22.69	−27.88
	G, 0.9	−16.51	−20.43	−17.58	−22.68	−27.87
	S, 0.5	−13.28	−17.18	−14.17	−19.41	−24.74
	S, 0.9	−14.03	−17.93	−14.91	−20.16	−25.47
Full sample (1966:Q1–2015:Q4)	G, 0.5	−17.28	−20.18	−18.29	−20.38	−26.84
	G, 0.9	−17.27	−20.18	−18.24	−20.35	−26.84
	S, 0.5	−14.39	−17.33	−15.22	−17.57	−24.25
	S, 0.9	−15.12	−18.07	−16.00	−18.26	−24.95

Notes: The table reports log QML for the Galí-Gertler GNKPC (1), NKPC (5), and GNKPC with indexation, as well as the GNKPC and NKPC with no inflation inertia, i.e., $\omega_r = 0$. In the second column, "G" and "S" represent the modified harmonic mean estimators proposed by Geweke (1999) and by Sims et al. (2008), respectively, and 0.5 and 0.9 are values of the truncation parameter for each estimator.

features from canonical NKPCs, thereby generating important implications for policy and welfare. Therefore, our findings suggest that GNKPCs should be preferred to canonical NKPCs for the analysis of the Federal Reserve's monetary policy.

Before proceeding to the next model selection, we examine whether the presence of ROT price setters could improve the performance of the GNKPC. Comparing the third and sixth columns of Table 3 shows that the GNKPC with ROT price setters has higher QML than that without ROT price setters (i.e., $\omega_r = 0$) in all the three estimation periods.[22] This result indicates that the presence of ROT price setters has played a nonnegligible role in accounting for inflation dynamics both during and after the Great Inflation period as well as the full sample period. Therefore, to better describe inflation dynamics, such a backward-looking component needs to be included in the GNKPC, along with some unchanged prices in each

[22]The NKPC with ROT price setters also performs better than that without ROT price setters, as shown by comparing the fourth and last columns of Table 3.

quarter.

4.2 Comparison of Galí-Gertler and Woodford GNKPCs

In addition to the Galí-Gertler NKPC analyzed above, there are more widely used hybrid NKPCs in previous studies. The NKPCs introduce dynamic price indexation (DPI) to lagged inflation as in Woodford (2003). Thus we examine a generalized version of the Woodford NKPC to compare it with the Galí-Gertler GNKPC.

The Woodford GNKPC is derived from a Calvo staggered price model in which firms set prices using DPI to an average of lagged and trend inflation with probability $\lambda \in [0, 1)$ and optimize prices with the remaining probability in each period. Consequently, all prices change in every period. This feature contrasts sharply with that of the Galí-Gertler GNKPC in which some prices remain unchanged in each period in line with micro evidence. The Woodford GNKPC can be obtained as

$$\hat{\pi}_t = \gamma_{b,w}\hat{\pi}_{t-1} + \gamma_{f,w}E_t\hat{\pi}_{t+1} + \kappa_w\left[\hat{ulc}_t - \kappa_{\Delta,w}\sum_{j=0}^{\infty}\rho^j_{\Delta,w}\left(\hat{\pi}_{t-j} - \omega_i w\,\hat{\pi}_{t-j-1}\right)\right]$$
$$+ \kappa_{f,w}\sum_{j=1}^{\infty}\rho^j_{f,w}\left(E_t\hat{gy}_{t+j} + \theta E_t\hat{\pi}_{t+j} - \omega_i w\,(\theta-1)E_t\hat{\pi}_{t+j-1} - E_t\hat{r}_{t+j-1}\right) \tag{8}$$

under the assumption $\lambda\pi^{\theta(1-\omega_i)} < \min(1, \pi^{1-\omega_i})$, where $\omega_i \in [0, 1]$ denotes the degree of price indexation, $w \in [0, 1]$ is the weight on lagged inflation relative to trend inflation in the indexation, and the reduced-form coefficients are given by $\gamma_{b,w} \equiv \omega_i w/\phi_w$, $\gamma_{f,w} \equiv \beta\pi^{1-\omega_i}/\phi_w$, $\kappa_w \equiv (1-\lambda\pi^{(\theta-1)(1-\omega_i)})(1-\beta\lambda\pi^{\theta(1-\omega_i)})/(\phi_w\lambda\pi^{(\theta-1)(1-\omega_i)})$, $\kappa_{\Delta,w} \equiv \theta\lambda\pi^{(\theta-1)(1-\omega_i)}(\pi^{1-\omega_i} - 1)/(1-\lambda\pi^{(\theta-1)(1-\omega_i)})$, $\rho_{\Delta,w} \equiv \lambda\pi^{\theta(1-\omega_i)}$, $\kappa_{f,w} \equiv (\pi^{1-\omega_i}-1)(1-\lambda\pi^{(\theta-1)(1-\omega_i)})/(\phi_w\lambda\pi^{(\theta-1)(1-\omega_i)})$, $\phi_w \equiv 1 + \omega_i w\beta\pi^{1-\omega_i}$, and $\rho_{f,w} \equiv \beta\lambda\pi^{(\theta-1)(1-\omega_i)}$.

In the special case of $\omega_i = 1$, the Woodford GNKPC is reduced to its NKPC counterpart

$$\hat{\pi}_t = \gamma_{b,w1}\hat{\pi}_{t-1} + \gamma_{f,w1}E_t\hat{\pi}_{t+1} + \kappa_{w1}\hat{ulc}_t, \tag{9}$$

where $\gamma_{b,w1}$, $\gamma_{f,w1}$, and κ_{w1} correspond to $\gamma_{b,w}$, $\gamma_{f,w}$, and κ_w at $\pi = 1$, respectively. This type of hybrid NKPCs is employed in many previous studies, such as Christiano et al. (2005) and Smets and Wouters (2007). Moreover, the Woodford GNKPC includes a constant trend inflation version of the GNKPC of Cogley and Sbordone (2008) as the special case of $w = 1$:

$$\hat{\pi}_t = \gamma_{b,cs}\hat{\pi}_{t-1} + \gamma_{f,cs}E_t\hat{\pi}_{t+1} + \kappa_{cs}\left[\hat{ulc}_t - \kappa_{\Delta,cs}\sum_{j=0}^{\infty}\rho_{\Delta,cs}^{j}\left(\hat{\pi}_{t-j} - \omega_i\hat{\pi}_{t-j-1}\right)\right]$$
$$+ \kappa_{f,cs}\sum_{j=1}^{\infty}\rho_{f,cs}^{j}\big(E_t\hat{gy}_{t+j} + \theta E_t\hat{\pi}_{t+j} - \omega_i(\theta-1)E_t\hat{\pi}_{t+j-1} - E_t\hat{r}_{t+j-1}\big), \tag{10}$$

where $\gamma_{b,cs}$, $\gamma_{f,cs}$, κ_{cs}, $\kappa_{\Delta,cs}$, $\rho_{\Delta,cs}$, $\kappa_{f,cs}$, $\rho_{f,cs}$, and ϕ_{cs} correspond to $\gamma_{b,w}$, $\gamma_{f,w}$, κ_w, $\kappa_{\Delta,w}$, $\rho_{\Delta,w}$, $\kappa_{f,w}$, $\rho_{f,w}$, and ϕ_w at $w = 1$, respectively.[23]

In addition to the Galí-Gertler and the Woodford GNKPCs, we can consider a GNKPC that nests both of them. Such a GNKPC can be derived by introducing ROT firms in the above model setting (for the Woodford GNKPC). The nested GNKPC can be obtained as

$$\hat{\pi}_t = \gamma_{b1,ggw}\hat{\pi}_{t-1} + \gamma_{b2,ggw}\hat{\pi}_{t-2} + \gamma_{f,ggw}E_t\hat{\pi}_{t+1} + \kappa_{ggw}\left[\hat{ulc}_t - \kappa_{\Delta,ggw}\sum_{j=0}^{\infty}\rho_{\Delta,ggw}^{j}\left(\hat{\pi}_{t-j} - \omega_i w\,\hat{\pi}_{t-j-1}\right)\right]$$
$$+ \kappa_{f,ggw}\sum_{j=1}^{\infty}\rho_{f,ggw}^{j}\big(E_t\hat{gy}_{t+j} + \theta E_t\hat{\pi}_{t+j} - \omega_i w\,(\theta-1)E_t\hat{\pi}_{t+j-1} - E_t\hat{r}_{t+j-1}\big) \tag{11}$$

under the same assumption as above, where $\omega_r \in [0,1)$ is the fraction of ROT firms and the reduced-form coefficients are given by $\gamma_{b1,ggw} \equiv [\omega_r + \omega_i w\lambda\pi^{(\theta-1)(1-\omega_i)}(1+\omega_r\beta\lambda\pi^{\theta(1-\omega_i)})]/\phi_{ggw}$, $\gamma_{b2,ggw} \equiv -\omega_r\omega_i w\lambda\pi^{(\theta-1)(1-\omega_i)}/\phi_{ggw}$, $\gamma_{f,ggw} \equiv \beta\lambda\pi^{\theta(1-\omega_i)}/\phi_{ggw}$, $\kappa_{ggw} \equiv (1-\lambda\pi^{(\theta-1)(1-\omega_i)})(1-\beta\lambda\pi^{\theta(1-\omega_i)})(1-\omega_r)/\phi_{ggw}$, $\kappa_{\Delta,ggw} = \kappa_{\Delta,w}$, $\rho_{\Delta,ggw} = \rho_{\Delta,w}$, $\kappa_{f,ggw} \equiv (\pi^{1-\omega_i}-1)(1-\lambda\pi^{(\theta-1)(1-\omega_i)})(1-\omega_r)/\phi_{ggw}$, $\phi_{ggw} \equiv \lambda\pi^{(\theta-1)(1-\omega_i)} + \omega_r[1-\lambda\pi^{(\theta-1)(1-\omega_i)}(1-\beta\pi^{1-\omega_i})] + \omega_i w\beta\lambda\pi^{\theta(1-\omega_i)}[1-\omega_r(1-\lambda\pi^{(\theta-1)(1-\omega_i)})]$, and $\rho_{f,ggw} = \rho_{f,w}$. This GNKPC contains the second lagged inflation as well as the first one through the combined effect of the two specifications of backward-looking

[23]The GNKPC of Cogley and Sbordone (2008) features time-varying trend inflation, which is modeled as a random walk under the assumption of subjective expectations based on the anticipated utility model of Kreps (1998).

price setting: DPI to lagged inflation and ROT price setters. The nested GNKPC (11) includes the Galí-Gertler GNKPC (1) and the Woodford GNKPC (8) as the special cases of $w = \omega_i = 0$ and $\omega_r = 0$, respectively.

We compare the empirical performance of the Woodford GNKPC (8) and NKPC (9), the Cogley-Sbordone GNKPC (10), and the nested GNKPC (11), as well as the Galí-Gertler GNKPC (1). To this end, we set the priors for the degree of price indexation ω_i, the relative weight on lagged inflation w, and the fraction of ROT firms ω_r to be beta distributions with mean 0.5 and standard deviation 0.1. Table 4 reports log QML for each of the five.

Table 4: QML for Galí-Gertler GNKPC, Woodford GNKPC and NKPC, Cogley-Sbordone GNKPC, and their nested GNKPC

Period	Estimator	Galí-Gertler GNKPC	Woodford GNKPC	Woodford NKPC	Cogley-Sbordone GNKPC	Nested GNKPC
Great Inflation	G, 0.5	−7.48	−11.42	−10.47	−9.18	−8.46
(1966:Q1–1982:Q3)	G, 0.9	−7.46	−11.42	−10.46	−9.17	−8.46
	S, 0.5	−4.39	−8.41	−7.45	−6.17	−5.41
	S, 0.9	−5.16	−9.14	−8.20	−6.93	−6.14
Post-Great Inflation	G, 0.5	−16.52	−24.65	−25.10	−22.09	−19.06
(1982:Q4–2015:Q4)	G, 0.9	−16.51	−24.65	−25.11	−22.09	−19.06
	S, 0.5	−13.28	−21.42	−21.92	−18.86	−15.85
	S, 0.9	−14.03	−22.16	−22.67	−19.62	−16.59
Full sample	G, 0.5	−17.28	−22.18	−26.20	−23.00	−19.24
(1966:Q1–2015:Q4)	G, 0.9	−17.27	−22.18	−26.19	−23.00	−19.24
	S, 0.5	−14.39	−19.35	−23.40	−20.16	−16.43
	S, 0.9	−15.12	−20.09	−24.14	−20.92	−17.16

Notes: The table reports log QML for the Galí-Gertler GNKPC (1), the Woodford GNKPC (8) and NKPC (9), the Cogley-Sbordone GNKPC (10), and the nested GNKPC (11). In the second column, "G" and "S" represent the modified harmonic mean estimators proposed by Geweke (1999) and by Sims et al. (2008), respectively, and 0.5 and 0.9 are values of the truncation parameter for each estimator.

In Table 4, two findings can be detected. First, the Cogley-Sbordone GNKPC has higher QML than the Woodford GNKPC and NKPC both during and after the Great Inflation period. That is, in the Woodford GNKPC (8), the case of $w = 1$ is better than the cases of no restriction and $\omega_i = 1$ in terms of QML during both periods. This finding points to the importance of DPI only to lagged inflation in the Woodford GNKPC when a shift in trend inflation is allowed around the time of the Volcker disinflation.

Second, and more importantly, the Galí-Gertler GNKPC has higher QML than the Woodford GNKPC and NKPC, the Cogley-Sbordone GNKPC, and the nested GNKPC in all the three estimation periods. This finding indicates that the Galí-Gertler GNKPC describes inflation dynamics better than other NKPCs both during and after the Great Inflation period as well as the full sample period. The result that the Galí-Gertler GNKPC has higher QML than the Woodford GNKPC both during and after the Great Inflation period is analogous to the result of Inoue and Shintani (2018) on the NKPC counterparts. Their result is confirmed by comparing the fourth column of Table 3 and the fifth column of Table 4. As they point out, while the number of model parameters is the same between the Galí-Gertler NKPC (5) and the Woodford NKPC (9), the joint restrictions on the range of model parameters are different. For example, the ratio of the reduced-form coefficients on expected future inflation and on lagged inflation in the Galí-Gertler NKPC (i.e., $\gamma_{f1}/\gamma_{b1} = \beta\lambda/\omega_r$) depends on the three model parameters β, λ, and ω_r, whereas the ratio in the Woodford NKPC (i.e., $\gamma_{f,w1}/\gamma_{b,w1} = \beta/w$) depends only on the two model parameters β and w. Such a tighter restriction in the Woodford NKPC can make the difference in the empirical performance of the two NKPCs. An analogous argument could apply to the Galí-Gertler and the Woodford GNKPCs, and it might coincide with the argument that the Galí-Gertler GNKPC involves the three possible price-setting stances (i.e., optimizing prices, setting prices with the ROT, and keeping prices unchanged), while the Woodford GNKPC has only the two possible ones (i.e., optimizing prices and setting prices with the DPI), so the Galí-Gertler GNKPC is more flexible in fitting to the data.

Our second finding also implies that ROT price setters (in the Galí-Gertler GNKPC and NKPC) provide a better specification of backward-looking price setting for the GNKPC (and the NKPC) than DPI to lagged inflation (in the Woodford counterparts). In this context, Cogley and Sbordone (2008) reach the conclusion that there is no need for backward-looking price setting in their GNKPC once drifting trend inflation is incorporated in it. Even in the absence of such drifting trend inflation, comparing the second to last columns of Tables 3 and 4 shows that the Cogley-Sbordone GNKPC (10) has higher QML in the absence of DPI to lagged inflation than in its presence during the Great Inflation period (because the Cogley-Sbordone GNKPC without the DPI, i.e., $\omega_i = 0$, coincides with the Galí-Gertler GNKPC without ROT price setters, i.e., $\omega_r = 0$). Moreover, when we estimate the Galí-Gertler GNKPC (1), the Cogley-Sbordone GNKPC (10), and the GNKPC with no inflation inertia (i.e., $\omega_r = 0$ in (1) or $\omega_i = 0$ in (10)) during the period from 1982:Q4 until 2003:Q4, which is the end of the sample period in Cogley and Sbordone (2008), Table 5 demonstrates that the GNKPC with no inflation inertia has higher QML than the Cogley-Sbordone GNKPC, even after the Great Inflation period as well as during that period.[24] The table also indicates that the Galí-Gertler GNKPC (with ROT price setters) has higher QML than the GNKPC with no inflation inertia and the Cogley-Sbordone GNKPC (with the DPI) in all the three estimation periods. These results suggest that the DPI to lagged inflation played no role in the Cogley-Sbordone GNKPC both during and after the Great Inflation period (at least within the sample period of Cogley and Sbordone, 2008), even in the absence of the drifting trend inflation (introduced by them), and that their conclusion may depend on the specification of backward-looking price setting, that is, the DPI, in addition to the drifting trend inflation.

4.3 Quasi-posterior estimates of selected model

The preceding subsections have shown that the Galí-Gertler GNKPC is the best description of inflation dynamics both during and after the Great Inflation period among those considered. This subsection thus analyzes the GNKPC in detail.

For each of the model parameters and reduced-form coefficients of the GNKPC, its quasi-posterior mean and 90 percent highest quasi-posterior density interval are reported in Table 6. The quasi-posterior mean estimates show that when the annualized trend inflation rate $\bar{\pi}$ ($\equiv 400 \log \pi$) fell from 5.74 percent during the Great Inflation period to 2.23 percent during

[24] In Table 5, the Great Inflation period starts from 1960:Q1, which is the beginning of the sample period in Cogley and Sbordone (2008). In the estimation, we set the prior mean of the annualized trend inflation rate $\bar{\pi}$ at the average inflation rate of 3.68 over their sample period 1960:Q1–2003:Q4.

Table 5: QML for Galí-Gertler and Cogley-Sbordone GNKPCs

Period	Estimator	Galí-Gertler GNKPC	Cogley-Sbordone GNKPC	GNKPC with no inertia
Great Inflation	G, 0.5	−8.88	−12.97	−9.97
(1960:Q1–1982:Q3)	G, 0.9	−8.88	−12.97	−9.96
	S, 0.5	−6.16	−10.27	−7.17
	S, 0.9	−6.92	−11.02	−7.94
Post-Great Inflation	G, 0.5	−12.34	−19.59	−18.13
(1982:Q4–2003:Q4)	G, 0.9	−12.33	−19.59	−18.13
	S, 0.5	−9.12	−16.51	−15.04
	S, 0.9	−9.87	−17.26	−15.80
Full sample	G, 0.5	−13.53	−20.26	−18.34
(1960:Q1–2003:Q4)	G, 0.9	−13.52	−20.24	−18.33
	S, 0.5	−10.67	−17.44	−15.75
	S, 0.9	−11.41	−18.19	−16.48

Notes: The table reports log QML for the Galí-Gertler GNKPC (1), the Cogley-Sbordone GNKPC (10), and the GNKPC with no inflation inertia, i.e., $\omega_r = 0$ in (1) or $\omega_i = 0$ in (10). In the second column, "G" and "S" represent the modified harmonic mean estimators proposed by Geweke (1999) and by Sims et al. (2008), respectively, and 0.5 and 0.9 are values of the truncation parameter for each estimator.

the Post-Great Inflation period, the probability of no price change λ increased from 0.61 to 0.85,[25] while both the fraction of ROT price setters ω_r and the elasticity of substitution θ remained roughly unchanged. Then, the GNKPC slope κ diminished from 0.04 to 0.00, whereas its inflation-inertia coefficient γ_b remained roughly unchanged. These evolutions are also detected in the quasi-posterior distribution of the model parameters and reduced-form coefficients of the GNKPC illustrated in Figure 1.

In the estimated Galí-Gertler GNKPC, two points are worth noting. First, the increase in the probability of no price change λ, that is, the decrease in the probability of price change

[25]The estimated probability of no price change of $\lambda = 0.85$ during the period 1982:Q4–2015:Q4 implies an average duration of 19.6 months, which is comparable to the micro evidence provided by Kehoe and Midrigan (2015), who report an implied average duration of regular price changes of 14.5 months during the period 1988–2005. Although this duration is somewhat longer than those of Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008), who point to a figure of 7 to 11 months, the difference is ascribed to the fact that the latter two studies identify temporary price increases as regular price changes, which unsurprisingly shortens the duration.

Table 6: Quasi-posterior estimates and priors of model parameters and reduced-form coefficients of selected model (Galí-Gertler GNKPC)

	Great Inflation (1966:Q1–1982:Q3)		Post-Great Inflation (1982:Q4–2015:Q4)		Full sample (1966:Q1–2015:Q4)		Prior	
	Mean	90% interval	Mean	90% interval	Mean	90% interval	Mean	90% interval
$\bar{\pi}$	5.74	$[5.08, 6.39]$	2.23	$[2.03, 2.44]$	3.21	$[2.77, 3.66]$	3.53	$[1.06, 6.00]$
λ	0.61	$[0.54, 0.68]$	0.85	$[0.80, 0.89]$	0.84	$[0.80, 0.88]$	0.50	$[0.34, 0.66]$
ω_r	0.51	$[0.39, 0.63]$	0.56	$[0.42, 0.70]$	0.59	$[0.46, 0.72]$	0.50	$[0.34, 0.66]$
θ	9.37	$[7.81, 11.07]$	9.60	$[7.98, 11.34]$	9.66	$[8.06, 11.39]$	9.32	$[7.74, 11.02]$
γ_b	0.42	$[0.35, 0.50]$	0.38	$[0.31, 0.45]$	0.39	$[0.33, 0.45]$	0.48	$[0.36, 0.60]$
γ_f	0.58	$[0.51, 0.65]$	0.62	$[0.55, 0.69]$	0.61	$[0.55, 0.67]$	0.52	$[0.40, 0.64]$
κ	0.04	$[0.02, 0.06]$	0.00	$[0.00, 0.01]$	0.00	$[0.00, 0.00]$	0.12	$[0.03, 0.27]$
κ_f	0.00	$[0.00, 0.00]$	0.00	$[0.00, 0.00]$	0.00	$[0.00, 0.00]$	0.00	$[0.00, 0.00]$
κ_Δ	0.31	$[0.20, 0.46]$	0.45	$[0.26, 0.73]$	0.77	$[0.43, 1.31]$	0.11	$[0.02, 0.27]$

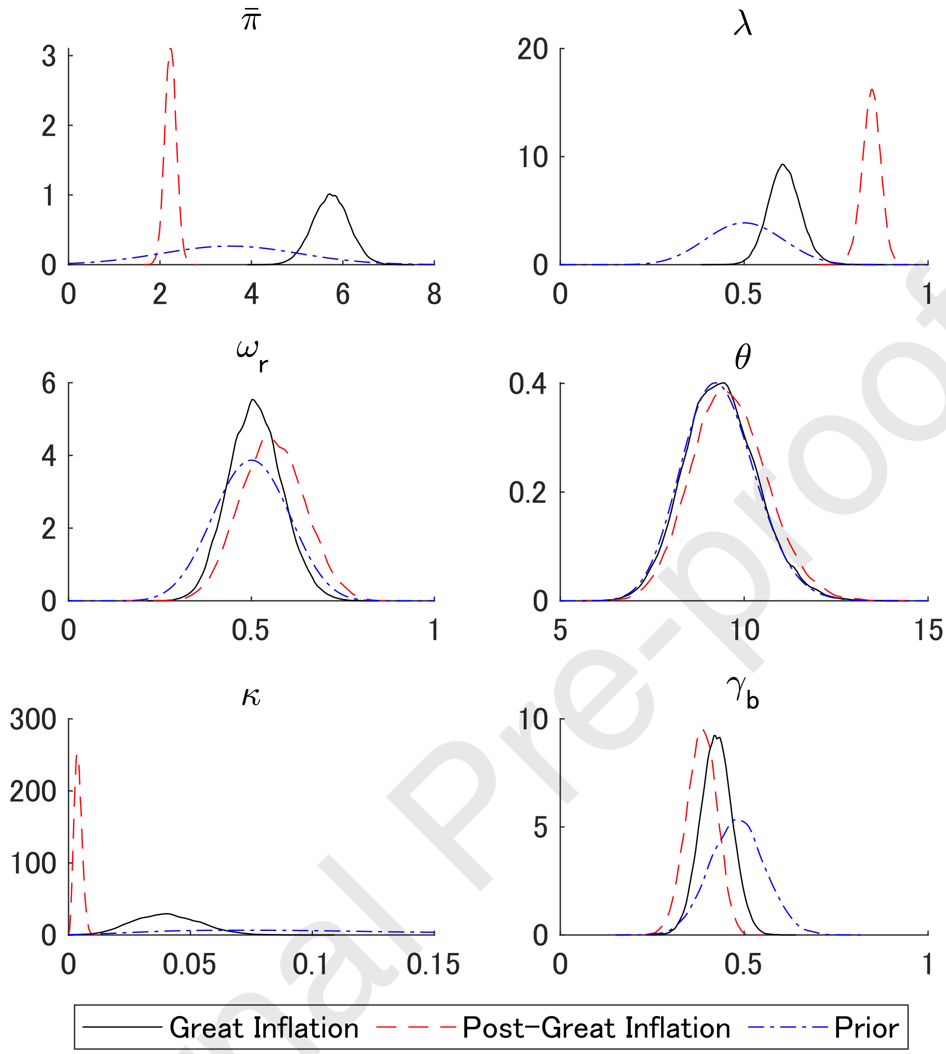
Note: $\bar{\pi} \equiv 400 \log \pi$.

$1-\lambda$ in the estimated GNKPC after the Great Inflation period is consistent with the micro evidence reported by Nakamura et al. (2018) that the frequency of regular price change decreased after that period. Moreover, the increased probability of no price change flattens the GNKPC.[26] The flattening of the estimated GNKPC is consistent with the empirical results of Benati (2007), Ball and Mazumder (2011), and the International Monetary Fund (2013), among others.

Second, the estimated GNKPC indicates that when trend inflation fell after the Great Inflation period, the probability of price change decreased, thereby flattening the GNKPC. The concurrence of the fall in trend inflation, the decrease in the probability of price change, and the flattening of the slope in the estimated GNKPC coincides with the theoretical prediction in the literature on endogenous price stickiness, initially started by Ball et al. (1988) and recently developed by Levin and Yun (2007) and Kurozumi (2016). Therefore, as conjectured by Ball et al. (1988), the Phillips curve Greenspan (and Bernanke) faced is not identical to the one Volcker had faced.

[26]Recall that, as shown in Table 1, the theoretical factors behind a flattening of the GNKPC are a higher probability of no price change, as well as a larger fraction of ROT price setters, higher trend inflation, and a larger elasticity of substitution under positive trend inflation.

Figure 1: Quasi-posterior and prior distributions of model parameters and reduced-form coefficients of selected model (Galí-Gertler GNKPC)



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

5 Concluding Remarks

This paper has investigated inflation dynamics by estimating the Galí-Gertler GNKPC during and after the Great Inflation period using Bayesian GMM. US macroeconomic data has suggested that the Galí-Gertler GNKPC outperforms the Galí-Gertler and the Woodford NKPCs, the Galí-Gertler GNKPC with indexation, the Woodford and the Cogley-Sbordone GNKPCs, and the GNKPC that nests both Galí-Gertler and Woodford GNKPCs, in terms of QML. The estimated Galí-Gertler GNKPC then indicates that when trend inflation fell after the Great Inflation period, the probability of price change decreased in line with the micro evidence reported by Nakamura et al. (2018). This decrease in the probability of price change in turn flattened the GNKPC. The concurrence of the fall in trend inflation, the decrease in the probability of price change, and the flattening of the slope in the estimated GNKPC coincides with the theoretical prediction in the literature on endogenous price stickiness, including Ball et al. (1988). Moreover, the flattening of the estimated GNKPC after the Great Inflation period is consistent with the empirical results of Benati (2007), Ball and Mazumder (2011), and the International Monetary Fund (2013), among others.

In the GNKPC, we have considered ROT price setters as the source of inflation inertia and have shown that such backward-looking price setters played a nonnegligible role in inflation dynamics both during and after the Great Inflation period. However, ROT price setters are an ad hoc assumption that relies on non-optimizing price-setting behavior.[27] To incorporate inflation inertia in a theoretically coherent manner, existing studies suggest introducing sticky information (Dupor et al., 2010), an upward-sloping hazard function (Sheedy, 2010), and a positive superelasticity of demand (Kurozumi and Van Zandweghe, 2023) in staggered price models. Empirical investigation of GNKPCs augmented with these sources of inflation inertia is left as a possible agenda for future research.

[27] Galí and Gertler (1999) suggest that "it is worth searching for explanations of inflation inertia beyond the traditional ones that rely heavily on arbitrary lags" (p. 219).

Appendix

This appendix presents the derivation of the Galí-Gertler GNKPC (1). This GNKPC is derived from a Calvo staggered price model with a representative composite-good producer and two types of firms, optimizing and ROT price setters.

The composite-good producer combines the output of a continuum of firms $f \in [0,1]$ using the CES aggregator $Y_t = \left[\int_0^1 (Y_t(f))^{(\theta-1)/\theta}\, df\right]^{\theta/(\theta-1)}$, where Y_t is the output of the composite good and $Y_t(f)$ is firm f's output of an individual differentiated good. Given the composite good's price P_t and individual goods' prices $\{P_t(f)\}$, the producer maximizes its profit $P_t Y_t - \int_0^1 P_t(f) Y_t(f)\, df$ subject to the CES aggregator. The first-order condition for profit maximization yields the demand curve for each individual good

$$Y_t(f) = Y_t \left(\frac{P_t(f)}{P_t}\right)^{-\theta}, \tag{A1}$$

and thus the CES aggregator leads to the composite good's price equation

$$P_t = \left[\int_0^1 (P_t(f))^{1-\theta}\, df\right]^{\frac{1}{1-\theta}}. \tag{A2}$$

Each firm f produces one kind of differentiated good $Y_t(f)$ using the Cobb–Douglas production technology $Y_t(f) = A_t (K_t(f))^{\alpha} (l_t(f))^{1-\alpha}$, where A_t is total factor productivity (TFP), $K_t(f)$ and $l_t(f)$ are firm f's capital and labor inputs, and $\alpha \in (0,1)$ is the capital elasticity of output. The TFP is assumed to follow the nonstationary stochastic process

$$\log (A_t)^{\frac{1}{1-\alpha}} = \log gy + \log (A_{t-1})^{\frac{1}{1-\alpha}} + \varepsilon_t, \tag{A3}$$

where gy is the steady-state rate of technological change $(A_t/A_{t-1})^{1/(1-\alpha)}$, which coincides with the steady-state rate of output growth $gy_t = Y_t/Y_{t-1}$, and ε_t is an i.i.d. technology shock. In the presence of the economy-wide factor markets with the capital rental rate $P_t r_{k,t}$ and the wage rate $P_t W_t$, the firm minimizes its production cost $P_t r_{k,t} K_t(f) + P_t W_t l_t(f)$

subject to the Cobb–Douglas production technology. Combining the first-order conditions for cost minimization shows that all firms face the same real marginal cost mc_t, and thus aggregating the labor input condition $W_t l_t(f) = (1-\alpha) mc_t Y_t(f)$ over firms $f \in [0,1]$ and using the demand curve (A1) lead to

$$mc_t = \frac{\int_0^1 W_t l_t(f)\, df}{(1-\alpha)\int_0^1 Y_t(f)\, df} = \frac{W_t l_t}{(1-\alpha) Y_t \Delta_t} = \frac{ulc_t}{(1-\alpha)\Delta_t}, \tag{A4}$$

where the labor market clearing condition $l_t = \int_0^1 l_t(f)\, df$ is used, $ulc_t \equiv W_t l_t / Y_t$ is the *composite-good-based* real unit labor cost, and

$$\Delta_t \equiv \int_0^1 \left(\frac{P_t(f)}{P_t}\right)^{-\theta} df \tag{A5}$$

is the relative price distortion. It is worth noting that the marginal cost equation (A4) shows that each firm's real marginal cost mc_t is equal to the *individual-good-based* real unit labor cost $\int_0^1 W_t l_t(f)\, df \Big/ \int_0^1 Y_t(f)\, df$ divided by the labor elasticity of output $1-\alpha$. Therefore, the role of the distortion Δ_t in (A4) is to merely shift the basis of unit labor cost from individual-good to composite-good production.

Firms set their product prices, as in Galí and Gertler (1999). There are two types of firms, optimizing and ROT firms, and $\omega_r \in [0,1)$ denotes the fraction of ROT firms. Both types of firms keep prices unchanged with probability $\lambda \in [0,1)$. With the remaining probability, optimizing firms choose prices given the demand curve (A1) and the real marginal cost (A4), while ROT firms adjust prices using a backward-looking ROT. Specifically, optimizing firms set prices to maximize the relevant profit $E_t \sum_{j=0}^{\infty} \lambda^j M_{t,t+j} \left(P_t(f) - P_{t+j} mc_{t+j}\right) Y_{t+j} \left(P_t(f)/P_{t+j}\right)^{-\theta}$, where $M_{t,t+j}$ is the nominal stochastic discount factor between period t and period $t+j$, which satisfies $M_{t,t+j} = \prod_{k=1}^{j} M_{t+k-1,t+k}$. The first-order condition for profit maximization can be written as

$$E_t \sum_{j=0}^{\infty} \lambda^j \prod_{k=1}^{j} M_{t+k-1,t+k}\, \pi_{t+k}\, gy_{t+k}\, (p_t^o)^{-\theta}\, \pi_{t+k}^{\theta} \left(p_t^o \prod_{k=1}^{j} \pi_{t+k}^{-1} - \frac{\theta}{\theta-1} mc_{t+j}\right) = 0, \tag{A6}$$

where $p_t^o \equiv P_t^o/P_t$, P_t^o is the price chosen by firms that optimize prices in period t, and $\pi_t \equiv P_t/P_{t-1}$. On the other hand, ROT firms adjust prices according to the backward-looking ROT

$$P_t^r = P_{t-1}^a \pi_{t-1}, \tag{A7}$$

where

$$P_t^a \equiv (P_t^o)^{1-\omega_r} (P_t^r)^{\omega_r}. \tag{A8}$$

Under the aforementioned price setting, the composite good's price equation (A2) and the relative price distortion equation (A5) can be reduced to, respectively,

$$1 = \lambda \pi_t^{\theta-1} + (1-\lambda)\Big[(1-\omega_r)(p_t^o)^{1-\theta} + \omega_r (p_t^r)^{1-\theta}\Big], \tag{A9}$$

$$\Delta_t = \lambda \pi_t^{\theta} \Delta_{t-1} + (1-\lambda)\Big[(1-\omega_r)(p_t^o)^{-\theta} + \omega_r (p_t^r)^{-\theta}\Big], \tag{A10}$$

where $p_t^r \equiv P_t^r/P_t$.

In the presence of one-period nominal bonds, the nominal interest rate r_t satisfies

$$1 = E_t(M_{t,t+1} r_t). \tag{A11}$$

Let $\beta_{t,t+1} \equiv M_{t,t+1}\, \pi_{t+1}\, (A_{t+1}/A_t)^{1/(1-\alpha)}$. Then, log-linearizing (A3), (A6)–(A9), and (A11) under assumption (2) and combining the resulting equations give rise to the Galí-Gertler GNKPC (1). In addition, the marginal cost equation (3) can be obtained from (A4), and the law of motion of the relative price distortion (4) can be derived from (A9) and (A10).

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