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Time to Innovate and Aggregate Fluctuations: A New Keynesian Model with Endogenous Technology

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Endogenous Technological Change and the New Keynesian Model

(The old title: Time to Innovate and Aggregate Fluctuations: A New Keynesian Model with Endogenous Technology)

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Abstract

This paper develops and estimates a new Keynesian (NK) model with endogenous technological change and explores, by means of Monte Carlo simulations, the role of endogenous technology in macroeconomic fluctuations. This paper shows that introducing endogenously-determined technology can solve three important puzzles faced by conventional NK models. The first is the "inflation persistence puzzle." The paper explains the persistence in inflation without relying on the ad hoc and empirically inconsistent assumptions made by conventional NK models. The second is the "disinflationary news shock puzzle." It explains the disinflationary effect of a news shock, which conventional NK models have difficulty explaining. The third is the "zero lower bound (ZLB) supply shock puzzle." The model avoids the conventional NK models' paradoxical, empirically inconsistent prediction that a negative supply shock is expansionary at the ZLB on nominal interest rates.

JEL codes: E3, O4

Keywords: new Keynesian models, endogenous technology, Phillips curve, inflation, news shocks, ZLB on nominal interest rates, fluctuations.

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1 Introduction

Dynamic stochastic general equilibrium (DSGE) models have been major workhorses in business cycle studies. DSGE models have recently been substantially improved to provide much more realistic representations of macroeconomic dynamics than they had previously. The most widely accepted DSGE models are now called new Keynesian (NK) models, e.g., Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007). These models have become popular and a number of central banks now use them to analyze their policies. NK models have come into such intensive use largely because they have been shown to provide better or at least equal empirical performance (i.e., data fits and forecasts) compared to statistical models, i.e., vector autoregression (VAR) models. Another reason for their popularity is that because an NK model has a coherent theoretical framework, one can identify various shocks to an economy by structurally estimating the model and then can analyze its implications, more easily than with a VAR model.

Apart from the development and increased popularity of NK models, the literature on macroeconomic fluctuations has recently made another important development. Several studies have demonstrated the importance of endogenously determined technology changes for macroeconomic fluctuations.[1] For example, the seminal paper of Comin and Gertler (2006) introduces a research and development (R&D)-based endogenous technological change into a two-sector real business cycle model and connects business cycle fluctuations to medium-term fluctuations. The paper successfully explains medium-term fluctuations in key U.S. macroeconomic variables.

These two important developments in the literature, however, have yet to be fully combined. Although there have been so many different versions of NK models, it has not yet been standard practice to incorporate endogenous technological change in the models. Thus, there are very few NK models that introduce endogenous technological change. This is probably because the focus of conventional NK models is usually business cycle fluctuations and *endogenous* technological changes have been largely considered to be only relevant to long-term economic growth.

This paper develops and estimates a DSGE model to examine whether the introduction of endogenous technological change into an NK model offers quantitatively important implications for our understanding of aggregate fluctuations. The paper extends a quantitative NK model to allow for endogenous changes in total factor productivity (TFP). It models an endogenous TFP change as a change in variety of goods, following Romer (1990). Furthermore, the model introduces the Kydland and Prescott (1977)'s "time-to-build" structure to model a delayed effect of technology investments: *time to innovate*.

[1] See, for example, Francois and Lloyd-Ellis (2003), Comin and Gertler (2006) and Bilbiie, Ghironi, and Melitz (2012).

To take the model to data, some standard frictions (i.e., habit formation and investment adjustment cost) are included. The model is then estimated by a Bayesian maximum likelihood method. With the estimated model, this paper then performs Monte Carlo and other exercises to analyze the role of endogenous technological change in an NK model.

The results suggest that incorporating endogenous technological change in an NK model is necessary because doing so solves three important puzzles faced by conventional new Keynesian models. The first puzzle considered is the "inflation persistence puzzle", which is probably the most severe criticism of new Keynesian models. When estimating the NK Phillips curve (henceforth, NKPC), the backward-looking term (i.e., lagged inflation) is usually found to enter into the regressions significantly and positively, and the coefficient is found to be sizable, although the *basic* NK model gives the purely forward-looking Phillips curve: the *inflation persistence puzzle*. To solve this puzzle, conventional new Keynesian models make ad hoc assumptions on pricing, e.g., backward indexation of prices: some fraction of firms simply index their prices to past inflation.[2] The ad hoc assumptions generate the well-known "hybrid" NKPC, which includes both forward- and backward-looking terms (i.e., expected and lagged inflation), e.g., see Gali and Gertler (1999) and Christiano et al. (2005).[3] However, this treatment is simply a mechanical way to fit a new Keynesian model to observed inflation persistence. Chari, Kehoe and McGrattan (2009) argue that this is a dubious feature of new Keynesian models and inconsistent with U.S. micro data. This paper shows that the present model, which does not make such ad hoc assumption about pricing, is consistent with the above-mentioned finding in the estimation of the NKPC. This is because the NKPC of the present model includes an endogenously-predetermined technology level (i.e., a predetermined state variable) and this endogenous term causes extra inflation persistence as observed in the estimation of the NKPC. More precisely, this paper shows that, because the regression specification for the conventional NKPC estimation omits the endogenously-determined technology levels, the estimation is subject to a misspecified functional form and the misspecification leads to an upwardly biased estimate of the parameter on the lagged inflation term.

The second puzzle tackled is the "disinflationary news shock puzzle." Recent semi-structural VAR studies examine the effect of TFP news shocks (i.e., news about future productivity) on fluctuations. For example, Barsky and Sims (2011), Kurmann and Otrok (2013), and Barsky, Basu, and Lee (2015), using U.S. data, report that a positive TFP (i.e., technology) news shock generates a sharp and persistent decline in both inflation

[2] The sticky information model of Makiw and Reiss (2002) can also explain the inflation persistence puzzle. Coibion (2010) however provides the evidence that sticky price Phillips curve (i.e., the basic NKPC) dominates the sticky information Phillips curve.

[3] The hybrid NKPC can replicate a delayed response of inflation to monetary policy shocks, which the basic NK model cannot do.

and nominal interest rates.[4] In these VAR studies, a TFP news shock is identified as the innovation that does not affect TFP on impact but maximally explains the amount of TFP forecast error variance over a long period (usually, a 10-year period). The persistent and negative effects of a TFP (technology) news shock on inflation and nominal interest rates are found to be robust. Barsky et al. (2015) state the following: " By far the most robust result we obtain across different specifications is that good news shocks are highly disinflationary." However, conventional NK models have difficulty explaining this empirical finding: the *disinflationary news shock puzzle* (see, for example, Kurmann and Otrok 2014 and Barsky et al. 2015). The present paper's model can solve this puzzle, too. The analysis shows the following. Assuming that the present model is correct, the TFP news shock identification method, which is developed by Barsky and Sims (2011) and is applied by various studies, confounds TFP news shocks with "non-TFP news" shocks. This is because TFP is endogenously determined in the present model, and thus, even "preference and demand" shocks, which do not affect TFP on impact, cause a long-lasting effect on TFP. The confounding causes the repeatedly observed disinflationary effect of a TFP news shock.

The last puzzle considered is the "*zero lower bound (ZLB) supply shock puzzle.*" Based on the estimated model, this paper shows that including endogenous technology avoids a conventional NK model's paradoxical, empirically inconsistent prediction of the effect of a supply shock at the effective lower bound on nominal interest rates (i.e., ZLB). The standard NK model predicts that a *negative* supply shock is *expansionary* if the ZLB is expected to last long enough. To see the reasoning behind this prediction, consider a simple textbook NK model without capital. A negative and persistent supply shock increases current and expected marginal costs, and raises current and expected future inflation. In normal times this would lead to expected real interest rate increases because the central bank raises nominal interest rates responding to more than one-to-one to changes in inflation (the Taylor principle). However, at the ZLB, expected future real interest rates decrease, because the central bank does not (and is not expected to) respond. Because current consumption and output are determined by the expected future path of real interest rates, decreased future real interest rates stimulate aggregate demand, which has a large enough effect to offset the direct negative effect of a negative supply shock. This increases current output.[5] However, recent empirical studies found no evidence for this prediction of conventional new Keynesian models: the *ZLB supply shock*

[4] Barsky and Sims (2011) do not include a nominal interest rate in their VAR, and hence, they do not report the effect on a nominal interest rate.

[5] See, for example, Eggertson (2011) and Eggertson, Ferrero, and Raffo (2014) for the NK model's prediction of the expansionary effect of a negative supply shock at the ZLB. Wieland (2018) and Garin, Lester, and Sims (2018) show that the expansionary effect of a negative supply shock at the ZLB also applies to a medium-scaled new Keynesian model with capital and some frictions such as habit formation and investment adjustment costs, by using Smets and Wouters (2007) model. The reasoning for the expansionary effect is more or less same as the simple textbook NK model's case.

puzzle.[6] For example, Wieland (2018), using Japanese data, finds that negative productivity shocks (i.e., the Great East Japan earthquake and oil supply shocks) are in fact contractionary at the ZLB, and Garin, Lester, and Sims (2018), using U.S. utilization-adjusted TFP data, find that, compared to normal times, negative productivity shocks are more contractionary at the ZLB. The present paper's model gives a prediction consistent with these recent empirical findings and, thus, solves the puzzle. The reasoning is as follows. A negative and persistent productivity shock increases current and expected future marginal costs. In addition to this (direct) "positive" effect on future marginal costs, endogenously-determined technology incorporated in the model generates the indirect "negative" effect of a negative productivity shock on future marginal costs, resulting in decreased output. Let me explain this in a little more detail. Decreased future productivity levels caused by the shock, ceteris paribus, lower expected monopoly profits from new differentiated products created in the future. This lowers PD spending now and, thus, reduces future endogenously-determined technology levels (i.e., the number of differentiated products) and future aggregate income levels. Decreased future aggregate income levels, in turn, reduce future demands for new differentiated products and, thus, future demands for labor. Lower expected future demands for labor then reduce future real wages and, thus, lower future marginal costs. If this negative feedback effect of a negative productivity shock on future marginal costs is larger than the direct positive effect, it puts a downward pressure on current and future inflation rates and, thus, puts an upward pressure on the real interest rate path, so that current aggregate demand is suppressed. This can cause current output to decline.

This paper is not the first to investigate the above-mentioned puzzles (see, e.g., the sticky information model of Mankiw and Reis 2003 for the inflation persistence puzzle; the endogenous technology new Keynesian model of Jinnai 2014 and the real wage rigidity new Keynesian model of Barsky et al. 2015 for the disinflationary news shock puzzle; and the sticky information model of the Kiley 2018 for the ZLB supply shock puzzle).[7] To my knowledge, however, this paper is the first attempt to show, using a single model, that incorporating endogenous technology can solve all of the above three puzzles. The paper shows that the model can replicate the puzzling empirical findings and that endogenous technology is the key to the successful replications.

In addition to the aforementioned papers, this paper is closely related to the literature

[6] Walsh (2017) presents the ZLB supply shock puzzle and other important features of the new Keynesian model with the ZLB.

[7] Other important papers that address the puzzles include the following studies. Coibion, Gorodnichenko, and Kamadar (2018) show that deviating from full-information rational expectation in estimation of the Phillips curve, i.e., incorporating survey-based expectations (i.e., subjective expectations), can solve many puzzles in the NKPC, including the inflation persistence puzzle. Jinnai (2013) uses a sticky nominal wage new Keynesian model with a consumption growth monetary policy rule to solve the disinflationary news shock puzzle. Boneva, Braun, and Waki (2016), Cochrane (2017), and Bodenstein, Erceg, and Guerrieri (2018) tackle the ZLB supply shock puzzle within the framework of a standard new Keynesian model.

that incorporates endogenous technological change into a NK model. Among the limited number of such studies, Bilbiie, Ghironi, and Melitz (2008), Jinnai (2014), Bianchi, Kung, and Morales (2018) and Anzoategui, Comin, Gertler, and Martinez (2018) are most closely related to the present paper, which complements these studies.

Bianchi, et al. (2018) and Anzoategui et al. (2018) develop and estimate NK models with endogenous technology, as this paper does. They consider U.S. fluctuations and find that an endogenous TFP mechanism can explain a large share of the post-Great Recession decline in productivity. The present paper differs from their studies in two main ways. First, the present paper has a different aim from them. They focus on examining the source of a sustained decline in productivity following a severe recession, such as the Great Recession, and argue that the persistent decline in productivity following the Great Recession is largely explained by an endogenous TFP mechanism. Second, to consider the fact that it takes some time for investments in new technologies to affect an economy, they introduce a technology adoption lag by using an endogenous technology adoption rate. They assume that for a new technology to have an impact on an economy, the new technology must be adopted in production after it is invented. In contrast to their studies, this paper uses the time-to-innovate structure to model a delayed effect of technology investments.

Bilbiie et al. (2008) and Jinnai (2014) also develop new Keynesian models with endogenous technology. Bilbiie et al. (2008) address issues that are absent in conventional NK models. In one of those issues, they *hint* that their version of NKPC has a potential ability to solve the inflation persistence puzzle because their NKPC includes a change in the number of endogenous product varieties. They point out that this endogenously-predetermined term may lead to extra persistence in inflation as is empirically found. This argument is somewhat similar to the one presented in this paper. The present paper, however, differs in several important ways. First, the existence of the extra variable does not necessarily mean a positive, sizable, and significant coefficient on the lagged inflation term in the NKPC estimation. The present paper provides clear evidence for a solution to the inflation persistence puzzle, using Monte Carlo simulations with the estimated model economy. Second, Bilbiie et al. (2008) assume that it takes only one period to innovate a new product and also that there is no technology adaptation lag. In contrast, the present model assumes the time-to-innovate structure, in which product innovation requires consecutive investments over multiple periods. This paper shows that the time-to-innovate structure plays a necessary role in solving the inflation persistence puzzle. Third, Bilbiie et al. (2008) use a quadratic cost of price adjustment (Rotemberg 1982) to model price rigidity.[8] In contrast, this paper uses Calvo (1980) pricing, which is more common in the NK literature.

[8] In Rotemberg (1982), firms can freely set prices at any time but they face a cost of price adjustment. This implies that the extent of price changes is smaller than one under flexible prices.

Jinnai (2014) tackles the disinflationary news shock puzzle. He argues that what the Barsky and Sims (2011)'s VAR decomposition identifies as news shocks are R&D sector specific shocks and that this is the reason for the disinflationary news shock effect. The model of Jinnai (2014) markedly differs from the present paper's model, e.g., Jinnai (2014) assumes one-period innovation process as Bilbiie et al. (2008) does and it gives a largely different version of NKPC. Another important difference is that Jinnai (2014)'s simulation exercise with its calibrated model economy does not include TFP news shocks. Because TFP news shocks are found to play a significant role (if not, at least a non-negligible role) in fluctuations according to empirical studies (see, Beaudry and Lucke 2010 and Görtz and Tsoukalas 2017), and a TFP news shock is known to have a strong *inflationary* impact in conventional NK models, it seems unclear whether Jinnai (2014)'s result holds when TFP news shocks are included in his model. In contrast to Jinnai (2014), the present paper's model includes TFP news shocks and solves the disinflationary puzzle without relying on R&D shocks.

In addition, to my knowledge, this paper is the first study to show that the incorporation of endogenous technology can solve the ZLB supply shock puzzle.

The remainder of the paper is organized as follows. Section 2 presents the model. Section 3 estimates the model and then, using a Monte Carlo method, analyzes endogenous technology's role in macroeconomic fluctuations. Section 4 concludes this paper.

2 Model

The paper extends a quantitative NK model (i.e., a simplified version of the models of Christiano et al. 2005 and Smets and Wouters 2007) to include the endogenous knowledge production of Romer (1990). The model assumes two types of firms: final goods firms and intermediate goods firms. Intermediate goods firms conduct time-consuming product development (henceforth PD) to create blueprints (i.e., "ideas" and "designs") for constructing differentiated new intermediate goods. A blueprint is needed for intermediate goods production. Once a firm produces a blueprint for an intermediate good (i.e., develops a new product), the firm can produce and sell the good monopolistically. In this paper, PD does not exactly mean R&D. R&D activity in general includes several categories, e.g., basic research , applied research, advanced development and product development. This paper considers a development-type R&D activity, which is less time consuming than a research-type R&D activity.

Following Christiano et al. (2005) and Smets and Wouters (2007), the model incorporates several frictions that are now standard in NK models: staggered prices, consumption habit persistence, and adjustment costs in investment.[9] In addition to standard shocks

[9] Christiano et al. (2005) and Smets and Wouters (2007) incorporate staggered wages and prices. The present model does not include wage rigidity for simplification.

(i.e., shocks to monetary policy, consumption and leisure preferences, government spending, and TFP), TFP news shocks are considered.[10]

2.1 Firms

2.1.1 Final goods firms

Final goods firms produce Y_t using intermediate goods $Y_t(j)$. The production function is given by:

$$Y_t = \left[\int_0^{A_{t-1}} Y_t(j)^{\frac{\phi-1}{\phi}} dj \right]^{\frac{\phi}{\phi-1}}, \phi > 1, \tag{1}$$

where A_{t-1} is the number of types of intermediate goods at time $t-1$, i.e., the number of blueprints at time $t-1$. It is assumed that there exists a continuum of types of intermediate goods indexed along the interval $[0, A_{t-1}]$. A_{t-1} rather than A_t enters in equation (1). This is because it is assumed that an intermediate goods firm that invents a blueprint for a good at time $t-1$ can produce and sell the good only from time t onwards. Another way to explain this is that for stock variables (i.e., predetermined variables) a "stock at the end of the period" concept is used throughout this paper.

The maximization problem is as follows:

$$\max_{Y_t(j)} P_t \left[\int_0^{A_{t-1}} Y_t(j)^{\frac{\phi-1}{\phi}} di \right]^{\frac{\phi}{\phi-1}} - \int_0^{A_{t-1}} P_t(j) Y_t(j) dj,$$

where P_t and $P_t(j)$ denote the price of a final good and that of intermediate good j, respectively. From the first-order condition and equation (1), one can obtain

$$P_t = \left[\int_0^{A_{t-1}} P_t(j)^{1-\phi} dj \right]^{\frac{1}{1-\phi}}. \tag{2}$$

2.1.2 Intermediate goods firms: goods production decision

The inventor of good j's blueprint retains a monopoly right over the production and sales of $Y(j)$. Firm j employs the following production function:

$$Y_t(j) = \mu_t K_{t-1}(j)^{\theta} H_t(j)^{1-\theta} \tag{3}$$

where K_{t-1} is capital stock at the end of period $t-1$, H_t is labor (the number of workers times hours worked, i.e., $H_t = h_t N_t$ where h_t is hours worked and N_t is the number of workers), and μ_t is a stochastic technology shock component with a mean of one. A zero

[10] Fujiwara et al. (2011) and Khan and Tsouklas (2012) incorporate TFP news shocks into a New Keynesian model and analyze the effects on U.S. business cycles (Fujiwara et al. (2011) also analyze the effect on Japanese business cycles).

population growth rate is assumed for the later analysis, i.e., $N_t = N$. μ_t is given by:

$$\ln \mu_t = \rho_\mu \ln \mu_{t-1} + \varepsilon_t^\mu + \sum_{s=1}^{\bar{t}} \varepsilon_{s,\ t-s}^{news},\ 0 \leq \rho_\mu \leq 1 \ and\ 1 \leq \bar{t}, \tag{4}$$

where ε_t^μ and $\varepsilon_{s,t-s}^{news}$ are shocks to $\ln \mu_t$. The term ε_t^μ represents an unanticipated technology shock, which is an i.i.d. shock with $E_t[\varepsilon_{t+1}^\mu] = 0$ and $var[\varepsilon_t^\mu] = \sigma_\mu$. The term $\varepsilon_{s,t-s}^{news}$ represents a technology news shock (an anticipated technology shock) at time $t-s$ and is the s-period-ahead news received about $\ln \mu_t$ (i.e., news about $\ln \mu_t$ received at time $t-s$). It is assumed to be distributed with $E[\varepsilon_{s,\ t-s}^{news}] = 0$ and $var[\varepsilon_{s,\ t-s}^{news}] = \sigma_{s,news}$. Contemporaneous correlations among technology news shocks are allowed (but serial correlations are not allowed) because these shocks are highly likely to be correlated with one another. That is, $corr(\varepsilon_{s',\ t}^{news}, \varepsilon_{s'',\ t}^{news}) \neq 0$ for $s' \neq s''$ where $\varepsilon_{s',\ t}^{news}$ ($\varepsilon_{s'',\ t}^{news}$) denotes the $s'(s'')$-ahead news shock received at time t. Except for allowing for the correlations, the present approach to modelling news shocks is the same as in Fujiwara et al. (2011), Khan and Tsoukalas (2012), Schmitt-Grohé and Uribe (2012) and Görtz and Tsoukalas (2017).

Following Calvo (1983), it is assumed that only a fraction $1-\rho$ of firms can reset their prices at time t while the rest keep their prices unchanged. ρ is assumed to be independent of the number of periods. It is also assumed that any existing blueprints, in the next period, become obsolete and undemanded by final goods firms with probability $(1-\psi)$. Intermediate goods firm j that can set a price of $Y(j)$ facing the demand curve (i.e., the first-order condition of the final goods firm's problem) thus faces the following familiar maximization problem:

$$\begin{aligned} \max_{P_t^*(j)} E_t \sum_{l=0}^{\infty} Q_{t,t+l}^{-1} (\psi\rho)^l & \left[\begin{array}{c} P_t^*(j) Y_{t+l} \left(\frac{P_{t+l}}{P_t^*(j)}\right)^\phi - P_{t+l} r_{t+l} K_{t-1+l}(j) \\ -P_{t+l} w_{t+l} H_{t+l}(j) \end{array} \right] \\ \text{subject to } \ Y_{t+l} \left(\frac{P_{t+l}}{P_t^*(j)}\right)^\phi &= \mu_{t+l} K_{t-1+l}(j)^\theta H_{t+l}(j)^{1-\theta} \quad , \end{aligned} \tag{5}$$

where r_t is a real rental price of capital, w_t is a real wage, $P_t^*(j)$ is the price chosen by the price-setting firm ($P_t^*(j)$ turns out to be the same across firms, i.e., $P_t^*(j) = P_t^*$) and $Q_{t,t+l}^{-1}$ is a stochastic discount factor.[11]

Consider next the monopoly profit of a price-setting firm. Let us define $\Omega_{t+m,t+m+l}$ as an instantaneous nominal monopoly profit of a firm at time $t+m+l$ that set (set for the first time or reset) its price at time $t+m$ ($m \geq 0$), continues to be in the market at time $t+m+l$ ($l \geq 0$) and holds its price unchanged from time $t+m$ to time $t+m+l$.

[11] At a given point in time, there are two types of price-setting firms: (1) firms that reset their prices and (2) firms that newly enter the intermediate goods market and set their prices for the first time.

$\Omega_{t+m,t+m+l}$ can then be given by the following:

$$\begin{aligned}\Omega_{t+m,\ t+m+l}(j) &= P^*_{t+m}(j)Y_{t+m+l}(j) \\ &\quad - \left[P_{t+m+l}\frac{w_{t+m+l}}{1-\theta}\left(\frac{1-\theta}{\theta}\frac{r_{t+m+l}}{w_{t+m+l}}\right)^{\theta}\frac{Y_{t+m+l}(j)}{\mu_{t+m+l}}\right].\end{aligned} \tag{6}$$

Note that $\Omega_{t+m,t+m+l}(j)$ is the same across firms, i.e., $\Omega_{t+m,t+m+l}(j) = \Omega_{t+m,t+m+l}$, because $P^*_{t+m}(j) = P^*_{t+m}$ and $Y_{t+m+l}(j) = \left(\frac{P_{t+m+l}}{P^*_t}\right)^{\phi} Y_{t+m+l}$ (this is the first-order condition from the final goods firm's problem). Denoting $P^{-1}_{t+m+l}\,\Omega_{.,t+m+l}$ and $P^{-1}_{t+l}\,\Omega_{.,\ t+l}$ as $\Omega'_{.,t+m+l}$ and $\Omega'_{.,t+l}$, respectively, and using equation (6), one can write the expected present value of the stream of real monopoly profits for a firm that set its price at time t as follows:

$$\begin{aligned} &Z_t \\ &= E_t\left[\sum_{l=0}^{\infty}\left[Q'^{-1}_{t,t+l}(\psi\rho)^l\ \Omega'_{t,t+l} + (1-\rho)(\psi\rho)^l\left(\sum_{m=1}^{\infty}Q'^{-1}_{t,t+m+l}\psi^m\ \Omega'_{t+m,t+m+l}\right)\right]\right]\end{aligned} \tag{7}$$

where $Q'_{t,t+l} \equiv Q_{t,t+l}\frac{P_t}{P_{t+l}}$ and

$$\begin{aligned}&\Omega'_{t+m,t+m+l} \\ &= P^{-1}_{t+m+l}Y_{t+m+l}\left(\frac{P_{t+m+l}}{P^*_{t+m}}\right)^{\phi}\left[P^*_{t+m} - P_{t+m+l}\frac{w_{t+m+l}}{\mu_{t+m+l}\,(1-\theta)}\left[\frac{1-\theta}{\theta}\frac{r_{t+m+l}}{w_{t+m+l}}\right]^{\theta}\right].\end{aligned}$$

Note that the profits Z_t are the same across price-setting firms, which include the firms that newly enter the market upon successful product development. Equation (7) can be expressed as

$$Z_t - E_t\left[Q'^{-1}_{t,t+1}\psi Z_{t+1}\right] = \Omega'_{t,t} + E_t\left[\sum_{l=1}^{\infty}Q'^{-1}_{t,t+l}(\psi\rho)^l(\Omega'_{t,t+l} - \Omega'_{t+1,t+l})\right] \tag{8}$$

where

$$\Omega'_{t1,t2} = P^{-1}_{t2}Y_{t2}\left(\frac{P_{t2}}{P^*_{t1}}\right)^{\phi}\left[P^*_{t1} - P_{t2}\frac{w_{t2}}{\mu_{t2}(1-\theta)}\left[\frac{1-\theta}{\theta}\frac{r_{t2}}{w_{t2}}\right]^{\theta}\right]$$

for $t1 = t,\ t+1$ and $t2 = t,\ t+l$.

2.1.3 Intermediate goods firms: PD investment decision

The model assumes that an intermediate goods firm borrows money from households to invest in PD and creates a blueprint to construct a new type of intermediate good. It also assumes a "time-to-innovate" (i.e., a "time-to-build") type of structure for PD: a firm needs to invest in PD consecutively to create a blueprint.[12] Intermediate goods firm j that starts creating a blueprint for its new product at time t needs, in total, ${}_tPDC$ units of final goods to produce the blueprint and the cost is assumed to be the same across firms. Firms take the cost as given. Denoting $\overline{\varphi}$ as the number of PD periods needed to create a blueprint, the total PD cost of a firm that starts its PD at time t is given by

$$ {}_tPDC = \sum_{\varphi=1}^{\overline{\varphi}} (\eta_\varphi \, J_t) \text{ where } \sum\nolimits_{\varphi=1}^{\overline{\varphi}} \eta_\varphi = 1. \tag{9} $$

The term $\eta_\varphi J_t$ represents the PD cost at φ stages from the last. The term η_φ measures a relative importance of each PD stage, and the subscript φ means that there are φ further periods before the PD process is completed. J_t is given by:

$$ J_t = d \, (F_t)^\alpha, \; d > 0, \, 0 < \alpha \, , \tag{10} $$

where d is a scaling parameter and F_t is the number of firms creating blueprints (i.e., searching for new ideas).

Equation (10) assumes that the PD cost of a firm depends on the number of firms searching for new ideas (i.e., the number of firms creating blueprints) in the economy when the firm starts its PD process. When more firms are engaged in PD, some of the ideas created by individual firms become less likely to be new to the economy. Thus, an increase in the number of firms engaged in PD makes it more difficult for an individual firm to create a new blueprint. This effect is called the congestion effect and is captured by the term $(F_t)^\alpha$ with $0 < \alpha$ in equation (10).

Once an intermediate goods firm creates a blueprint for a good, the firm obtains a monopoly right over the production of the good. A constant success probability of PD is assumed and denoted by ϵ. Free entry into PD is also assumed. That is, any firm can pay the PD cost of ${}_tPDC$ to secure its monopoly profits upon its successful PD. In equilibrium, firm j's free entry into PD must thus guarantee the following:[13]

$$ \epsilon E_t[Z_{t+\overline{\varphi}}] = E_t[\sum_{\varphi=1}^{\overline{\varphi}} \left(\eta_\varphi J_t \frac{P_{t+\overline{\varphi}-\varphi}}{P_{t+\overline{\varphi}}} \prod_{l=\overline{\varphi}-\varphi}^{\overline{\varphi}-1} (1 + r_{N,t+l}) \right)], $$

where $r_{N,t}$ denotes a nominal interest rate at time t. Here, loans to PD firms are assumed to be rolled over until firms complete their PD project. This point will be discussed in more detail when the household problem is considered. Substituting equation (10) into

[12] Kydland and Prescott (1982) use the "time to build" structure for capital development.

[13] It is assumed that firms do not drop out of their PD. This can be due to a large initial (constant) fixed cost in PD, compared to PDC (including this cost does not affect the following analysis because it uses log-deviations from the steady state).

the above equation, one can rewrite the free entry condition as follows:

$$\epsilon E_t\left[Z_{t+\overline{\varphi}}\right]=d\left(F_t\right)^{\alpha}E_t\left[\sum_{\varphi=1}^{\overline{\varphi}}\left(\eta_{\varphi}\frac{P_{t+\overline{\varphi}-\varphi}}{P_{t+\overline{\varphi}}}\prod_{l=\overline{\varphi}-\varphi}^{\overline{\varphi}-1}\left(1+r_{N,t+l}\right)\right)\right]. \tag{11}$$

2.2 Households

The economy has a continuum mass of homogeneous households indexed by $i\in[0,1]$ and household i maximizes:

$$E_0\sum_{t=0}^{\infty}\Gamma^t N_{t,i}\left[\begin{array}{c}\upsilon_{c,t}\frac{\left[C_{t,i}/N_{t,i}-\lambda_h(C_{t-1,i}/N_{t-1,i})\right]^{1-\sigma_c}}{1-\sigma_c}\\ -\upsilon_{h,t}\frac{(H_{t,i}/N_{t,i})^{1+\sigma_h}}{1+\sigma_h}+\frac{\left[M_{t,i}/(P_tN_{t,i})\right]^{1-\sigma_m}}{1-\sigma_m}\end{array}\right],$$

s.t.

$$C_{t,i}+INV_{t,i}+\frac{M_{t,i}}{P_t}+\frac{B_{t,i}}{P_t}\leq w_tH_{t,i}+r_tK_{t-1,i}-TX_t+(1+r_{N,t-1})\frac{B_{t-1,i}}{P_t}+\frac{M_{t-1,i}}{P_t}+\Xi_{t,i}, \tag{12}$$

$$K_{t,i}=(1-\delta)K_{t-1,i}+INV_{t,i}-S(\frac{INV_{t,i}}{INV_{t-1,i}})INV_{t,i}, \tag{13}$$

where Γ is a discount factor, $C_{t,i}$ is household i's consumption, $N_{t,i}$ is the number of members of household i, $INV_{t,i}$ is household i's investment in capital, TX_t is a per household real tax, $B_{t,i}$ is household i's one-period nominal loan to intermediate goods firms (the loan is made at time t and repaid at time $t+1$), δ is the depreciation rate of capital, $M_{t,i}$ is household i's nominal money holding, and $\Xi_{t,i}$ is household i's gains or losses from holding the shares of intermediate goods firms in period t. λ_h captures an (internal) habit persistence. Following Christiano et al. (2005), the model also incorporates the adjustment cost of capital $S(\frac{INV_{t,i}}{INV_{t-1,i}})$, as in equation (13), and the expressions below are assumed to hold:

$$S(1)=S^{'}(1)=0,\ S^{''}(1)=\xi,\ \xi>0.$$

The stochastic discount factor $Q_{t,t+l}^{-1}$ in equation (5) can then be given by

$$Q_{t,t+l}^{-1}=\Gamma^l\frac{\varrho_{t+1}}{\varrho_t}\frac{P_t}{P_{t+l}}$$

where ϱ_t is the marginal value of an extra unit of income (see Section 1A of the Appendix).[14]

Loans to PD firms are rolled over until the firms complete their PD projects. When the PD firms, which have rolled over their loans during their PD periods, complete their PD, they repay all of their rolled over loans by issuing shares. This implies that households as

[14]Solving the household's maximization problem gives $\varrho_t=(c_{t,i}-\lambda_hc_{t-1,i})^{-\sigma_c}\upsilon_{c,t}-(1+n)\lambda_h\Gamma E_t\left[(c_{t+1,i}-\lambda_hc_{t,i})^{-\sigma_c}\upsilon_{c,t+1}\right]$ where $c_{t,i}\equiv C_{t,i}/N_{t,i}$.

buyers of the shares, on the one hand, invest the amount equivalent to the loan payments, and households as the owners of the firms, on the other hand, disinvest the same amount (i.e., lose the firms' assets due to the loan payments). Because these two transactions cancel each other out, they are not shown in the budget constraint above. Household i as an owner of an intermediate goods firm gains or loses due to a change in the value of the firm over time.

The terms $\upsilon_{c,t}$ and $\upsilon_{h,t}$ in the expected utility function represent shocks to consumption preferences and leisure preferences, respectively. They are stochastic components with a mean of one and defined by:

$$\ln \upsilon_{c,t} = \rho_{\upsilon_c} \ln \upsilon_{c,t-1} + \varepsilon_t^{\upsilon_c} \text{ and } \ln \upsilon_{h,t} = \rho_{\upsilon_h} \ln \upsilon_{h,t-1} + \varepsilon_t^{\upsilon_h},\ 0 \leq \rho_{\upsilon.} \leq 1,$$

where $\varepsilon_t^{\upsilon_c}$ and $\varepsilon_t^{\upsilon_h}$ represent i.i.d. shocks with $E_t[\varepsilon_{t+1}^{\upsilon_c}] = 0$, $E_t[\varepsilon_{t+1}^{\upsilon_h}] = 0$, $var[\varepsilon_t^{\upsilon_c}] = \sigma_{\upsilon_c}$and $var[\varepsilon_t^{\upsilon_h}] = \sigma_{\upsilon_h}$.

2.3 Monetary policy: interest rate rule

Assume that the central bank follows a simple interest rate rule of the following form:

$$R_{N,t} = \Lambda R_{N,t-1}^{\vartheta} \left[\left(\frac{P_t/P_{t-1}}{\overline{P}_t/\overline{P}_{t-1}} \right)^{\varpi_p} \left(\frac{Y_t}{Y_t^n} \right)^{\varpi_y} \right]^{1-\vartheta} u_t, \tag{14}$$

where $R_{N,t} \equiv 1 + r_{N,t}$, $\overline{P}_t$ is an aggregate price level in a steady state (a balanced growth path), Y_t^n is the equilibrium level of output under flexible prices, and u_t is a monetary policy shock with a mean of one.[15] It is also assumed that $0 \leq \vartheta \leq 1$, $0 \leq \varpi_\pi$, $0 \leq \varpi_y$,and $0 \leq \Lambda$ are satisfied, and that the values of Λ, ϑ, ϖ_p and ϖ_y are chosen by the central bank (Λ is needed for the economy to have a steady state). u_t is characterized by:

$$\ln u_t = \rho_u \ln u_{t-1} + \varepsilon_t^u,\ 0 \leq \rho_u \leq 1,$$

where ε_t^u is an i.i.d. shock with $E_t[\varepsilon_{t+1}^u] = 0$ and $var[\varepsilon_t^u] = \sigma_u$.

2.4 The dynamics of P_t and A_t

As mentioned above, an intermediate goods firm can produce its goods at time t only if it owns the blueprint for the goods at time $t-1$. Thus, the number of intermediate goods firms selling goods to final goods firms at time t is equal to A_{t-1}. Because ψA_{t-2} is the number of firms that exist in the intermediate goods market at time $t-1$, $A_{t-1} - \psi A_{t-2}$ shows the number of firms that newly enter the market at time t by having completed

[15] Following Smets and Wouters (2007), Y_t^n is used as a target for the monetary policy rule (14). Also, with the monetary policy rule and the separable utility function, the money demand equation derived from the household's problem becomes redundant.

their PD processes. Thus, at time t, $(A_{t-1} - \psi A_{t-2})$ firms set their price for the first time as they enter the market, $(1-\rho)\psi A_{t-2}$ firms reset their prices, and $\rho\psi A_{t-2}$ firms hold their prices unchanged. Using equation (2) one can therefore obtain the following:

$$P_t = \left[\int_0^{\rho\psi A_{t-2}} P_{t-1}(j)^{1-\phi} dj + \int_{\rho\psi A_{t-2}}^{A_{t-1}} P_t^*(j)^{1-\phi} dj \right]^{\frac{1}{1-\phi}} . \tag{15}$$

Equation (15) can be rewritten as:[16]

$$P_t = \left[\rho\psi (P_{t-1})^{1-\phi} + (A_{t-1} - \rho\psi A_{t-2})(P_t^*)^{1-\phi} \right]^{\frac{1}{1-\phi}} . \tag{16}$$

Regarding the dynamics of A_t, because a firm that spends PDC units of final goods produces one blueprint with probability ϵ and the existing blueprints become obsolete in the next period with probability $1-\psi$, the dynamics of A_t is given by:[17]

$$A_t = \epsilon F_{t-\overline{\varphi}+1} + \psi A_{t-1} . \tag{17}$$

2.5 Equilibrium

The labor, capital, money and lending market equilibrium conditions are as follows:

$$H_t = \int_0^{A_{t-1}} H_t(j)\ dj, \quad K_{t-1} = \int_0^{A_{t-1}} K_{t-1}(j)\ dj, \ M_t = M_{t,i},$$

$$\begin{aligned} B_t \ &= \ P_t \left(\sum_{\varphi=1}^{\overline{\varphi}} \left(F_{t-\varphi+1}(J_{t-\varphi+1}) \eta_{\overline{\varphi}-\varphi+1} \right) \right) \\ &\quad + \sum_{m=1}^{\overline{\varphi}-1} \left[P_{t-m} \prod_{l=1}^{m} (1 + r_{N,t-l}) \left(\sum_{\varphi=m}^{\overline{\varphi}-1} \left(F_{t-\varphi}(J_{t-\varphi}) \eta_{\overline{\varphi}-\varphi+m} \right) \right) \right] , \end{aligned} \tag{18}$$

where $M_t = \int_0^1 M_{t,i}\ di$ and $B_t = \int_0^1 B_{t,i}\ di$ (recall that $B_{t,i}$ represents one-period nominal loans to intermediate goods firms made by household i at time t).[18] The second term on the right-hand side of equation (18) represents the sum of rollover loans, and the first term represents the sum of new loans to PD firms.

[16] $\int_0^{\rho\psi A_{t-2}} P_{t-1}(j)^{1-\phi} dj \approx \rho\psi \int_0^{A_{t-2}} P_{t-1}(j)^{1-\phi} dj$, $\rho\psi \int_0^{A_{t-2}} P_{t-1}(j)^{1-\phi} dj = \rho\psi (P_{t-1})^{1-\phi}$ (from equation 2) and $P_t^*(j) = P_t^*$ are used.

[17] Note that A_t is the stock of blueprints at the end of period t and $F_{t-\overline{\varphi}+1}$ is the number of PD firms at the beginning of period $t - \overline{\varphi} + 1$. If the number of periods required for PD, $\overline{\varphi}$, is 1, the equation becomes $A_t = \epsilon F_t + \psi A_{t-1}$.

[18] See Section 1B of the Appendix for more details about equilibrium conditions.

The goods market equilibrium condition is given by:

$$Y_t = \int_0^1 C_{t,i}\ di + \int_0^1 INV_{t,i}\ di + \int_0^1 ID_{t,i}\ di + G_t = C_t + INV_t + ID_t + G_t, \tag{19}$$

where

$$ID_t = \sum_{\varphi=1}^{\overline{\varphi}} \left(\eta_\varphi (J_{t-\overline{\varphi}+\varphi}) F_{t-\overline{\varphi}+\varphi}\right) \tag{20}$$

$$G_t = \tau_t\ Y_t. \tag{21}$$

$$\tau_t = (1-\rho_\tau)\overline{\tau} + \rho_\tau \tau_{t-1} + \varepsilon_t^\tau,\ \ 0 \leq \rho_\tau \leq 1. \tag{22}$$

$ID_{t,i}$ is household i's investment in PD, and INV_t and ID_t are total capital investment and total PD investment, respectively. G_t is government expenditure and equal to a fraction τ_t of output.[19] Equation (22) shows the dynamics of τ_t, where $\overline{\tau}$ is a steady-state level of τ, and ε_t^τ (i.e., a government spending shock) is an i.i.d. shock with $E_t[\varepsilon_{t+1}^\tau] = 0$ and $var[\varepsilon_t^\tau] = \sigma_\tau$.

2.6 Aggregate dynamics

By combining the optimization conditions and constraints with the equilibrium conditions, one can obtain the system of equations describing the aggregate economy's dynamics. As in conventional business cycle studies, the model is log-linearized around the steady state. The linearized model is reported in Section 2 of the Appendix.

For ease of estimation, we make the following assumption regarding the relative importance of each PD stage.

$$\eta_\varphi = \eta_1 \overline{\eta}^{\varphi-1},\ \ 0 < \overline{\eta}. \tag{23}$$

This assumption implies that the importance of each stage of PD changes monotonically, i.e., if $\overline{\eta} > 1$ ($\overline{\eta} < 1$), an earlier stage of PD is more (less) important than a later stage.[20]

3 Estimation and results

The linearized model is estimated by using Bayesian methods. For comparison, a basic NK model is also estimated. The basic NK model is basically the same as the above model except that it does not have the PD process. The linearized basic NK model is shown in Section 3 of the Appendix. I call the model presented above the endogenously-determined product development NK model (henceforth, the EPD-NK model).

[19] The government budget constraint is given by $G_t = \frac{M_t - M_{t-1}}{P_t} + TX_t$.

[20] Because $\sum_{\varphi=1}^{\overline{\varphi}} \eta_\varphi = 1$, under the assumption (23) we only need to estimate $\overline{\eta}$ to identify each η_φ.

Bayesian techniques are now widely used to estimate DSGE models, e.g., Smets and Wouters (2007), An and Schorfheide (2007), Schmitt-Grohé and Uribe (2012), Anzoategui et al. (2018), and Bianchi et al. (2018). To estimate the models, I use six U.S. macroeconomic quarterly time series ranging from 1957:q1 to 2004:q4 as observable variables, and the data are taken from Smets and Wouters (2007). The data include real GDP, real consumption, real wage, hours worked, the GDP deflator, and the federal funds rate.[21] Demeaned growth rates (demeaned log differences) are used, except for the federal funds rate (the federal funds rate is demeaned in levels). As mentioned above, correlations among TFP news shocks are allowed because those shocks are highly likely to be correlated with one another. With forty-eight years of quarterly data, i.e., 191 observations, allowing correlated TFP news shocks could however lead to a serious reduction in the precision of the estimates because a very large number of parameters needs to be estimated (the news horizon is assumed to be sixteen periods, i.e., sixteen quarters). The following estimation thus includes only four news shocks: 4-, 8-, 12-, and 16-period (quarter) ahead news shocks (i.e., $\varepsilon^{news}_{4,\ t-4}$, $\varepsilon^{news}_{8,\ t-8}$, $\varepsilon^{news}_{12,\ t-12}$ and $\varepsilon^{news}_{16,\ t-16}$) in equation (4). Regarding the time required for product development $\overline{\varphi}$, it is assumed that firms need 8 quarters to develop their new products, and thus, under the specification in equation (1), it takes 9 quarters before their new products become available on the market. This is consistent with the finding of Griffin (2002), who uses a survey data to quantify the average product development time for the physical goods of industrial firms (116 sample firms) and finds that, on average, industrial firms spend 2.25 years developing their new innovative products.

Table 1 reports the parameter estimates of the EPD-NK model along with those of the basic NK model.[22] The prior distributions of the estimated parameters and the calibrated parameters are explained in Section 4 of the Appendix. According to Table 1, the estimates of the two models generally have similar values, but some estimates show noticeable differences. The estimate of the parameter describing the monetary policy rule for output is higher for the EPD-NK model. The estimate of price stickiness (Calvo price) is also slightly higher for the EPD-NK model. The estimate of the intertemporal elasticity of substitution is lower for the EDP-NK model. The degree of persistence of an unanticipated TFP shock is also lower for the EPD-NK model. This lower persistence

[21] I decide not to use the data on investment because (i) some of measured capital investments are possibly used as PD investments, (ii) it is difficult to obtain good measures of product development investment, and (iii) some R&D spending may or may not be apropriately regarded as product development spending. In 2013, Bureau of Economic Analysis (BEA) changed the treatment of R&D spending and counted it as part of private fixed investment in intellectual property products. This affects not only total investment but also GDP. The new System of National Accounts (SNA) data are not used in the present paper because (i) the data from Smets and Wouters (2007) are used for comparison purposes, and (ii) the present paper considers only the development side of an R&D activity (it does not consider the research side).

[22] As in Smets and Wouters (2007), σ_m, which appears only in the money demand equation, is neither estimated nor calibrated because the money demand equation is redundant (see note 15).

likely results from additional persistence that the endogenously-determined PD process contributes to the model. Differences are also observed in the estimates of parameters related to news shocks. For example, the highest standard deviation among the news shocks for the EPD-NK model is the 8-period-ahead news shock, but that for the basic NK model is the 4-period-ahead news shock.

Table 1 also reports the marginal likelihoods of the EPD-NK and basic NK models. Incorporating the endogenously-determined PD process into the NK model improves the marginal likelihood. This indicates that the EPD-NK model is empirically better than the basic NK model.

3.1 Inflation persistence puzzle: the Phillips curve

When researchers estimate the NKPC using limited-information methods (e.g., single-equation generalized method of moments, GMM), the lagged inflation term is found to significantly and positively enter into the regressions and the coefficient is found to be sizable, although a "basic" NK model gives the purely forward-looking Phillips curve: the *inflation persistence puzzle*.[23] To reconcile theory with this empirical finding, the business cycle literature has usually relied on rather ad hoc assumptions. More specifically, conventional NK models extend a basic NK model generally in one of the following two ways: one is to allow for a subset of firms that uses a backward-looking rule of thumbs to set prices (e.g., Gali and Gertler 1999), and the other is to allow for a subset of firms that cannot optimize their price and instead index it to past inflation (e.g., Christiano et al. 2005 and Smets and Wouters 2007). The conventional NK models then give the well-known hybrid NKPC, which includes both forward- and backward-looking terms (i.e., expected and lagged inflation).[24]

The purpose of this subsection is to show whether the EPD-NK model with reasonable parameter values (i.e., with the parameters estimated above) is able to reproduce the presence of lagged inflation in the empirical NKPC. To do this, I conduct Monte Carlo analyses.

The following analysis shows that the EPD-NK model is consistent with what many empirical studies on the NKPC have found, and thus, the ad hoc and empirically inconsistent assumptions about pricing in NK models are not needed as long as endogenous

[23] The studies that find the role of lagged inflation in the NKPC using limited-information methods (single-equation methods) include, for example, Fuhrer (1997), Gali and Gertler (1999), Subordone (2002), Gali, Gertler and Lopez-Salido (2005), Roberts (2005) and Ravenna and Walsh (2008). Most of the empirical studies on the NKPC use the limited-information methods largely because it is well known that the full-information (system) estimation methods face a greater risk of misspecification in other equations rather than the NKPC equation, which can lead to bias of the NKPC parameters.

[24] Interestingly, although Smets and Wouters (2007) estimate the NK model that incorporates the price indexation to past inflation (using a full-information Bayesian maximum likelihood method), they find that empirically it would be better "not" to incorporate the indexation according to the comparison of marginal likelihood.

technological change is incorporated. This is because, according to the EDP-NK model, the estimation of the NKPC is subject to a misspecified functional form, leading to an upwardly biased estimate of the parameter on the lagged inflation term in the NKPC. The following analysis demonstrates the misspecification source and examines how it affects NKPC estimation.

The EPD-NK model yields the following NKPC (see Section 2 of the Appendix):

$$\begin{aligned}\pi_t &= \Gamma E_t\left[\pi_{t+1}\right] + \frac{(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi}\widetilde{mc}_t \\ &+ \left\{\frac{\Gamma}{\phi-1}\left(\widetilde{A}_t - \rho\psi\widetilde{A}_{t-1}\right) - \frac{1}{\rho\psi(\phi-1)}\left(\widetilde{A}_{t-1} - \rho\psi\widetilde{A}_{t-2}\right)\right\},\end{aligned} \tag{24}$$

where $\pi_t = \widetilde{P}_t - \widetilde{P}_{t-1}$ and mc_t denotes a real marginal cost. A variable with "$\sim$" shows log deviation from its steady-state value. Bilbiie et al. (2008) obtain the NKPC similar to equation (24). $\widetilde{A}_t$, $\widetilde{A}_{t-1}$ and $\widetilde{A}_{t-2}$ are included also in their version of NKPC, but are not in the same manner as equation (24). The difference comes from the fact that the present model uses Calvo pricing and in contrast, they use Rotemberg pricing. Another, more important difference is that the present model introduces the "time-to-build (innovate)" structure for PD. This makes the present model's effect of a shock on $\widetilde{A}_t$ differ from theirs. The persistence of the effect of a shock on $\widetilde{A}_t$ is considerably larger in the present model.[25] As will be shown later, this difference due to the time-to-innovate structure plays a significant role in explaining the inflation persistence puzzle.

Equation (24) can be rewritten in the following form:

$$\begin{aligned}\pi_t \;=\; & \frac{(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi}E_t\sum_{s=0}^{\infty}\Gamma^s\,\widetilde{mc}_{t+s} - \frac{\Gamma(1-\rho\psi\Gamma)(1-\rho\psi)}{(\phi-1)\rho\psi}E_t\sum_{s=0}^{\infty}\widetilde{A}_{t+s} \\ & -\frac{1}{\phi-1}\left[\frac{\rho\psi+(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi}\widetilde{A}_{t-1} - \widetilde{A}_{t-2}\right].\end{aligned}$$

The key difference from the standard NKPC lies in the existence of $\widetilde{A}$. Inflation decreases with $E_t\sum_{s=0}^{\infty}\widetilde{A}_{t+s}$ in the case of the EPD-NK model. This role of $\widetilde{A}$ is explained as follows. Firm i's markup is given by $\frac{P(i)_t}{nmc(i)_t} = \frac{P(i)_t}{P_t}\frac{1}{mc(i)_t}$ where nmc is a nominal marginal cost. Thus, an increase in $\frac{P(i)_t}{P_t}$ or a decrease in $mc(i)_t$ from its desired level (i.e., its steady state level) implies an increase in firm i's markup from its desired level. Also, under the CES given by equation (1) and under the fact that price-setting firms all charge the same price, $\frac{P(i)_t}{P_t}$ increases with A (note that $\frac{P(i)_t}{P_t} = A_{t-1}^{1/(\phi-1)}$ under a flexible-price situation). Thus, an expected increase in A from its desired level means an expected increase in $\frac{P(i)_t}{P_t}$

[25] Bilbiie et al. (2008) point out that $\widetilde{A}_t$, $\widetilde{A}_{t-1}$ and $\widetilde{A}_{t-2}$ may give an extra endogenous persistence in inflation. However, as one can see, the terms do not necessarily lead to a significant and positive lagged (backward-looking) inflation term in NKPC estimation.

from its desired level, which in turn implies an expected increase in firm i's markup from its desired level. Because firms know that they may not be able to change their prices in the future (Calvo pricing), if they expect markups to increase above their desired levels due to an expected increase in $\widetilde{A}$, they charge lower prices now.

Equation (24) reveals important implications for the estimation of the NKPC. To show this, I first briefly illustrate the usual regression specification of the NKPC estimation employed by researchers and the result. Empirical researchers on the NKPC, in general, use the following regression specification:

$$\pi_t = \omega_f \ E_t\pi_{t+1} + \omega_{mc} \ \widetilde{mc}_t + \omega_b \ \pi_{t-1} + e_t, \tag{25}$$

where ω_f, ω_{mc} and ω_b are coefficients to be estimated, and e_t is an error term. For example, Gali and Gertler (1999) report that ω_b is estimated to be in the interval 0.2-0.4. Because ω_b is estimated to be significant, sizable and positive by many researchers, the purely forward-looking Phillips curve (i.e., $\omega_b = 0$), derived from a "basic" NK model, is rejected: the inflation persistence puzzle. To reconcile theory with this empirical finding of significant, positive and sizable ω_b, conventional NK models therefore generate the hybrid NKPC, which includes both $E_t\pi_{t+1}$ and π_{t-1} (i.e., $\omega_f > 0$ and $\omega_b > 0$), by making the ad hoc and empirically inconsistent assumptions on pricing.

Comparing equation (24) with equation (25), one can see that, if the EPD-NK model holds, the regression specification (25) is misspecified. That is, in equation (25), the relevant variables, $\widetilde{A}_t$, $\widetilde{A}_{t-1}$ and $\widetilde{A}_{t-2}$, are omitted. This misspecification causes two problems in estimating the NKPC of equation (25). The first problem is endogeneity. Let us assume, for the moment, that we can correctly measure all of the variables in equation (25), including expected inflation rates $E_t [\pi_{t+1}]$. The problem in estimating equation (25) lies in the fact that the terms in $\{ \ \}$ of equation (24) are absorbed in e_t. Because the endogenous variables, $\widetilde{A}_t$, $\widetilde{A}_{t-1}$ and $\widetilde{A}_{t-2}$, are included in e_t if the EPD-NK model holds, the error term e_t is most probably highly correlated with π_{t-1}. Thus, even if all of the variables are measured correctly, an OLS estimate of ω_b (and estimates of the other parameters) could be seriously biased.

The second problem in estimating equation (25), which is more relevant to the present paper's analysis, is related to the estimation method. Because of the unobsevability of expected inflation rates, a GMM approach is intensively used in estimating the NKPC of the regression specification (25).[26] The use of GMM under the above misspecification,

[26] See, for example, Gali and Gertler (1999), Fuhrer and Olivei (2004), Gali et al. (2005), Roberts (2005), Rudd and Whelan (2005, 2006, 2007), Nason and Smith (2008), Ravenna and Walsh (2008), and Dees, Pesaran, Smith and Smith (2009). The estimated importance of the forward- and backward-looking inflation terms, however, varies substantially across studies. Mavroeidis, Plagborg-Mølller and Stock (2014) review the empirics of the NKPC (especially studies using limited-information methods). They conclude that although they do not reject the NKPC, it is difficult to accurately specify the importance of forward- and backward-looking inflation terms in the NKPC due to, for example, a weak

however, causes a serious problem in the estimation, as is demonstrated in detail below.

Considering the unobsevability of $E_t\pi_{t+1}$, the regression specification (25) is rewritten as follows:

$$\pi_t = \omega_f \ \pi_{t+1} + \omega_{mc} \ \widetilde{mc}_t + \omega_b \ \pi_{t-1} + v_t, \tag{26}$$

where

$$v_t = e_t - \omega_f \ \varepsilon_{t+1}$$

and ε_{t+1} represents an expectation errors, i.e., $\pi_{t+1} = E_t [\pi_{t+1}] + \varepsilon_{t+1}$. Assuming full-information rational expectations, ε_{t+1} is an i.i.d. shock. It is clear that v_t is correlated with π_{t+1} due to $\omega_f \ \varepsilon_{t+1}$ ($\omega_f \neq 0$). Treating v_t as an error term, many researchers thus, assuming that e_t is an i.i.d. shock, estimate equation (26) with GMM using lagged variables, i.e., variables dated $t-1$ or earlier, as instruments for π_{t+1}. [27] However, this GMM estimator has a serious flaw if the EPD-NK model holds because e_t is included in v_t. Under the EPD-NK model, any lagged variables that are correlated with π_{t+1} are likely to be highly correlated with e_t because e_t includes the endogenous variables, $\widetilde{A}_t$, $\widetilde{A}_{t-1}$ and $\widetilde{A}_{t-2}$ and the time-to-innovate structure exists. Thus, if the EPD-NK model is valid, any lagged variables cannot be valid instruments for π_{t+1} even under the assumption of full-information rational expectations.

Considering the above problem in the GMM estimation of the NKPC, by means of Monte Carlo simulations, I examine the effect of endogenous technology on the coefficient estimates of the NKPC, especially the estimate of ω_b. To do so, equation (26) is estimated with GMM on simulated data sets from the model presented in the previous section. This approach is similar to the one taken by Lindė (2005).[28] For comparison, the equation is also estimated on simulated data sets from the basic NK model estimated in the previous section, in which the PD process is not included and the NKPC does not have a lagged inflation term. The reason for using the basic NK model is not only to examine the endogenous PD effect, but also to consider the possibility that the frequent findings of a significant and positive estimate of ω_b are likely to emerge simply because of using GMM with a small sample.

Many empirical studies of the NKPC use different sets of instruments (i.e., lagged variables) for their estimations, and some of the instruments used in the literature do not correspond to any of the variables in the EPD-NK and basic NK models of this paper. To address this matter, the following procedure is used. First, I obtain simulated data on $E_{t-1} [\pi_{t+1}]$ and $E_{t-1} [\widetilde{mc}_t]$ and then apply an instrumental variables (IV) procedure

instruments problem.

[27] Most researchers studying the NKPC use only lagged variables as instruments, considering unobserved shocks and measurement errors in independent variables.

[28] Lindė (2005) uses Monte Carlo simulations to examines the NKPC. He uses a simple calibrated NK model, which gives the hybrid NKPC. He argues that GMM is likely to give imprecise and biased estimates and full information maximum likelihood gives better estimates.

using those two variables and π_{t-1} as instruments. Here, the simulated $E_{t-1}[\pi_{t+1}]$ and $E_{t-1}[\widetilde{mc}_t]$ correspond to the empirical variables that are obtained by regressing each π_{t+1} and $\widetilde{mc}_t$ on instruments (i.e., lagged variables) chosen by the researcher in the first-stage least squares regression of a two-stage least squares (2SLS) procedure.[29] The IV approach employed here is equivalent to GMM, because the regression specification (26) is linear and is exactly identified (i.e., the number of instruments used is the same as the number of independent variables).[30]

As already argued, the important point here is that the simulated $E_{t-1}[\pi_{t+1}]$ and $E_{t-1}[\widetilde{mc}_t]$ are "*invalid*" instruments for π_{t+1} and $\widetilde{mc}_t$ in the case of the EPD-NK model, because they should be correlated with the errors (v_t) in equation (26) due to the endogenously-determined PD effect. In contrast, in the case of the basic NK model, the simulated $E_{t-1}[\pi_{t+1}]$ and $E_{t-1}[\widetilde{mc}_t]$ are "*valid*" instruments, because they are, by construction, not correlated with the errors (v_t) and are correlated with π_{t+1} and $\widetilde{mc}_t$.

In the following exercises, the effect of measurement errors in marginal costs is also considered.[31] To do so, noises are added to simulated $\widetilde{mc}_t$ series. The basic idea is as follows. Define V as a random noise vector and $\widetilde{mc}_{err,\ t}$ as a marginal cost series with measurement errors. First, generate a random noise vector V that has no correlation with the simulated $\widetilde{mc}_t$ series. Then, construct $\widetilde{mc}_{err,\ t}$ by finding some linear combination of V and $\widetilde{mc}_t$ that has exactly the desired correlation between $\widetilde{mc}_t$ and $\widetilde{mc}_{err,\ t}$ (the correlation coefficient is set to 0.9). $\widetilde{mc}_{err,\ t}$ is also restricted to have the same standard deviation as the standard deviation of the simulated $\widetilde{mc}_t$ series.[32]

A joint density of three estimates, $\widehat{\omega}_b$, $\widehat{\omega}_f$ and $\widehat{\omega}_{mc}$ from Monte Carlo simulations is examined. I use 200 draws from the posterior distribution of the model parameters and simulate the model 200 times by feeding shocks for each parameter set of the draws. Therefore, in total, 40,000 estimation replications are obtained. Regarding the sample size of the each estimation, two sample sizes are considered. One is a small sample size of 150 (150 quarters), and the other is a large sample size of 7,000. The small sample size is consistent with the sample sizes of the empirical studies in the literature.

Figures 1-4 show joint scatter density plots of $\widehat{\omega}_b$, $\widehat{\omega}_f$ and $\widehat{\omega}_{mc}$ from the Monte Carlo simulations. Tables 2-5 present how likely the coefficient estimates are to become statistically significant and report mean t-statistic values for the coefficient estimates. To make the tables, mean t-statistic values for $\widehat{\omega}_b$, $\widehat{\omega}_f$ and $\widehat{\omega}_{mc}$ are calculated on intervals of

[29] Under conditional homoskedasticity, a 2SLS estimator is a GMM estimator.

[30] Since $E_{t-1}[\pi_{t+1}]$ and $E_{t-1}[\widetilde{mc}_t]$ serve as instruments for π_{t+1} and $\widetilde{mc}_t$, and π_{t-1} serves as an instrument for itself, the regression equation is exactly identified.

[31] In the literature researchers use labor's share of income (i.e., a real unit labor cost) as a proxy for a real marginal cost. This is legitimate if the production functionis is Cobb-Douglas, which is the case of the present model. However, measurement errors in labor input and wages can be large so that labor income share data can be measured with large errors.

[32] To construct $\widetilde{mc}_{err,\ t}$, I use the matlab code, "randwithcorr.m", written by John D'Errico. The code can be found in https://au.mathworks.com/matlabcentral.

corresponding $\widehat{\omega}_b$ values. The procedure is as follows. First, group the resulting estimates of ($\widehat{\omega}_b$, $\widehat{\omega}_f$, $\widehat{\omega}_{mc}$) with respect to the level of $\widehat{\omega}_b$: the first group consists of estimates of ($\widehat{\omega}_b$, $\widehat{\omega}_f$, $\widehat{\omega}_{mc}$) that have $\widehat{\omega}_b$ from -0.02 and 0.00, the next group consists of those that have $\widehat{\omega}_b$ from 0.00 and 0.02, and so forth. Then, for the each group, calculate mean t-statistic values for $\widehat{\omega}_b$, $\widehat{\omega}_f$ and $\widehat{\omega}_{mc}$. For example, the value of -0.35 around the top left in Table 2 means that when regressions based on the simulated data with the large sample size from the basic NK model obtain the values of $\widehat{\omega}_b$ in the range -0.02 and 0.00, the mean t-statistic value for those $\widehat{\omega}_b$s is -0.35.

Figure 1 shows the large-sample results. The highest density area for the EPD-NK model is located around the point where $\widehat{\omega}_b$ = 0.07, $\widehat{\omega}_f$ = 0.95 and $\widehat{\omega}_{mc}$ =0.1, and that for the basic NK model is located around the point where $\widehat{\omega}_b$ = 0, $\widehat{\omega}_f$ = 0.99 and $\widehat{\omega}_{mc}$ = 0.07. According to Table 2, in the case of the EPD-NK model, when its $\widehat{\omega}_b$ is around in the highest-density area, the $\widehat{\omega}_b$ and the corresponding $\widehat{\omega}_f$, and $\widehat{\omega}_{mc}$ are all highly likely to be significant (the average t-statistic value for the $\widehat{\omega}_b$s that are around in the highest-density area is 3.84). In the case of the basic NK model, when its $\widehat{\omega}_b$ is around in the highest-density area, the $\widehat{\omega}_b$ is highly likely to be insignificant (the average t-statistic value for the $\widehat{\omega}_b$s that are around in the highest-density area is between -0.35 and 0.36). It is clear that $\widehat{\omega}_b$ is positively biased in the case of the EPD-NK model.

Turning to the small sample results shown in Figures 2 and 3, the highest-density area for the EPD-NK model is located around where $\widehat{\omega}_b$ = 0.18 ($\widehat{\omega}_b$ = 0.22 when the measurement errors are included), and that for the basic NK model is located around where $\widehat{\omega}_b$ = 0.02 ($\widehat{\omega}_b$ = 0.16 when the measurement errors are included). The result for the EDP-NK model is consistent with the findings by Gali and Gertler (1999). Compared with the large sample result, the bias in $\widehat{\omega}_b$ increases considerably in the case of the EDP-NK model. Regarding statistical significance, according to Table 3, in the case of the EPD-NK model, when its $\widehat{\omega}_b$ is around in the highest-density area, the $\widehat{\omega}_b$ and the corresponding $\widehat{\omega}_f$, and $\widehat{\omega}_{mc}$ are all likely to be significant: the average t-statistic value for the $\widehat{\omega}_b$s that are around in the highest-density area is between 1.94 and 2.26 (between 1.87 and 2.09 when the measurement errors are included as shown in Table 4). In contrast, in the case of the basic NK model, when its $\widehat{\omega}_b$ is around in the highest-density area, the $\widehat{\omega}_b$ is likely to be insignificant: the average t-statistic value for the $\widehat{\omega}_b$s that are around in the highest-density area is between 0.07 and 0.21 (between 0.88 and 0.98 when the measurement errors are included). When the measurement errors are included, although the basic NK model is likely to give a level of $\widehat{\omega}_b$ that is close to that of the EPD-NK model, not only $\widehat{\omega}_b$ but also $\widehat{\omega}_{mc}$ of the basic NK model are likely to be insignificant, as shown in Table 4. As a robustness check, three additional lags of inflation have also been allowed to be on the right-hand side of the estimated equation (Gali and Gertler 1999 include three additional lags of inflation for their robustness check). However, doing so does not significantly alter the finding.[33]

One might argue that the above results could be driven by the two frictions introduced in the model (i.e., consumption habit persistence and adjustment costs in investment). To check the relevance of those frictions, I perform a counterfactual simulation in which consumption habit persistence and the elasticity of investment adjustment costs are reduced and set to extremely low levels ($\lambda_h = \xi = 0.0001$).[34] Section 5 of the Appendix shows that this does not change the finding.

To assess the effect of the time-to-innovate structure of PD, I perform another counterfactual simulation in which the time required for PD ($\overline{\varphi}$) is set to to 1 rather than 8. Figures 4-b1 and 4-b2 show that, compared to the results in Figures 2-b1 and 2-b2, the bias in $\widehat{\omega}_b$ decreases and the highest-density area is now located around where $\widehat{\omega}_b = 0.16$. Furthermore and more importantly, Table 5 shows that, when its $\widehat{\omega}_b$ is around in the highest-density area, the $\widehat{\omega}_b$ is highly likely to be insignificant. The reason for this result is that, because the number of "time-to-innovate" periods is reduced from 8 to 1, further lagged variables (i.e., variables lagged more than two periods) have a smaller effect on $\widetilde{A}_t$, $\widetilde{A}_{t-1}$, and $\widetilde{A}_{t-2}$. The smaller effect on $\widetilde{A}_t$, $\widetilde{A}_{t-1}$, and $\widetilde{A}_{t-2}$ implies that the instruments (i.e., the simulated $E_{t-1}[\pi_{t+1}]$ and $E_{t-1}[\widetilde{mc}_t]$) become less correlated with the errors v_t, so that the resulting $\widehat{\omega}_b$ is more likely to be insignificant and smaller.

Overall, the above results show that endogenously-determined PD (i.e., endogenous technological change) largely contributes to the presence of lagged inflation in the empirical NKPC, and that the time-to-innovate structure enhances the contribution. According to the EPD-NK model, the regression misspecification (i.e., the omission of endogenously-determined technology levels), which causes biased estimates, is the key to the inflation persistence puzzle. The results also show that the basic NK model with small-sample bias cannot explain the puzzle.

3.2 Disinflationary news shock puzzle: news shock effects on nominal variables

Recent semi-structural VAR studies on news shock effects, e.g., Kurmann and Otrok (2013), Kurmann and Otrok (2014) and Barsky et al. (2015) report that a positive news shock (i.e., TFP news shock) generates a sharp and persistent decline in both inflation and nominal interest rates. However, Kurmann and Otrok (2014) and Barsky et al. (2015) show that the conventional NK models have difficulty explaining this finding: the *disinflationary news shock puzzle.* Note here that, in this paper, new shocks indicate *TFP* (technology) news shocks.

This subsection examines whether the incorporation of endogenous PD (i.e., endoge-

[33] The results are available upon request.

[34] The other parameters are drawn from the posterior distribution as before.

nous technological change) can help to solve the disinflationary news shock puzzle. To do so, Monte Carlo simulation analyses are conducted. The impulse responses to a technology news shock are estimated from a VAR run on a simulated data from the parameterized model. Then, the obtained model-based impulse responses are compared to actual empirical impulse responses.[35] The parameters used to obtain the simulated data are those from Table 1. To obtain the impulse responses, news shocks are identified by applying the same method as that used in the above-mentioned studies.[36] The method is initially developed by Barsky and Sims (2011). Their method is a semi-structural VAR that identifies a technology news shock as the innovation that is orthogonal to the innovation to current TFP and maximally explains the forecast error variance of TFP over a long period (e.g., a 10-year horizon).

Figure 5 presents impulse responses to a (realized) news shock from six-variable VARs which include TFP, output, consumption, hours, inflation, the federal fund rate (nominal interest rate). The thick lines and thick dashed lines show Monte Carlo estimated impulse responses (median impulse responses) for the EPD-NK model and those for the basic NK model, respectively. The impulse responses are calculated by estimating the VARs on 500 random samples of 190 observations generated from the basic NK and EPD-NK models (the models are simulated at the posterior modes given by Table 1). The double lines show empirical impulse responses with one standard deviation confidence intervals (thin double-dashed lines).[37] The empirical data except for TFP are the same as those used for the estimation. The TFP data are Fernald (2012)'s utilization-adjusted TFP.

Figure 5 shows that the EPD-NK model reproduces the persistent negative impacts on inflation and nominal interest rates, but the basic NK model cannot (the empirical responses of the variables are generally in line with those found by the above-mentioned studies). The EPD-NK model's impulse responses of inflation and nominal interest rates both decline substantially immediately at the time of a positive news shock and remain lower for a long time. The other impulse responses in Figure 5, except hours, are reasonably close to the empirical impulse responses, considering the fact that the model's parameters are from the posterior sample of Table 1 and are not estimated in a way that minimizes the measure of the distance between the model and empirical impulse response

[35] The approach taken by the present paper is similar to that of Barsky et al. (2015), which follows Kehoe (2006). Kehoe (2006) argues that due to small-sample bias and lag-truncation bias, one should not compare empirical impulse responses to theoretical impulse responses and instead compare structural VARs run on on actual data to identical structural VARs run on data of the same sample size obtained by simulating the model. The present paper's approach, however, differs from that of Barsky et al. (2015). The model-based impulse responses given by Barsky et al. (2015) are the results of the estimation run on data from the model with an arbitrarily chosen set of parameters, which seems to provide a good fit to the empirical impulse responses (they fit the impulse responses "by eye"). Kurmann and Otrok (2014) also fit the impulse responses of the news shocks in choosing the parameters of their models. Differently from these studies, rather than fitting the model impulses to empirical ones, the present paper obtains the simulated data using parameters from the posterior sample of Table 1.

[36] To identify news shocks, I use the program code provided by Kurman and Otrok (2013).

[37] The confidence intervals are from 2000 bias-corrected bootstrap replications.

functions. Contrary to the EPD-NK model, the basic NK model's impulse responses of inflation and nominal interest rates both increase substantially at the time of the news shock, and the early responses are not within the confidence intervals.

To be noted, the confidence intervals in Figure 5 are quite wide compared to those of other studies (e.g., Barsky and Sims 2011 and Barsky et al. 2015). In Figure 5, the confidence interval for inflation at the time of the shock contains zero. However, this does not mean invalidating the existence of the disinflationary news shock puzzle reported in various studies. Other studies report that the confidence interval of inflation stays below zero for the first several periods.[38] (The median empirical impulse responses are in general similar to those of Figure 5.) The reason that the wide confidence interval for inflation in Figure 5, which contains zero at the time of the shock, is most probably because the VAR in this paper uses a different set of variables from those used in other studies.[39]

There are two possible explanations for the finding in Figure 5 that the EPD-NK model reproduces the persistent negative impacts on inflation and nominal interest rates. One is theoretical and the other is methodological. I first consider the theoretical explanation, which is that news shocks actually induce the disinflationary effect in the EPD-NK model. (As will be shown later, the theoretical explanation, however, turns out to be invalid.) The theoretical explanation is closely related to the EPD-NK model's forward-looking nature of inflation, as illustrated below.

The EPD-NK model gives the following equation for inflation:

$$\begin{aligned}\pi_t \;=\;& \frac{(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi} E_t \sum_{s=0}^{\infty} \Gamma^s \, \widetilde{mc}_{t+s} - \frac{\Gamma(1-\rho\psi\Gamma)(1-\rho\psi)}{(\phi-1)\rho\psi} E_t \sum_{s=0}^{\infty} \widetilde{A}_{t+s} \\ & -\frac{1}{\phi-1}\left[\frac{\rho\psi+(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi}\widetilde{A}_{t-1} - \widetilde{A}_{t-2}\right] . \end{aligned} \tag{27}$$

For comparison, the corresponding equation for the basic NK model is shown below:

$$\pi_t = \frac{(1-\rho\Gamma)(1-\rho)}{\rho} E_t \sum_{s=0}^{\infty} \Gamma^s \, \widetilde{mc}_{t+s}. \tag{28}$$

Barsky et al. (2015) argue that, with equation (28), introducing real wage rigidity into a basic NK model can account for falling inflation in response to a news shock. They argue that, if real wages, responding to a positive news shock, do not increase as much as output

[38] Barsky et al. (2015) run a number of specifications in their VAR analyses and conclude that TFP news shocks are deflationary.

[39] For exmaple, Barsky and Sims (2011) perform seven-variable VARs which include TFP, output, *non-durables and services* consumption, hours, *stock prices*, *consumer confidence*, and inflation. This paper's VAR analysis does not use non-durables and services consumption in order to be consistent with the data used for the above-described estimation of this paper, which uses total consumption. Also, the present VAR analysis does not uses stock prices and consumer confidence, becasue the present model does not include the variables which appropriately correspond to stock prices and consumer confidence.

on impact or over time, expected real marginal costs and thus inflation will decline and stay low for a number of periods.[40] Kurmann and Otrok (2014), however, argue that, with a reasonable parameterization, the NK model with real wage rigidity cannot produce a sharp and persistent decline in both inflation and nominal interest rates.[41] Apart from Barsky et al. (2015)'s argument, equation (27) of the EPD-NK model's NKPC provides another theoretical reason for the disinflationary effect of news shocks. Equation (27) shows that, even if marginal costs are expected to rise due to an expected sharp increase in real wages responding to a positive news shock, as long as a an expected rise in A, responding to the positive news shock, is large enough and persistent, inflation will jump down and remain low for a number of periods.

Next, I consider the methodological explanation. Although the above theoretical explanation is one way to reconcile with the finding in Figure 5, the finding can also be due to the possibility that the identification method (i.e., the method advocated by Barsky and Sims 2011) confounds *true* news shocks with other kinds of shocks. The method characterizes a news shock as the innovation that does not affect TFP on impact but maximally explains the amount of TFP forecast error variance over the given forecast horizon. However, the EPD-NK model shows that not only technology (TFP) news shocks, but also all of the other shocks (e.g., preference and interest rate shocks), which are orthogonal to current TFP, affect future TFP *through their effect on A*. Thus, the identification method might, to a large extent, lead to mismeasurement of the effect of *true* news shocks.[42]

The following examines which of the above two explanations (i.e., the theoretical and methodological explanations) is more likely to be true. First, the theoretical explanation is examined. Figure 6 depicts theoretical impulse responses to a positive news shock regarding the T-period-ahead future TFP (a one-standard-deviation shock), where T is 4, 8, 12 and 16. The theoretical impulse responses are calculated based on the posterior modes given by Table 1. Figures 6-(a), 6-(b) and 6-(c) are for the EPD-NK model, the basic NK model and the EPD-NK model that shuts down the EPD effect, respectively. To shut down the EPD effect, α is set to 500. This value of α implies that the PD investment's steady-state elasticity is equal to approximately 0.002. According to the figures, for all of the models, news shocks "as a whole" are highly *unlikely* to generate the disinflationary effect, although, in the case of the EPD-NK model, an 8-period-ahead positive news shock leads to a decrease in inflation both on impact and in the long run. Except for an 8-period-ahead news shock, positive news shocks increase inflation on

[40]For basic standard NK models without capital, the log deviation of real marginal cost is given by: $\widetilde{mc}_t = \widetilde{w}_t - \widetilde{y}_t$.

[41]The large immediate increase in inflation and nominal interest rates is also found in Fujiwara et. al (2011)'s theoretical impulse response analysis.

[42]Barsky and Sims (2011), in fact, mention the possibility that some structural shocks that are not news shocks, e.g., R&D shocks, can affect future TFP, causing their identification method to confound true news shocks with those shocks and to mismeasure the effect of true news shocks.

impact in the case of the EPD-NK model.

Next, the methodological explanation is examined. Figures 7 and 8 depict Monte Carlo estimated impulse responses (median impulse responses) of inflation and TFP to a news shock, which are obtained by estimating the VARs on 500 random samples of 190 observations generated from the three models. The posterior modes in Table 1 are used to generate the samples. Each panel of the figures shows three kinds of impulse responses: (i) "*only news shocks*" impulse response is the one where only news shocks (4-, 8-, 12- and 16-period-ahead TFP news shocks) are included, (ii) "*news and unanticipated TFP shocks*" impulse response is the one where news shocks and unanticipated TFP shocks are included, and (iii) "*all shocks*" impulse response is the one where all of the model's shocks are included. According to Figure 7, in the cases of the basic NK model and the EPD-NK model without the EPD effect, the three inflation impulse responses show similar patterns, such that inflation sharply *increases* on impact and gradually decreases over time. In contrast, in the case of the EPD-NK model, the inflation impulse response of "all shocks" clearly differs from those of the other two (i.e., "*only news shocks*" and "*news and unanticipated TFP shocks*"): inflation sharply *declines* on impact when all of the shocks are included, but, in contrast, inflation sharply *increases* on impact and remains high for a relatively long period when only news shocks are included or news and unanticipated TFP shocks are included. This dissimilarity in inflation response for the EPD-NK model comes from the misidentification of news shocks. Figure 8 shows that, regarding the EPD-NK model (Figure 8-a), the Monte Carlo estimated TFP impulse response of "all shocks" differ substantially from those of the other two (i.e., "*only news shocks*" and "*news and unanticipated TFP shocks*"). This difference is, however, not found for the basic NK model and the EPD-NK model without the EPD effect (Figures 8-b and 8-c). This strongly suggests that *non-news* shocks largely affect future TFP due to the EPD effect, as the model predicts. This means that the identification method confounds *true news* shocks with *non-news* shocks.

3.3 ZLB supply shock puzzle

The standard NK model predicts that a negative supply shock is expansionary if the ZLB on nominal interest rates is expected to last long enough. However, recent empirical studies (e.g., Wieland 2018 and Garin et al. 2018) find the opposite: that a negative supply shock is actually contractionary at the ZLB. This is the *ZLB supply shock puzzle.*

This subsection shows that incorporating endogenous PD can solve the ZLB supply shock puzzle, too. To do so, I use the estimated models (i.e., EPD-NK and basic NK models) as before, and construct impulse response functions for a negative (exogenous) TFP shock to examine whether the EPD-NK model can generate a contractionary response to a negative TFP shock at the ZLB. Following Wieland (2018) and Garin et al.(2018), the deterministic interest rate peg is used to solve the models.[43] That is, nominal interest rates are set to be constant at the steady state level (i.e., $\widetilde{r}_{N,t} = 0$) for a known number of periods, T_{ZLB} . The value of T_{ZLB} is chosen to match the U.S. ZLB period (i.e., $T_{ZLB} = 28$ quarters is chosen). I also consider the shorter ZLB period of $T_{ZLB} = 20$. The impulse responses are then calculated based on the posterior modes given by Table 1. The persistence of an exogenous technology shock, ρ_μ, is set to 0.952, which is the the EPD-NK model's posterior mode.

Figure 9 plots the impulse responses of various variables to a one percent decrease in exogenous productivity, μ_t. First, consider the basic NK model's case. The blue lines show the responses in normal times (i.e., under the no ZLB regime) and the red lines show those under the ZLB regime ($T_{ZLB} = 28$). The result is consistent with what other studies have reported. In responding to a negative technology shock, output, consumption and investment decline under the no ZLB regime, but, under the ZLB regime, they increase immediately at the time of the negative technology shock and remain above zero until period 5. This positive response of output at the ZLB in the basic NK model is explained as follows. A negative and persistent technology shock leads to an increase in current and future real marginal costs, which raises current and future inflation. Because nominal interest rates are fixed (i.e., are expected to be fixed), expected future real interest rates decrease and stimulate current aggregate demand. This stimulation of aggregate demand is more than enough to offset the negative effect of the negative technology (supply) shock on output.

Next, consider the EPD-NK model. As before, in Figure 9, the blue lines show the responses under the no ZLB regime and the red lines show those under the ZLB regime ($T_{ZLB} = 28$). The black lines show the responses for a counterfactual simulation in which the endogenous PD effect is shut down under the ZLB regime.[44] The figure shows that, in contrast to the basic NK model, output, consumption and investment now decrease under the ZLB regime in response to a negative technology shock. The counterfactual simulation (i.e., simulation for the EPD-NK model without endogenous PD channel at the ZLB) yields the same results as the basic NK model at the ZLB: output, consumption and investment all increase, as shown by the black lines. This suggests that endogenous PD accounts for the negative responses to a negative technology shock under the ZLB regime. Shortening the ZLB period from 28 to 20 quarters still gives a similar result, as shown in Figure 10.[45]

The effect of endogenous PD (i.e., endogenous technological change), found in the fig-

[43] To analyze the effects of the ZLB, following Laseen and Svensson (2011) and Garin et. al (2018), the monetary policy rule of (14) is augmented with monetary policy news shocks.

[44] As before, to shut down the EPD effect, α is set at 500.

[45] The extent of the contractionary responses in the EPD-NK model under the ZLB regime is larger when the ZLB period is shortened to 20 quarters. This is because of the earlier start of a contractionary monetary policy upon the ZLB lift, which leads to an upward shift in the real interest rate path.

ures, is explained as follows. A negative technology shock increases current and expected future marginal costs. This is the direct *positive* effect of a negative supply shock on marginal costs. This positive effect on marginal costs is a key driver of the expansionary effect of a negative technology shock under the ZLB in the standard NK model. However, in the EPD-NK model, owing to endogenously-determined PD (i.e., endogenous technological change), there also exists an indirect *negative* effect of a negative technology shock on marginal costs, as illustrated below. Decreased future productivities, ceteris paribus, reduce expected monopoly profits from new differentiated products created in the future. This lowers current and expected future PD spendings and, thus, reduces future endogenously-determined technology levels and future aggregate income levels. Reduced future aggregate income levels, in turn, reduce future demands for new differentiated products and demands for labor and capital. This decrease in expected future demands for labor and capital then lowers expected future marginal costs, because future real wages and rental prices of capital decline. This negative feedback effect of a negative supply shock on marginal costs puts a downward pressure on current and expected future inflation. This puts an upward pressure on the real interest rate path at the ZLB, so that current aggregate demand is suppressed. This results in a decrease in current output, because it reduces the positive effect on current aggregate demand caused by the direct positive effect of a negative technology shock on marginal costs.

4 Conclusion

This paper develops and estimates an NK DSGE model with endogenous technological change to examine whether introducing endogenous technological change into an NK model offers quantitatively important implications for our understanding of aggregate fluctuations. By means of Monte Carlo and the other analyses, the paper shows that endogenous technology is the key to the three important puzzles faced by the NK model. First, the present model solves the inflation persistence puzzle, i.e., it explains the presence of the backward-looking term (i.e., lagged inflation) in the empirical NKPC without relying on the conventional NK models' ad hoc and empirically inconsistent assumptions. Second, the paper solves the disinflationary news shock puzzle, i.e., it explains the disinflationary effect of a news shock, which conventional new Keynesian models have difficulty explaining. Third, the paper solves the ZLB supply shock puzzle, i.e., the present model avoids the conventional NK models' paradoxical, empirically inconsistent prediction that a negative supply shock is expansionary at the ZLB. In addition to these, the paper shows that incorporating endogenous technological change rises volatility such that it increases the standard deviation of output growth by 12 percent and even monetary policy and government expenditure shocks have some persistent impacts on TFP and output.[46]

The results suggest that endogenous technological change should be incorporated into the NK model. In other words, they suggest that demand-side shocks endegenously affect the supply side (i.e., TFP), which should largely contribute to medium-term fluctuations. Incorporating endogenous technological change into a larger-sized NK model would improve its forecasting ability and allow for better analyses of various policies. To this end, the present model can be extended further. One can, within an NK framework, combine the endogenous mechanism of technology shown in this paper with a friction considered to be important, e.g., credit market imperfections. Such models could show that even a small (demand or news) shock generates a large, slow-moving supply-side effect and, thus, could provide better explanations for the large medium-term fluctuations reported by Comin and Gertler (2006).

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Table 1: Prior and Posterior Distribution of Model Paramters

	Parameters	Distribution	Prior Mean	Prior St. Dev.	Posterior EPD-NK Mode	EPD-NK 90 % interval	EPD-NK Mean	Posterior Basic-NK Mode	Basic-NK 90 % interval	Basic-NK Mean
	Structural									
ϖ_π	: monetary policy (Taylor) rule inflation	Normal	1.500	0.250	1.081	[1.067 , 1.105]	1.086	1.108	[1.085 , 1.185]	1.136
ϖ_y	: monetary policy (Taylor) rule output	Normal	0.125	0.050	0.360	[0.290 , 0.407]	0.347	0.172	[0.100 , 0.252]	0.177
ϑ	: monetray policy (Taylor) rule persistence	Beta	0.750	0.100	0.281	[0.242 , 0.396]	0.320	0.402	[0.280 , 0.463]	0.373
σ_c	: intertemporal elasticity substitution	Normal	1.500	0.375	0.685	[0.445 , 1.056]	0.753	1.124	[0.844 , 1.559]	1.200
λ_h	: habit persistence	Beta	0.700	0.100	0.680	[0.570 , 0.759]	0.664	0.687	[0.566 , 0.740]	0.652
ξ	: capital adjustment cost	Normal	4.000	1.500	6.132	[4.778 , 8.479]	6.628	7.393	[5.753 , 9.454]	7.602
ρ	: Calvo pricing	Beta	0.500	0.150	0.791	[0.761 , 0.812]	0.787	0.732	[0.713 , 0.756]	0.734
ϕ	: desired (flexible price) gross markup (=ϕ/(ϕ−1))	Normal	6.000	0.750	7.480	[6.093 , 8.079]	7.098	5.852	[4.034 , 6.852]	5.422
η	: product-development stage intensity	Normal	1.000	0.200	1.263	[0.980 , 1.459]	1.216	−	[− , −]	−
α	: product-development steady state elasticity (= 1/(1+α)	Normal	0.250	0.100	0.165	[0.098 , 0.257]	0.178	−	[− , −]	−
ψ	: product survival rate	Beta	0.975	0.020	0.906	[0.886 , 0.933]	0.910	−	[− , −]	−
	Persistence of shocks									
ρ_u	: monetary policy	Beta	0.500	0.200	0.666	[0.555 , 0.688]	0.622	0.575	[0.518 , 0.664]	0.589
ρ_g	: government expenditure	Beta	0.500	0.200	0.961	[0.936 , 0.974]	0.955	0.972	[0.947 , 0.981]	0.964
ρ_c	: consumption preference	Beta	0.500	0.200	0.043	[0.008 , 0.087]	0.049	0.022	[0.005 , 0.066]	0.035
ρ_h	: leisure preference	Beta	0.500	0.200	0.979	[0.974 , 0.991]	0.982	0.995	[0.990 , 0.999]	0.995
ρ_μ	: surprised TFP	Beta	0.500	0.200	0.952	[0.939 , 0.969]	0.954	0.993	[0.989 , 0.999]	0.993
	Standard deviations of shocks									
σ_u	: monetary policy	InvGamma	0.003	Inf	0.0029	[0.0026 , 0.0031]	0.0029	0.0027	[0.0025 , 0.0031]	0.0028
σ_τ	: government expenditure	InvGamma	0.010	Inf	0.0050	[0.0045 , 0.0055]	0.0050	0.0051	[0.0048 , 0.0057]	0.0053
$\sigma_{\upsilon c}$	: consumption preference	InvGamma	0.010	Inf	0.0103	[0.0074 , 0.0138]	0.0107	0.0169	[0.0119 , 0.0221]	0.0171
$\sigma_{\upsilon h}$	: leisure preference	InvGamma	0.010	Inf	0.0188	[0.0172 , 0.0216]	0.0194	0.0216	[0.0187 , 0.0241]	0.0215
σ_μ	: surprised TFP	InvGamma	0.008	Inf	0.0080	[0.0072 , 0.0089]	0.0081	0.0072	[0.0066 , 0.0081]	0.0073
$\sigma_{4,news}$	: 4-period-ahead TFP news	InvGamma	0.004	Inf	0.0022	[0.0014 , 0.0032]	0.0023	0.0032	[0.0026 , 0.0042]	0.0034
$\sigma_{8,news}$	: 8-period-ahead TFP news	InvGamma	0.004	Inf	0.0034	[0.0029 , 0.0046]	0.0037	0.0022	[0.0012 , 0.0027]	0.0020
$\sigma_{12,news}$	: 12-period-ahead TFP news	InvGamma	0.004	Inf	0.0020	[0.0012 , 0.0023]	0.0017	0.0022	[0.0015 , 0.0029]	0.0022
$\sigma_{16,news}$	: 16-period-ahead TFP news	InvGamma	0.004	Inf	0.0015	[0.0012 , 0.0021]	0.0017	0.0034	[0.0022 , 0.0039]	0.0031
	Contemporaneous correlations among news shocks									
$\rho_{news,4\_8}$	: 4-period-ahead news and 8-period-ahead news	Uniform	0.000	0.577	0.899	[0.267 , 0.921]	0.580	0.776	[0.309 , 0.959]	0.622
$\rho_{news,4\_12}$	: 4-period-ahead news and 12-period-ahead news	Uniform	0.000	0.577	0.113	[−0.227 , 0.763]	0.257	−0.025	[−0.513 , 0.272]	−0.132
$\rho_{news,4\_16}$	: 4-period-ahead news and 16-period-ahead news	Uniform	0.000	0.577	−0.184	[−0.221 , 0.849]	0.296	−0.928	[−0.972 , −0.630]	−0.795
$\rho_{news,8\_12}$	: 8-period-ahead news and 12-period-ahead news	Uniform	0.000	0.577	0.445	[−0.394 , 0.515]	0.059	0.486	[−0.248 , 0.743]	0.242
$\rho_{news,8\_16}$	: 8-period-ahead news and 16-period-ahead news	Uniform	0.000	0.577	0.186	[−0.329 , 0.597]	0.134	−0.574	[−0.825 , −0.168]	−0.492
$\rho_{news,12\_16}$	: 12-period-ahead news and 16-period-ahead news	Uniform	0.000	0.577	0.950	[0.436 , 0.988]	0.713	0.354	[0.083 , 0.756]	0.414
	Marginal likelihood					4110.42 (4110.90)			4096.08 (4099.75)	

Notes: The posterior distribution is obtained using the Metropolis-Hastings algorithm. The maginal likelihood is estimated by using the modified harmonic mean and the value in the blankets is the maginal likelihood based on the Laplace approximation around the posterior mode.

Table 2: Monte carlo simulation results (1): t-statistic values for coefficients of the Phillips curve estimations with large smaples

ωb range	Basic NK			EPD NK		
	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc
[−0.02 : 0.00]	−0.35	35.96	17.77	−0.26	44.12	21.35
[0.00 : 0.02]	0.36	36.84	17.70	0.56	46.37	22.16
[0.02 : 0.04]	1.11	36.58	17.02	1.56	47.28	22.04
[0.04 : 0.06]	1.87	35.86	16.03	2.65	47.98	21.67
[0.06 : 0.08]	2.49	33.56	14.54	3.84	49.05	21.44
[0.08 : 0.10]	2.84	29.01	11.78	5.13	49.88	21.05
[0.10 : 0.12]	−	−	−	6.52	50.63	20.57
[0.12 : 0.14]	−	−	−	8.01	51.44	20.10
[0.14 : 0.16]	−	−	−	9.73	52.87	19.78
[0.16 : 0.18]	−	−	−	11.55	53.75	19.13
[0.18 : 0.20]	−	−	−	13.12	53.27	18.00

Notes: Shaded areas indicate significant at the 10% level

Table 3: Monte carlo simulation results (2): t-statistic values for coefficients of the Phillips curve estimations with samll samples

ωb range	Basic NK			EPD NK		
	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc
[−0.02 : 0.00]	−0.07	6.48	3.26	−0.07	7.14	3.59
[0.00 : 0.02]	0.07	6.45	3.16	0.08	7.49	3.64
[0.02 : 0.04]	0.21	6.43	3.01	0.25	7.71	3.61
[0.04 : 0.06]	0.36	6.57	2.95	0.43	7.83	3.60
[0.06 : 0.08]	0.49	6.43	2.74	0.64	8.16	3.60
[0.08 : 0.10]	0.62	6.05	2.54	0.89	8.60	3.63
[0.10 : 0.12]	0.80	6.24	2.49	1.14	8.90	3.67
[0.12 : 0.14]	0.96	6.08	2.43	1.37	8.75	3.53
[0.14 : 0.16]	1.11	5.91	2.31	1.68	9.06	3.51
[0.16 : 0.18]	1.34	6.22	2.23	1.94	9.05	3.38
[0.18 : 0.20]	1.54	6.35	2.12	2.26	9.21	3.34
[0.20 : 0.22]	1.67	6.27	1.90	2.61	9.44	3.21
[0.22 : 0.24]	1.84	6.21	1.77	3.01	9.56	3.12
[0.24 : 0.26]	1.93	5.79	1.56	3.14	8.99	2.75
[0.26 : 0.28]	2.08	5.69	1.43	3.53	9.21	2.62
[0.28 : 0.30]	2.40	5.85	1.40	3.91	9.11	2.47

Notes: Shaded areas indicate significant at the 10% level

Table 4: Monte carlo simulation results (3): t-statistic values for coefficients of the Phillips curve estimations with samll samples and measurement errors in mc

ωb range	Basic NK			EPD NK		
	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc
[−0.02 : 0.00]	−0.05	4.68	2.09	−0.05	5.21	2.37
[0.00 : 0.02]	0.05	4.75	2.08	0.06	5.69	2.52
[0.02 : 0.04]	0.16	4.96	2.15	0.19	5.84	2.50
[0.04 : 0.06]	0.29	5.18	2.20	0.34	6.22	2.59
[0.06 : 0.08]	0.42	5.30	2.19	0.52	6.51	2.64
[0.08 : 0.10]	0.52	5.22	1.89	0.68	6.56	2.53
[0.10 : 0.12]	0.63	5.20	1.78	0.87	6.76	2.54
[0.12 : 0.14]	0.72	5.00	1.63	1.08	6.92	2.53
[0.14 : 0.16]	0.88	5.18	1.58	1.32	7.16	2.49
[0.16 : 0.18]	0.98	4.93	1.48	1.58	7.30	2.50
[0.18 : 0.20]	1.08	4.70	1.36	1.80	7.26	2.37
[0.20 : 0.22]	1.25	4.73	1.34	2.15	7.61	2.36
[0.22 : 0.24]	1.43	4.79	1.31	2.37	7.41	2.22
[0.24 : 0.26]	1.56	4.79	1.14	2.64	7.40	2.10
[0.26 : 0.28]	1.85	4.93	1.18	2.99	7.55	2.05
[0.28 : 0.30]	1.95	4.66	1.06	3.11	7.01	1.72

Notes: Shaded areas indicate significant at the 10% level

Table 5: Monte carlo counterfactual simulation results: t-statistic values for coefficients of the Phillips curve estimations (EPD-NK model without the "time to innovate" specification)

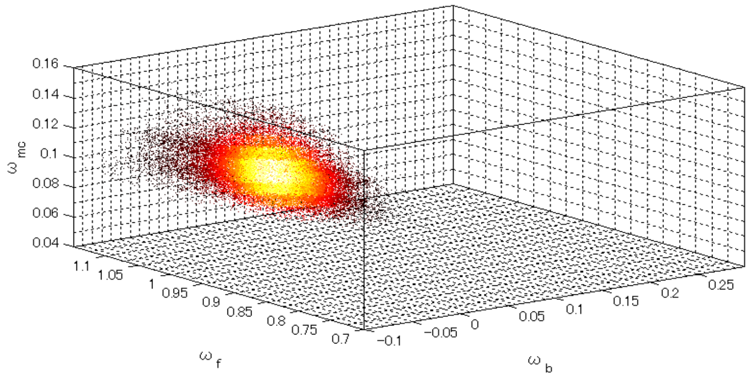
ωb range	Large samples			Small samples		
	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc	avg. t sts for ωb	avg. t sts for ωf	avg. t sts for ωmc
[−0.02 : 0.00]	0.46	56.73	39.41	−0.06	7.28	5.59
[0.00 : 0.02]	1.27	50.43	39.67	0.05	6.70	5.55
[0.02 : 0.04]	2.15	42.29	39.41	0.19	6.87	5.65
[0.04 : 0.06]	3.04	37.12	38.89	0.36	7.52	6.36
[0.06 : 0.08]	3.99	33.01	38.67	0.51	6.82	6.31
[0.08 : 0.10]	5.03	30.98	39.22	0.72	7.14	6.80
[0.10 : 0.12]	6.02	27.45	38.66	0.92	7.36	7.03
[0.12 : 0.14]	6.97	24.09	38.32	1.12	7.18	7.02
[0.14 : 0.16]	8.01	22.84	37.69	1.40	7.05	7.44
[0.16 : 0.18]	9.21	21.83	38.00	1.58	6.55	7.31
[0.18 : 0.20]	10.74	21.14	39.61	1.79	6.09	7.13
[0.20 : 0.22]	11.21	20.43	36.34	2.10	6.10	7.45
[0.22 : 0.24]	−	−	−	2.34	6.14	7.41
[0.24 : 0.26]	10.72	16.42	27.02	2.75	6.33	7.79
[0.26 : 0.28]	−	−	−	2.95	6.27	7.52
[0.28 : 0.30]	−	−	−	3.45	5.97	7.96

Notes: Shaded areas indicate significant at the 10% level

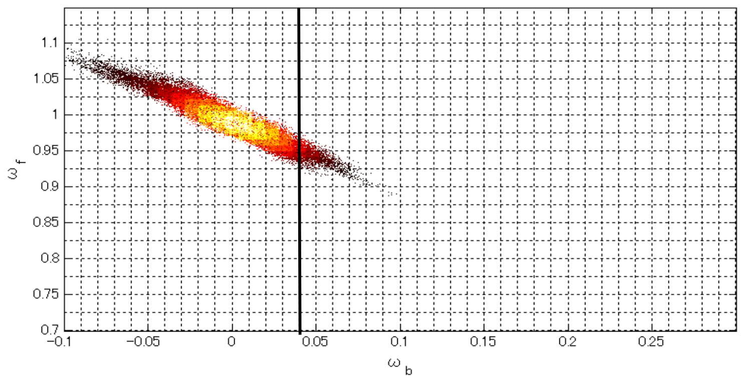
Figure 1: Monte carlo simulation results of the Phillips curve (large samples)

Basic NK model

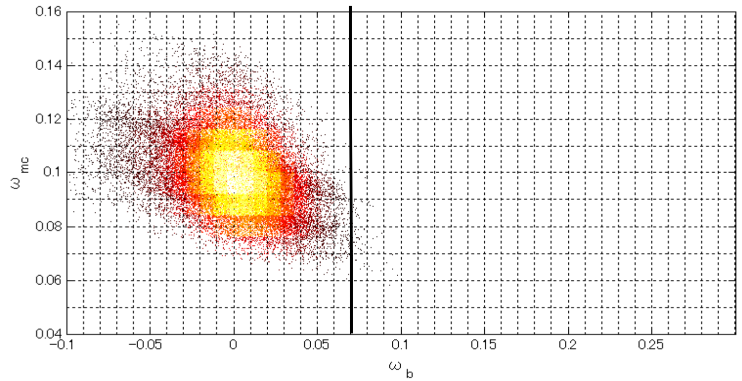
a1. Three-dimentional scatter density plots (ωb, ωf, ωmc)



a2. Two-dimentional scatter density plots (ωb, ωf), corresponding to a1

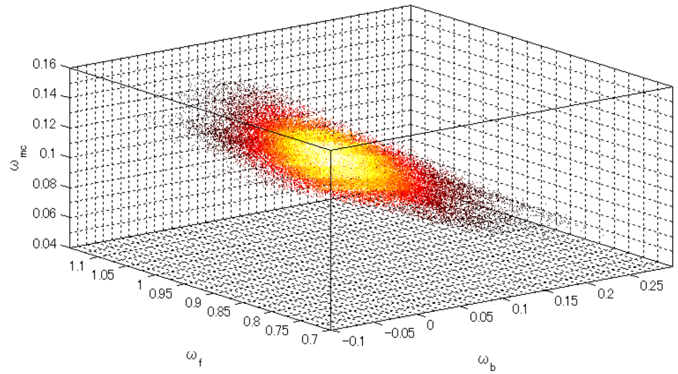


a3. Two-dimentional scatter density plots (ωb, ωmc), corresponding to a1

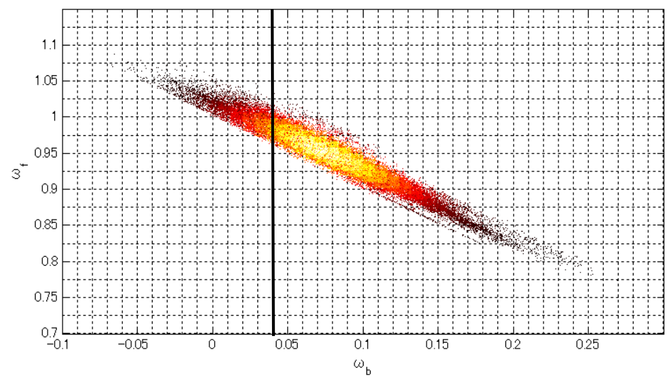


EPD NK model

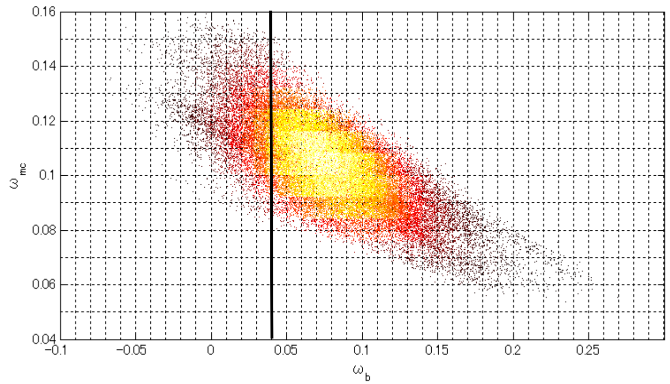
b1. Three-dimentional scatter density plots (ωb, ωf, ωmc)



b2. Two-dimentional scatter density plots (ωb, ωf), corresponding to b1



b3. Two-dimentional scatter density plots (ωb, ωmc), corresponding to b1

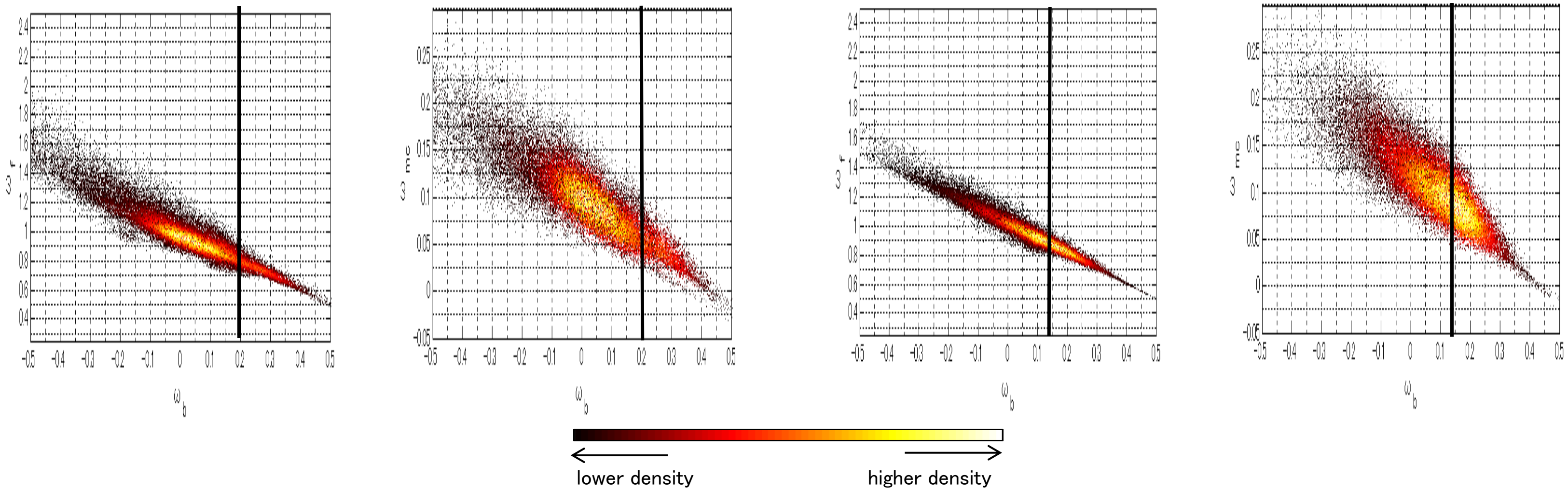


Notes: a2 (b2) is obained by viewing a1(b1) from directly overhead. a3 (b3) is obtained by setting the view along the ωf-axis in a1 (b1), with the ωb-axis extending horizontally and the ωmc-axis extending vertically in the figure. As for (a2), (a3), (b2) and (b3), ony in the area on the right hand side of a thick line, estimates of ωb are, on average, significant at the 10% level.

Figure 2 : Monte carlo simulation results of the Phillips curve estimation (samll samples)

Basic NK model | EPD NK model

a1. a2. b1. b2.

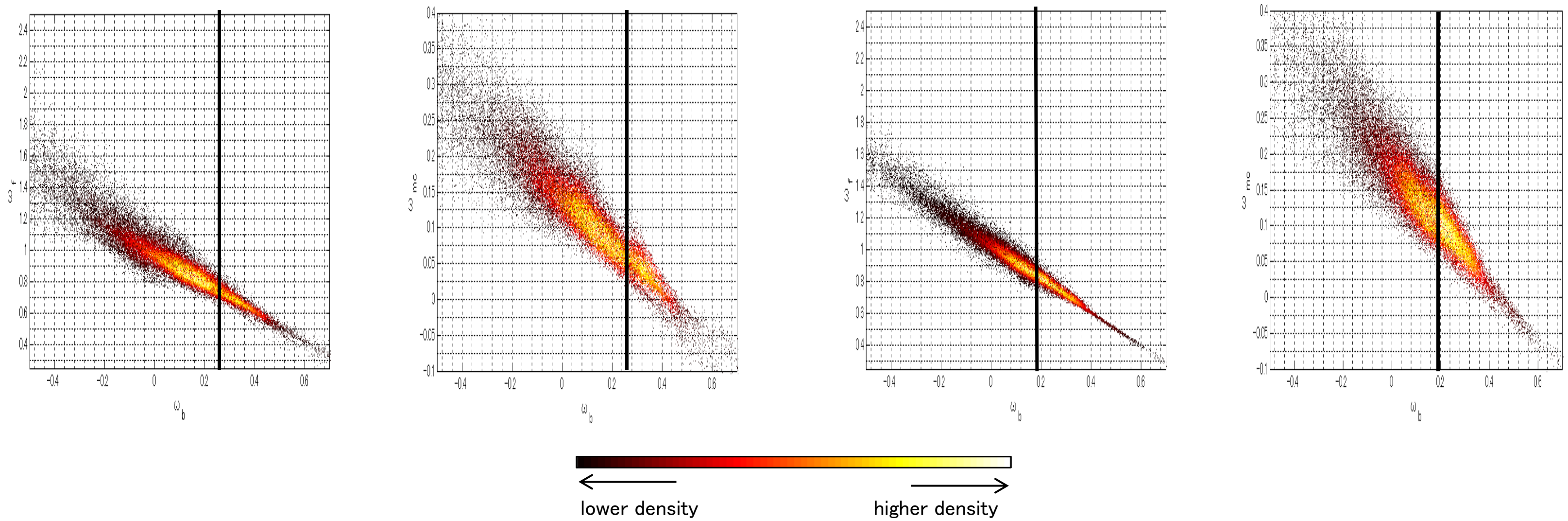


Notes: a1 and b1 are obained by viewing the corresponding three-dimentional scatter density plots of (ωb, ωf, ωmc) from directly overhead. a2 and b2 are obtained by setting the view along the ωf-axis in the corresponding three-dimentional scatter density plots, with the ωb-axis extending horizontally and the ωmc-axis extending vertically in the figures. Ony in the area on the right hand side of a thick line, estimates of ωb are, on average, significant at the 10% level.

Figure 3: Monte carlo simulation results of the Phillips curve estimation (samll samples) with measurement errors in mc

Basic NK model | EPD NK model

a1. a2. b1. b2.

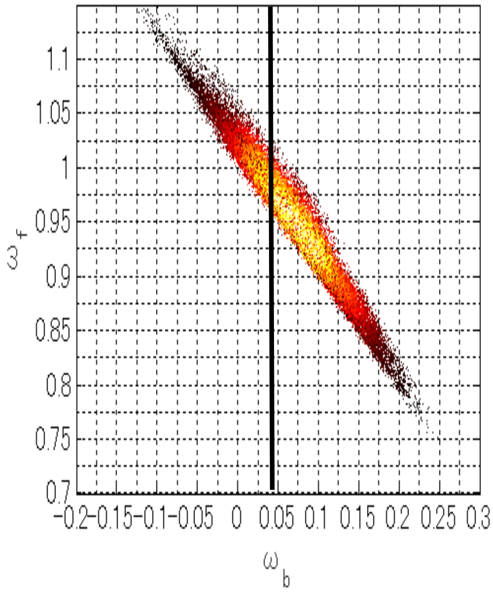


Notes: See the notes in Figure 2

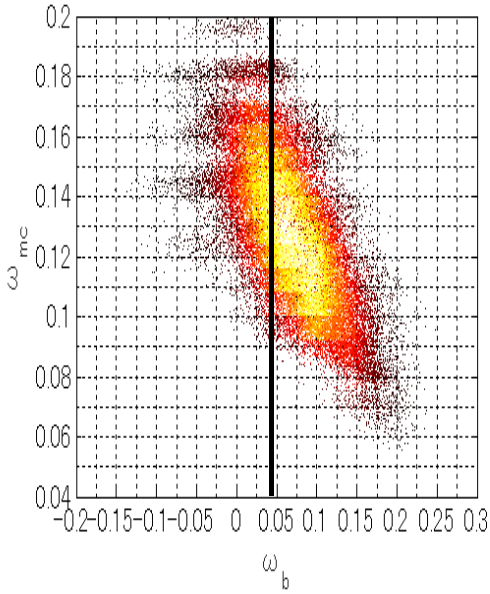
Figure 4 : Counterfactual simulation results of the Phillips curve estimation (EPD-NK model without the "time to innovate" specification)

Large samples

a1.

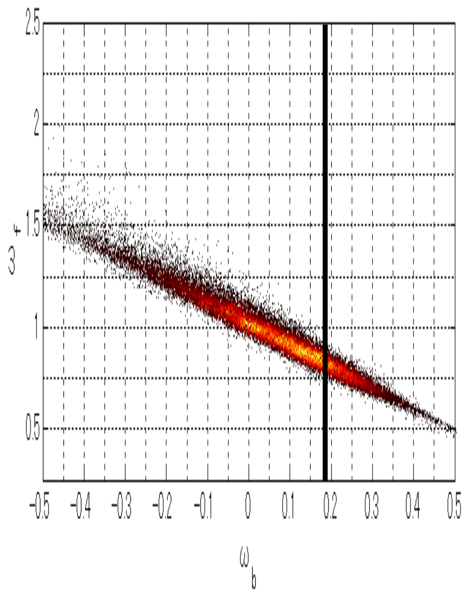


a2.

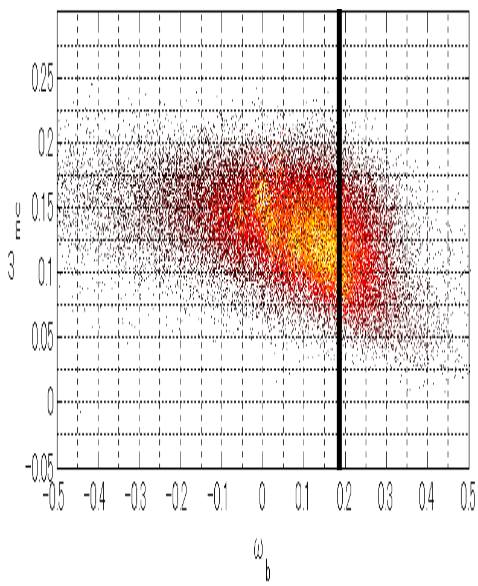


Small samples

b1.



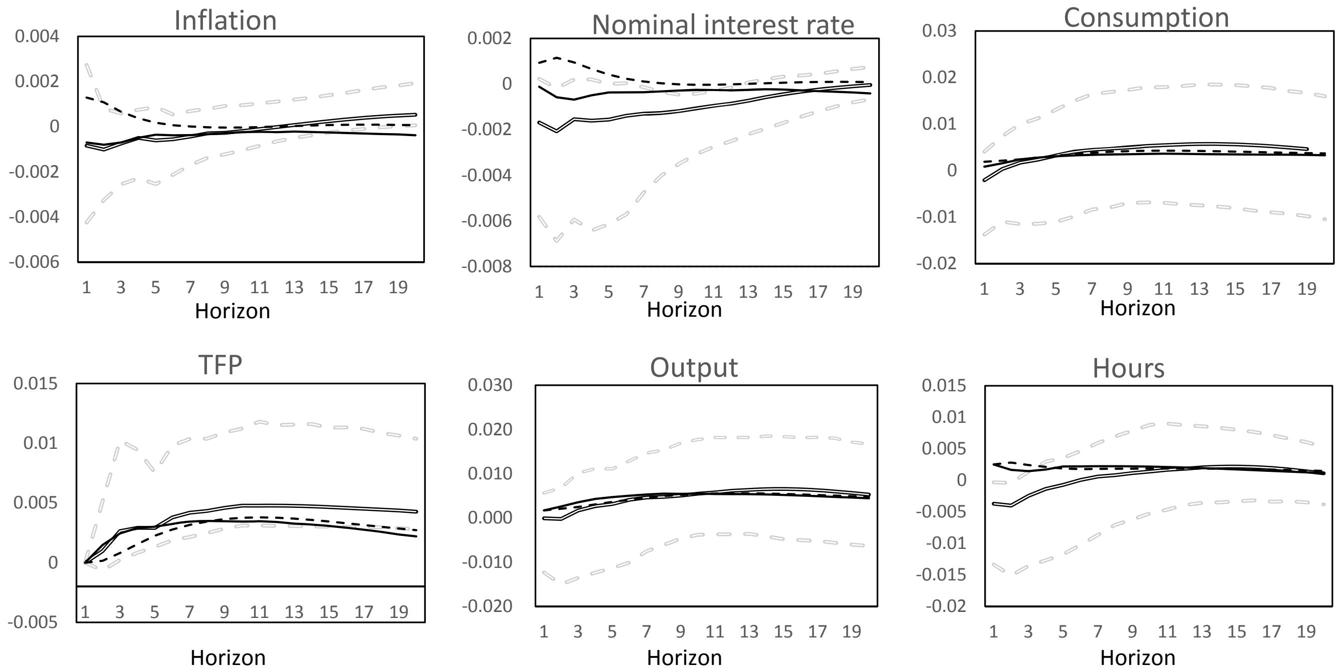
b2.



lower density higher density

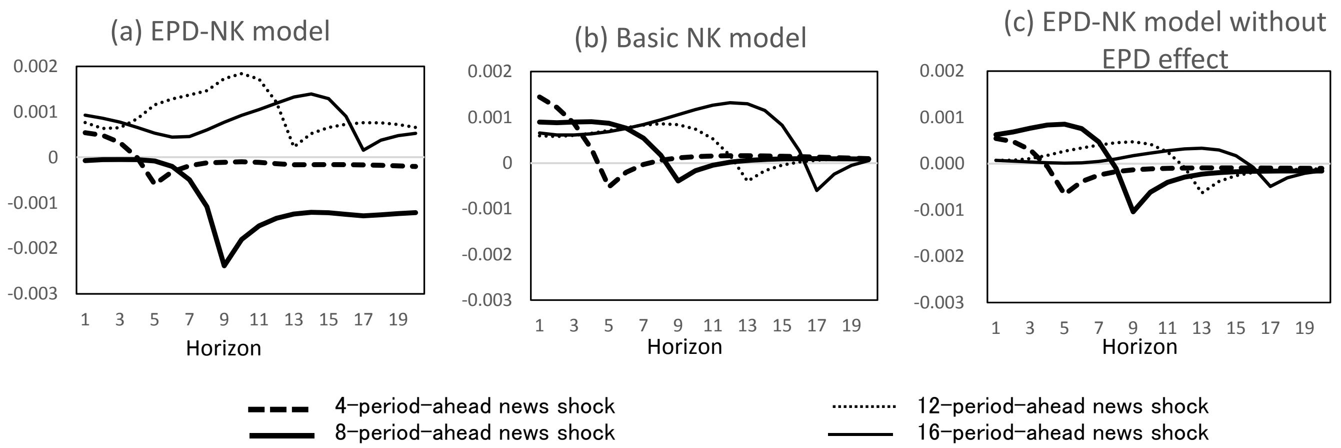
Notes: See the notes in Figure 1 and Figure 2

Figure 5: Empirical and Monte Carlo Estimated Impulse Responses to a News Shock



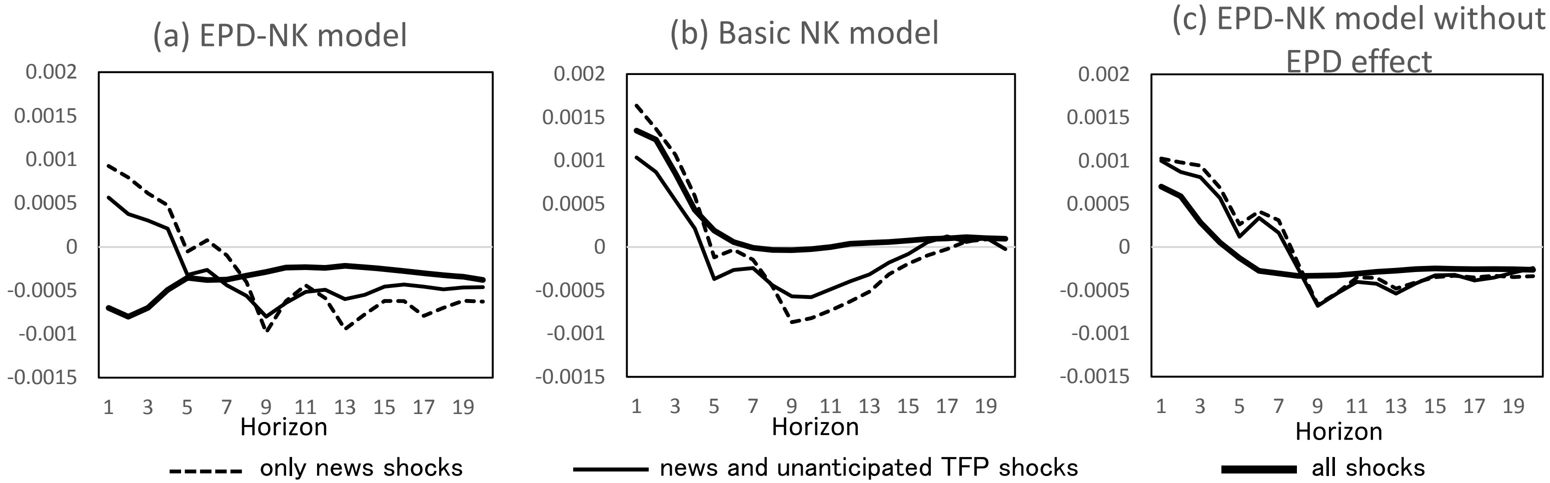
Notes: The double lines in each figure show the median empirically estimated impulse resposponses to a news shock obtained from a six variable VAR. The VAR includes TFP, output, consumption, hours, nominal interest rates and inflation rates. The gray dashed lines are the +/− one standard deviation confidence intervals that are obtained from 2000 bootstrap replications. The solid line are the median Monte Carlo estimated impulse resposponses to a news shock obtained from the VARs on 500 random samples of 190 observations generated from the EPD−NK model, and the dashed lines are those from the basic NK model. The vertical axes are percentage deviations.

Figure 6: Theoretical Impulse Responses of Inflation to News Shocks



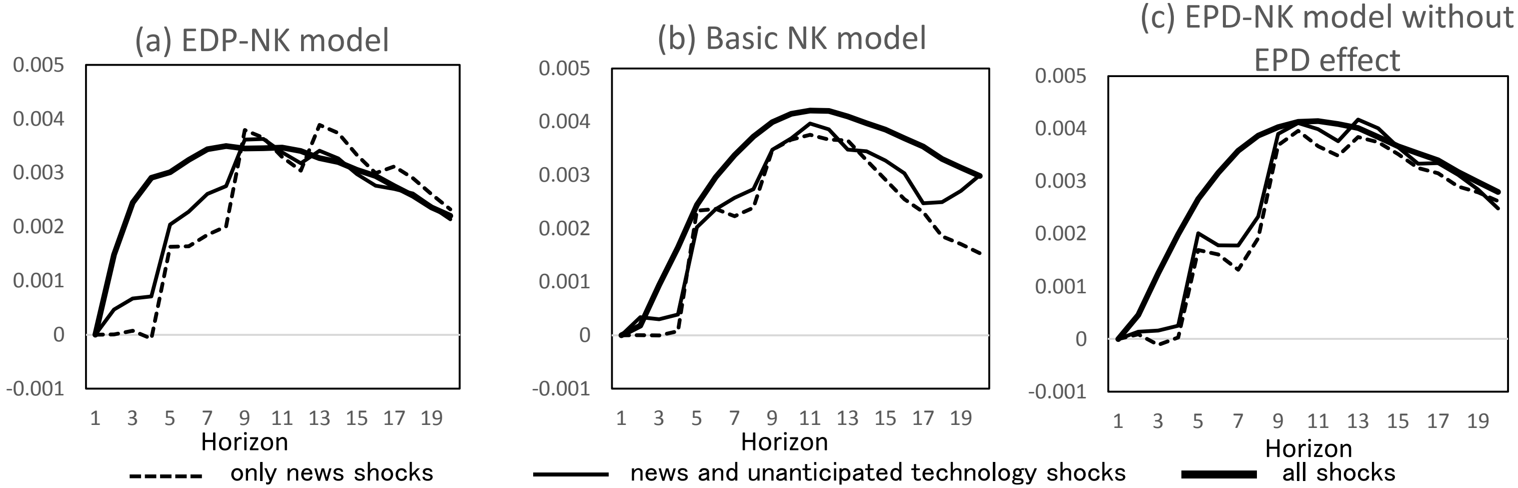
Notes: The lines in each figure show the theoretical impulse resposponses of inflation to a news shock. The dashed line is the impulse responses to the 4−period−ahead news shock, the thick solid line the 8−period−ahead news shock, the dotted line the 12−period−ahead news shock, and the solid line the 16−period−ahead news shock. The vertical axes are percentage deviations.

Figure 7: Monte Carlo Estimated Impulse Responses of Inflation to a News Shock



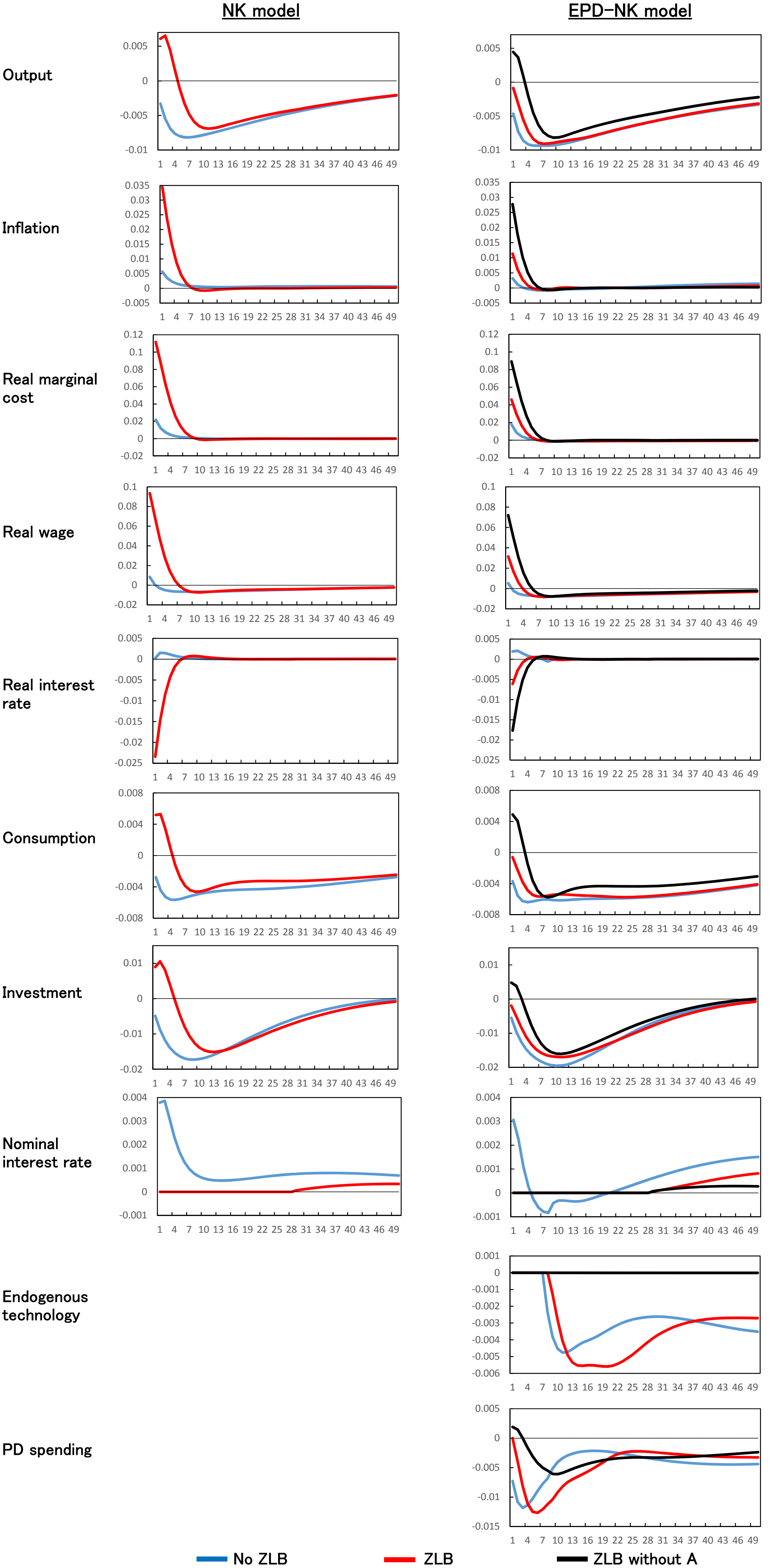
Notes: The lines in each figure show the median Monte Carlo estimated impulse resposponses to a news shock obtained from the VARs on 500 random samples of 190 observations generated from the corresponding model. The dashed line represents the impulse response from the model including only the news shocks, the solid line from the model including the news and unticipated technology shocks, and the thick solid line from the model including all of the shocks. The VAR includes TFP, output, consumption, hours, nominal interest rates and inflation rates. The vertical axes are percentage deviations.

Figure 8 : Monte Carlo Estimated Impulse Responses of TFP to a News Shock



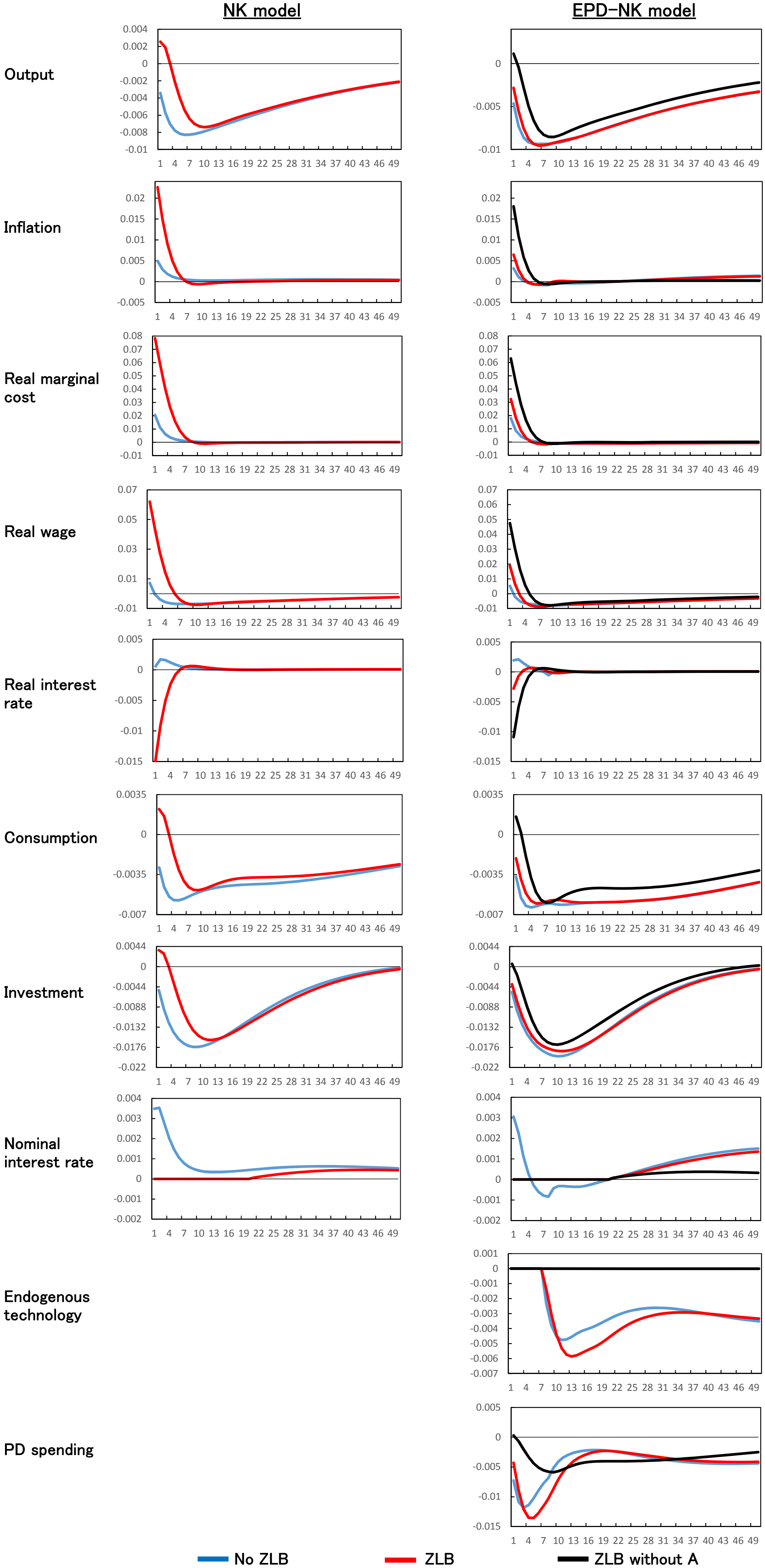
Notes: See the notes in Figure 7.

Figure 9: Impulse respose function for a negative exogenous technology shock (28 period ZLB)



Notes: Panels show impulase responses to a one percent decrease in exogenous productivity, μ_t.

Figure 10: Impulse respose function for a negative exogenous technology shock (20 period ZLB)



Notes: Panels show impulase responses to a one percent decrease in exogenous productivity, μ_t.

Appendix (not for publicatin): Endogenous Technological Change and the New Keynesian Model

1 Section1: Model details

In this section of the Appendix, I show some details of the model.

A: The Lagrangian for the household problem

The Lagrangian for household i's problem is given by:

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \Gamma^t \left\{ \begin{array}{c} N_{t,i} \left(\begin{array}{c} \upsilon_{c,t} \frac{[C_{t,i}/N_{t,i} - \lambda_h (C_{t-1,i}/N_{t-1,i})]^{1-\sigma_c}}{1-\sigma_c} - \upsilon_{h,t} \frac{(H_{t,i}/N_{t,i})^{1+\sigma_h}}{1+\sigma_h} \\ + \frac{[M_{t,i}/(P_t N_{t,i})]^{1-\sigma_m}}{1-\sigma_m} \end{array} \right) \\ + \varrho_{t,i} \left(\begin{array}{c} w_t H_{t,i} + r_t K_{t-1,i} - TX_t + (1 + r_{N,t-1}) \frac{B_{t-1,i}}{P_t} + \Xi_{t,i} \\ + \frac{M_{t-1,i}}{P_t} - C_{t,i} - INV_{t,i} - \frac{M_{t,i}}{P_t} - \frac{B_{t,i}}{P_t} \end{array} \right) \\ + \chi_{t,i} \left((1-\delta) K_{t-1,i} + INV_{t,i} - S(\frac{INV_{t,i}}{INV_{t-1,i}}) INV_{t,i} - K_{t,i} \right) \end{array} \right\},$$

where $\varrho_{t,i}$ and $\chi_{t,i}$ are the Lagrange multipliers.

B: Equilibrium and aggregate household budget constraint

The economy must fulfill the following aggregation conditions:

$$\begin{aligned} C_t &= C_{t,i} \; (= \int_0^1 C_{t,i} \; di), \; K_t = K_{t,i} (= \int_0^1 K_{t,i} \; di), \\ H_t &= H_{t,i} (= \int_0^1 H_{t,i} \; di), \; B_t = B_{t,i} (= \int_0^1 B_{t,i} \; di) \quad , \end{aligned}$$

where C_t, K_t, H_t and B_t are total consumption, total capital stock, total labor and total lending, respectively.

The labor, capital, money and lending market equilibrium conditions are as follows:

$$H_t = \int_0^{A_{t-1}} H_t(j) \; dj, \quad K_{t-1} = \int_0^{A_{t-1}} K_{t-1}(j) \; dj, \; M_t = M_{t,i},$$

$$\begin{aligned} B_t &= P_t \left(\sum_{\varphi=1}^{\overline{\varphi}} \left(F_{t-\varphi+1}(J_{t-\varphi+1}) \eta_{\overline{\varphi}-\varphi+1} \right) \right) \\ &+ \sum_{m=1}^{\overline{\varphi}-1} \left[P_{t-m} \prod_{l=1}^{m} (1 + r_{N,t-l}) \left(\sum_{\varphi=m}^{\overline{\varphi}-1} \left(F_{t-\varphi}(J_{t-\varphi}) \eta_{\overline{\varphi}-\varphi+m} \right) \right) \right] \end{aligned} \quad \text{(A1-1)}$$

where $M_{t,i} = \int_0^1 M_{t,i} \; di$. The second term on the right-hand side of equation (A1-1) represents the sum of rollover loans. The first term represents the sum of new loans to PD firms. The goods market equilibrium condition is given by:

$$Y_t = \int_0^1 C_{t,i} \; di + \int_0^1 INV_{t,i} \; di + \int_0^1 ID_{t,i} \; di + G_t = C_t + INV_t + ID_t + G_t, \quad \text{(A1-2)}$$

where

$$ID_t = \sum_{\varphi=1}^{\overline{\varphi}} \left(\eta_\varphi (J_{t-\overline{\varphi}+\varphi}) F_{t-\overline{\varphi}+\varphi} \right) \tag{A1-3}$$

$$G_t = \tau_t \; Y_t. \tag{A1-4}$$

$$\tau_t = (1-\rho_\tau)\overline{\tau} + \rho_\tau \tau_{t-1} + \varepsilon_t^\tau, \;\; 0 \leq \rho_\tau \leq 1. \tag{A1-5}$$

$INV_{t,i}$ and $ID_{t,i}$ are household i's investment in capital and in PD, respectively. I_t and ID_t are total capital investment and total PD investment, respectively. G_t is government expenditure and is equal to a fraction τ_t of output. Equation (A1-5) shows the dynamics of τ_t, where $\overline{\tau}$ is a steady-state level of τ and ε_t^τ represents a government spending shock. Furthermore, because $J_t = d \; (F_t)^\alpha$ from equation (10), equation (A1-3) can be rewritten as:

$$ID_t = \sum_{\varphi=1}^{\overline{\varphi}} \eta_\varphi \left\{ d \; (F_{t-\overline{\varphi}+\varphi})^{1+\alpha} \right\} \; . \tag{A1-6}$$

Next, it is shown that the aggregate household budget constraint satisfies the goods market equilibrium. In doing so, for illustrative purposes, the case of $\overline{\varphi} = 4$ is considered. From equation (12), the aggregate household budget constraint is given by:

$$C_t + INV_t + \frac{M_t}{P_t} + \frac{B_t}{P_t} = w_t H_t + r_t K_{t-1} - TX_t + (1 + r_{N,t-1}) \frac{B_{t-1}}{P_t} + \Xi_t + \frac{M_{t-1}}{P_t}.$$

Thus, one can obtain

$$C_t + INV_t + G_t + \frac{B_t}{P_t} = w_t H_t + r_t K_{t-1} + (1 + r_{N,t-1}) \frac{B_{t-1}}{P_t} + \Xi_t, \tag{A1-7}$$

where $G = (M_t - M_{t-1})/P_t + TX_t$ (this represents the government budget constraint). Substituting equation (A1-1) into equation (A1-7) for B_t and

B_{t-1}, the household budget constraint can be rewritten as:

$$
\begin{aligned}
& C_t + INV_t + G_t + \frac{1}{P_t}\left[\begin{array}{c} \eta_1 F_{t-3} J_{t-3} P_t + \eta_2 F_{t-2} J_{t-2} P_t \\ +\eta_3 F_{t-1} J_{t-1} P_t + \eta_4 F_t J_t P_t \end{array}\right] \\
& = w_t H_t + r_t K_{t-1} \\
& + \frac{1 + r_{N,t-1}}{P_t}\left[\begin{array}{c} F_{t-4} J_{t-4} \eta_1 P_{t-1} + (1 + r_{N,t-2}) F_{t-4} J_{t-4} \eta_2 P_{t-2} \\ +(1 + r_{N,t-2})(1 + r_{N,t-3}) F_{t-4} J_{t-4} \eta_3 P_{t-3} \\ +(1 + r_{N,t-2})(1 + r_{N,t-3})(1 + r_{N,t-4}) F_{t-4} J_{t-4} \eta_4 P_{t-4} \end{array}\right] + \Xi_t.
\end{aligned}
\tag{A1-8}
$$

Assuming that firms roll over product development loans, the following equation must hold:

$$
\begin{aligned}
& Y_t = w_t H_t + r_t K_{t-1} + \Xi_t \\
& + \left[\begin{array}{c} F_{t-4} J_{t-4} \eta_1 \frac{P_{t-1}}{P_t}(1 + r_{N,t-1}) + F_{t-4} J_{t-4} \eta_2 \frac{P_{t-2}}{P_t}(1 + r_{N,t-1})(1 + r_{N,t-2}) \\ +F_{t-4} J_{t-4} \eta_3 \frac{P_{t-3}}{P_t}(1 + r_{N,t-1})(1 + r_{N,t-2})(1 + r_{N,t-3}) \\ +F_{t-4} J_{t-4} \eta_4 \frac{P_{t-4}}{P_t}(1 + r_{N,t-1})(1 + r_{N,t-2})(1 + r_{N,t-3})(1 + r_{N,t-4}) \end{array}\right].
\end{aligned}
\tag{A1-9}
$$

Furthermore, the following two equations for total capital investment and PD investment hold:

$$
INV_t = K_t - (1 - \delta) K_{t-1} + S\left(\frac{INV_t}{INV_{t-1}}\right) INV_t \tag{A1-10}
$$

and

$$
ID_t = \eta_1 J_{t-3} F_{t-3} + \eta_2 J_{t-2} F_{t-2} + \eta_3 J_{t-1} F_{t-1} + \eta_4 J_t F_t. \tag{A1-11}
$$

Substituting equations (A1-9)-(A1-11) into equation (A1-8), the aggregate household budget constraint is finally rewritten as:

$$
Y_t = C_t + INV_t + ID_t + G_t.
$$

That is, the aggregate household budget constraint satisfies the goods market equilibrium.

Section2: Linearized model

In the following equations, except $\widetilde{i}_t$ and $\widetilde{\tau}_t$ where $\widetilde{r}_{N,t}$ and $\widetilde{\tau}_t$ measure deviations from its steady state values of $r_{N,t}$ and τ_t, a variable with "~" shows *log* deviations from the steady-state value, e.g., $\widetilde{y} = \ln y_t - \ln \overline{y}$ where $y_t = Y_t/N$ and $\overline{y}$ denotes the steady state value of y_t . A variable with "$-$" represents the steady state of the variable. I assume constant population, that is $N_t = N$ (this assumption does not affect the analysis of the paper because the fucus of the paper is the economy's fluctuations around the steady state).

The endogenous processes are described by the following equations:

$$\begin{aligned}\widetilde{c}_t - \lambda_h \widetilde{c}_{t-1} &= (1+\lambda_h\Gamma)E_t\left[\widetilde{c}_{t+1} - \lambda_h \widetilde{c}_t\right] - \lambda_h \Gamma E_t\left[\widetilde{c}_{t+2} - \lambda_h \widetilde{c}_{t+1}\right] \\ &\quad -\frac{1-\lambda_h}{\sigma_c}\left(1-\lambda_h\Gamma\right)E_t\left[\frac{1}{1+\overline{r}_N}\widetilde{r}_{N,t} + \widetilde{P}_t - \widetilde{P}_{t+1} + \widetilde{\upsilon}_{c,t+1}\right] \\ &\quad +\frac{1-\lambda_h}{\sigma_c}\widetilde{\upsilon}_{c,t} + \frac{1-\lambda_h}{\sigma_c}\lambda_h\Gamma E_t\left[\widetilde{\upsilon}_{c,t+2}\right], \end{aligned} \tag{A2-1}$$

$$\begin{aligned}\sigma_h \widetilde{h}_t &= \widetilde{w}_t - \widetilde{\upsilon}_{h,t} + \frac{1}{1-\lambda_h\Gamma}\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) + \widetilde{\upsilon}_{c,t}\right. \\ &\quad \left. +\frac{\lambda_h\Gamma}{1-\lambda_h\Gamma}E_t\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) - \widetilde{\upsilon}_{c,t+1}\right]\right], \end{aligned} \tag{A2-2}$$

$$\begin{aligned}\sigma_m\left(\widetilde{m}_t - \widetilde{P}_t\right) &= \frac{-1}{(1+\overline{r}_N)\overline{r}_N}\widetilde{r}_{N,t} + \frac{1}{1-\lambda_h\Gamma}\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) - \widetilde{\upsilon}_{c,t}\right. \\ &\quad \left. +\frac{\lambda_h\Gamma}{1-\lambda_h\Gamma}E_t\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) + \widetilde{\upsilon}_{c,t+1}\right]\right], \end{aligned} \tag{A2-3}$$

$$\begin{aligned}\widetilde{inv}_t &= \frac{\Gamma}{1+\Gamma}E_t\left[\widetilde{inv}_{t+1}\right] + \frac{1}{1+\Gamma}\widetilde{inv}_{t-1} + \frac{1}{\xi(1+\Gamma)}\widetilde{\chi}_t \\ &\quad \frac{1}{\xi(1+\Gamma)(1-\lambda_h\Gamma)}\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) - \widetilde{\upsilon}_{c,t}\right] \\ &\quad +\frac{\lambda_h\Gamma}{\xi(1+\Gamma)(1-\lambda_h\Gamma)}E_t\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) + \widetilde{\upsilon}_{c,t+1}\right], \end{aligned} \tag{A2-4}$$

$$\overline{y}\ \widetilde{y}_t = \overline{c}\ \widetilde{c}_t + \overline{inv}\ \widetilde{inv}_t + \overline{id}\ \widetilde{id}_t + \overline{g}\ \widetilde{g}_t, \tag{A2-5}$$

$$\widetilde{k}_t = (1-\delta)\widetilde{k}_{t-1} + \widetilde{inv}_t, \tag{A2-6}$$

$$\widetilde{id}_t = (1+\alpha)\left(\sum_{\varphi=1}^{\overline{\varphi}} \eta_\varphi \widetilde{F}_{t-\overline{\varphi}+\varphi}\right) \tag{A2-7}$$

$$\widetilde{g}_t = \frac{1}{\overline{\tau}}\widetilde{\tau}_t\ \widetilde{y}_t \tag{A2-8}$$

$$\widetilde{y}_t = \left(\frac{1}{\phi-1}\right)\widetilde{A}_{t-1} + \theta\widetilde{k}_{t-1} + (1-\theta)\widetilde{h}_t + \widetilde{\mu}_t, \tag{A2-9}$$

$$\widetilde{h}_t - \widetilde{k}_{t-1} - \frac{1}{\overline{r}}\widetilde{r}_t + \widetilde{w}_t = 0, \tag{A2-10}$$

$$\begin{aligned}\widetilde{P}_t - \widetilde{P}_{t-1} &= \Gamma E_t\left[\widetilde{P}_{t+1} - \widetilde{P}_t\right]\\ &+\frac{(1-\rho\psi\Gamma)(1-\rho\psi)}{\rho\psi}\left((1-\theta)\widetilde{w}_t + \theta\frac{1}{\overline{r}}\widetilde{r}_t - \widetilde{\mu}_t - \frac{1}{\phi-1}\widetilde{A}_{t-1}\right)\\ &+\frac{\Gamma}{\phi-1}\left(\widetilde{A}_t - \widetilde{A}_{t-1}\right) - \frac{1}{\phi-1}\left(\widetilde{A}_{t-1} - \widetilde{A}_{t-2}\right),\end{aligned} \tag{A2-11}$$

$$\begin{aligned}\overline{z}\widetilde{z}_t - \psi\Gamma\overline{z}E_t\left[\widetilde{z}_{t+1}\right] + \psi\Gamma\overline{z}E_t\left[\widetilde{Q'}_{t,t+1}\right] &= \frac{1}{\phi}\overline{y}\widetilde{y}_t + \frac{\phi-1}{\phi}\overline{y}\widetilde{\mu}_t\\ &-\frac{\phi-1}{\phi}(1-\theta)\overline{y}\widetilde{w}_t - \frac{\phi-1}{\phi}\frac{1}{\overline{r}}\theta\overline{y}\widetilde{r}_t,\end{aligned} \tag{A2-12}$$

$$\widetilde{Q'}_{t,t+1} = \widetilde{P}_t - \widetilde{P}_{t+1} + \widetilde{r}_{N,t}, \tag{A2-13}$$

$$E_t\left[\widetilde{z}_{t+\overline{\varphi}}\right] = \alpha\widetilde{F}_t + \frac{\left(\overline{F}\right)^\alpha}{\epsilon\left(\Delta\right)\overline{z}}E_t\left[\begin{array}{c}\sum_{\varphi=1}^{\overline{\varphi}}\left\{\widetilde{r}_{N,t+\overline{\varphi}-\varphi}\left(\sum_{l=\varphi}^{\overline{\varphi}}\left(\eta_l\right)\left(1+\overline{r}_N\right)^{l-1}\right)\right\}\\ +\sum_{\varphi=1}^{\overline{\varphi}}\left\{\left(\eta_\varphi(1+\overline{r}_N)^\varphi\left(\widetilde{P}_{t+\overline{\varphi}-\varphi} - \widetilde{P}_{t+\overline{\varphi}}\right)\right)\right\}\end{array}\right] \tag{A2-14}$$

$$\widetilde{A}_t = (1-\psi)\widetilde{F}_{t-\overline{\varphi}+1} + \psi\widetilde{A}_{t-1}, \tag{A2-15}$$

$$\widetilde{r}_{N,t} = (1+\overline{r}_N)^{\vartheta}\left[\vartheta\frac{1}{1+\overline{r}_N}\widetilde{r}_{N,t-1} + (1-\vartheta)\left(\varpi_{\pi}(\widetilde{P}_t - \widetilde{P}_{t-1}) + \varpi_y(\widetilde{y}_t - \widetilde{y}_t^n)\right) + \widetilde{u}_t\right], \tag{A2-16}$$

where $y_t = Y_t/N$, $c_t = C_t/N$, $inv_t = INV_t/N$, $k_t = K_t/N$, $b_t = B_t/N$, $h_t = H_t/N$, $m_t = M_t/N$, $id_t = ID_t/N$, $g_t = G_t/N$, $\Delta = N/d$, and $\xi = S''(1)$. Note that in equation (A2-11) $(1-\theta)\widetilde{w}_t + \theta\frac{1}{\overline{r}}\widetilde{r}_t - \widetilde{\mu}_t = \widetilde{mc}$ where $\widetilde{mc}$ denotes log deviation of the real marginal cost from its steady-state. For the ease of estimation, we make the following assumption regarding the relative importance of each PD stage:

$$\eta_{\varphi} = \eta_1\overline{\eta}^{\varphi-1},\ 0 < \overline{\eta}. \tag{A2-17}$$

The assumption implies that the importance of each stage of PD changes monotonically, i.e., if $\overline{\eta} > 1$ ($\overline{\eta} < 1$), an earlier stage of PD is more (less) important than a later stage.

The exogenous processes are described by the following equations:

$$\widetilde{\mu}_t = \rho_u\widetilde{\mu}_{t-1} + \varepsilon_t^{\mu} + \sum_{s=1}^{\overline{t}}\varepsilon_{s,t-s}^{news},. \tag{A2-18}$$

$$\widetilde{\upsilon}_{c,t} = \rho_{\upsilon,c}\widetilde{\upsilon}_{c,t-1} + \varepsilon_t^{\upsilon_c}, \tag{A2-19}$$

$$\widetilde{\upsilon}_{h,t} = \rho_{\upsilon,h}\widetilde{\upsilon}_{h,t-1} + \varepsilon_t^{\upsilon_h}, \tag{A2-20}$$

$$\widetilde{u}_t = \rho_u\widetilde{u}_{t-1} + \varepsilon_t^{u}\ , \tag{A2-21}$$

$$\widetilde{\tau}_t = \rho_{\tau}\widetilde{\tau}_{t-1} + \varepsilon_t^{\tau}. \tag{A2-22}$$

The steady state of the economy can be described by the following equations ("‾" indicates a steady state):[1]

$$\frac{1}{\Gamma} = 1 + \overline{r}_N,$$

$$\left(\overline{h}\right)^{\sigma_h} = \overline{w}\left(\overline{c}\right)^{-\sigma_c},$$

[1] $S'(1) = S(1) = 0$ and $\sum_{\varphi=1}^{\overline{\varphi}}\eta_{\varphi} = 1$ are used.

$$\overline{m} = [(1-\lambda_h)\overline{c}]^{\frac{\sigma_c}{\sigma_m}} \left(\frac{1+\overline{r}_N}{\overline{r}_N}\right)^{\frac{1}{\sigma_m}} (1-\lambda_h\Gamma)^{\frac{-1}{\sigma_m}},$$

$$\overline{\chi} = \Gamma\left[[(1-\lambda_h)\overline{c}]^{-\sigma_c}(\overline{r})(1-\lambda_h\Gamma) + (1-\delta)\overline{\chi}\right],$$

$$\overline{\chi} = (1-\lambda_h\Gamma)\left[(1-\lambda_h)\overline{\overline{c}}\right]^{-\sigma_c},$$

$$\overline{y} = \overline{c} + \overline{inv} + \overline{id} + \overline{g},$$

$$\overline{inv} = \delta\overline{k},$$

$$(\Delta)\overline{id} = \left(\overline{F}\right)^{1+\alpha},$$

$$\overline{g} = \overline{\tau}\;\overline{y},$$

$$\overline{y} = \overline{k}^{\theta}\overline{h}^{1-\theta},$$

$$\frac{1-\theta}{\theta}\frac{\overline{r}}{\overline{w}} = \frac{\overline{h}}{\overline{k}},$$

$$\frac{\phi-1}{\phi} = \frac{1}{1-\theta}\left(\frac{1-\theta}{\theta}\right)^{\theta}\overline{r}^{\theta}\;(\overline{w})^{1-\theta},$$

$$\left(1-\psi\left(\overline{Q'}\right)^{-1}\right)\overline{z} = \overline{y}\left[1-\left(\frac{1}{1-\theta}\left(\frac{1-\theta}{\theta}\right)^{\theta}\right)\overline{r}^{\theta}\;\overline{w}^{1-\theta}\right],$$

$$1+\overline{r}_N = \left(\overline{Q'}\right)^{-1},$$

$$\epsilon\overline{z} = (\Delta)^{-1}\left(\overline{F}\right)^{\alpha}\left(\sum_{\varphi=1}^{\overline{\varphi}}\eta_{\varphi}(1+\overline{r}_N)^{\varphi}\right),$$

$$\overline{F} = \frac{1-\psi}{\epsilon},$$

$$1+\overline{r}_N = \Lambda\left(1+\overline{r}_N\right)^{\vartheta}.$$

The steady-state values of the model's variables can be obtained (i.e., parameterized) by solving the above equations. When estimating the model, the above equations are used together with equations (A2-1)-(A2-22). Note that, when estimating the model, Δ and Λ are neither estimated directly nor calibrated because, with the other parameters given, the two parameters can be specified using the above steady-state equations.

Section 3: Basic NK model

The basic NK model does not include endogenous PD. Thus, the number of types of intermediate goods is constant. The remaining parts of the model are basically the same as those of the EPD-NK model. The linearized model is given by the following equations:

$$\begin{aligned}
\widetilde{c}_t - \lambda_h \widetilde{c}_{t-1} &= (1+\lambda_h\Gamma)E_t\left[\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right] - \lambda_h\Gamma E_t\left[\widetilde{c}_{t+2} - \lambda_h\widetilde{c}_{t+1}\right] \\
&\quad -\frac{1-\lambda_h}{\sigma_c}\left(1-\lambda_h\Gamma\right)E_t\left[\frac{1}{1+\overline{r}_N}\widetilde{r}_{N,t} + \widetilde{P}_t - \widetilde{P}_{t+1} + \widetilde{\upsilon}_{c,t+1}\right] \\
&\quad +\frac{1-\lambda_h}{\sigma_c}\widetilde{\upsilon}_{d,t} + \frac{1-\lambda_h}{\sigma_c}\widetilde{\upsilon}_{c,t} + \frac{1-\lambda_h}{\sigma_c}\lambda_h\Gamma E_t\left[\widetilde{\upsilon}_{c,t+2}\right],
\end{aligned}$$

$$\begin{aligned}
\sigma_h\widetilde{h}_t &= \widetilde{w}_t - \widetilde{\upsilon}_{h,t} + \frac{1}{1-\lambda_h\Gamma}\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) + \widetilde{\upsilon}_{c,t}\right] \\
&\quad +\frac{\lambda_h\Gamma}{1-\lambda_h\Gamma}E_t\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) - \widetilde{\upsilon}_{c,t+1}\right],
\end{aligned}$$

$$\begin{aligned}
\sigma_m\left(\widetilde{m}_t - \widetilde{P}_t\right) &= \frac{-1}{(1+\overline{r}_N)\overline{r}_N}\widetilde{r}_{N,t} + \frac{1}{1-\lambda_h\Gamma}\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) - \widetilde{\upsilon}_{c,t}\right] \\
&\quad +\frac{\lambda_h\Gamma}{1-\lambda_h\Gamma}E_t\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) + \widetilde{\upsilon}_{c,t+1}\right],
\end{aligned}$$

$$\begin{aligned}
&\widetilde{\chi}_t = \\
&(1-\delta)\Gamma E_t\left[\widetilde{\chi}_{t+1}\right] - \frac{1-(1-\delta)\Gamma}{1-\lambda_h\Gamma}E_t\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) - \frac{1}{\overline{r}}\widetilde{r}_{t+1} - \widetilde{\upsilon}_{c,t+1}\right] \\
&\quad + \frac{1-(1-\delta)\Gamma}{1-\lambda_h\Gamma}\lambda_h\Gamma E_t\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+2} - \lambda_h\widetilde{c}_{t+1}\right) - \frac{1}{\overline{r}}\widetilde{r}_{t+1} - \widetilde{\upsilon}_{c,t+2}\right],
\end{aligned}$$

$$\begin{aligned}
&\widetilde{inv}_t = \frac{\Gamma}{1+\Gamma}E_t\left[\widetilde{inv}_{t+1}\right] + \frac{1}{1+\Gamma}\widetilde{inv}_{t-1} + \frac{1}{\xi(1+\Gamma)}\widetilde{\chi}_t \\
&\frac{1}{\xi(1+\Gamma)(1-\lambda_h\Gamma)}\left[\frac{\sigma_c}{1-\lambda_h}\left(\widetilde{c}_t - \lambda_h\widetilde{c}_{t-1}\right) - \widetilde{\upsilon}_{c,t}\right] \\
&+\frac{\lambda_h\Gamma}{\xi(1+\Gamma)(1-\lambda_h\Gamma)}E_t\left[\frac{-\sigma_c}{1-\lambda_h}\left(\widetilde{c}_{t+1} - \lambda_h\widetilde{c}_t\right) + \widetilde{\upsilon}_{c,t+1}\right],
\end{aligned}$$

$$\overline{y}\ \widetilde{y}_t = \overline{c}\ \widetilde{c}_t + \overline{inv}\ \widetilde{inv}_t + \overline{g}\widetilde{g}_t,$$

$$\widetilde{k}_t = (1-\delta)\widetilde{k}_{t-1} + \delta\ \widetilde{inv}_t,$$

$$\widetilde{y}_t = \theta\widetilde{k}_{t-1} + (1-\theta)\widetilde{h}_t + \widetilde{\mu}_t,$$

$$\widetilde{h}_t - \widetilde{k}_{t-1} - \frac{1}{\overline{r}}\widetilde{r}_t + \widetilde{w}_t = 0,$$

$$\widetilde{P}_t - \widetilde{P}_{t-1} = \Gamma E_t\left[\widetilde{P}_{t+1} - \widetilde{P}_t\right] + \frac{(1-\rho\Gamma)(1-\rho)}{\rho}\left((1-\theta)\widetilde{w}_t + \theta\frac{1}{\overline{r}}\widetilde{r}_t - \widetilde{\mu}_t\right),$$

$$\widetilde{r}_{N,t} = (1+\overline{r}_N)^{\vartheta}\left[\vartheta\frac{1}{1+\overline{r}_N}\widetilde{r}_{N,t-1} + (1-\vartheta)\left(\varpi_\pi(\widetilde{P}_t - \widetilde{P}_{t-1}) + \varpi_y(\widetilde{y}_t - \widetilde{y}_t^n)\right) + \widetilde{u}_t\right],$$

$$\widetilde{\mu}_t = \rho_u\widetilde{\mu}_{t-1} + \varepsilon_t^{\mu} + \sum_{s=1}^{\overline{t}}\varepsilon_{s,\ t-s}^{news},$$

$$\widetilde{\upsilon}_{c,t} = \rho_{\upsilon,c}\widetilde{\upsilon}_{c,t-1} + \varepsilon_t^{\upsilon_c},$$

$$\widetilde{\upsilon}_{h,t} = \rho_{\upsilon,h}\widetilde{\upsilon}_{h,t-1} + \varepsilon_t^{\upsilon_h},$$

$$\widetilde{u}_t = \rho_u\widetilde{u}_{t-1} + \varepsilon_t^{u}\ ,$$

$$\widetilde{\tau}_t = \rho_\tau\widetilde{\tau}_{t-1} + \varepsilon_t^{\tau}.$$

The steady state is given by the following equations:

$$\frac{1}{\Gamma} = 1 + \overline{r}_N,$$

$$\left(\overline{h}\right)^{\sigma_h} = \overline{w}\left(\overline{c}\right)^{-\sigma_c},$$

$$\overline{m} = [(1-\lambda_h)\overline{c}]^{\frac{\sigma_c}{\sigma_m}}\left(\frac{1+\overline{r}_N}{\overline{r}_N}\right)^{\frac{1}{\sigma_m}}(1-\lambda_h\Gamma)^{\frac{-1}{\sigma_m}},$$

$$\overline{\chi} = \Gamma\left[[(1-\lambda_h)\overline{c}]^{-\sigma_c}(\overline{r})(1-\lambda_h\Gamma) + (1-\delta)\overline{\chi}\right],$$

$$\overline{\chi} = (1-\lambda_h\Gamma)\left[(1-\lambda_h)\overline{c}\right]^{-\sigma_c}$$

$$\overline{y} = \overline{c} + \overline{inv} + \overline{g},$$

$$\overline{inv} = \delta\overline{k},$$

$$\overline{g} = \overline{\tau}\ \overline{y},$$

$$\overline{y} = \overline{k}^{\theta}\overline{h}^{1-\theta},$$

$$\frac{1-\theta}{\theta}\frac{\overline{r}}{\overline{w}}=\frac{\overline{h}}{\overline{k}},$$

$$\frac{\phi-1}{\phi}=\frac{1}{1-\theta}\left(\frac{1-\theta}{\theta}\right)^{\theta}\overline{r}^{\theta}\;\left(\overline{w}\right)^{1-\theta},$$

$$1+\overline{r}_N=\Lambda\left(1+\overline{r}_N\right)^{\vartheta}.$$

Section 4: Prior and posterior distributions of parameters

Some parameters are not estimated and are calibrated. The discount factor Γ is set at 0.99, the capital elasticity of the production function θ at 0.33, the quarterly depreciation rate of capital δ at 0.025, and the inverse of labor elasticity σ_h at 2. They are all standard calibrations and commonly used values in the literature. ϵ, the success probability of PD, is set 0.025 (i.e., 0.1 per year). This follows Comin and Gertler (2006)'s choice of a success probability for R&D.

The priors of other parameters are shown in Table 1. Most of the prior distributions basically conform to those used in the literature (e.g., Smets and Wouters 2007, Fujiwara et al. 2011, Khan and Tsoukalas 2012). Following Fujiwara et al. (2011) and Khan and Tsoukalas (2012), we set the variance of an unanticipated TFP shock innovation equal to the sum of the variances of news shocks innovations (prior means of the correlations among TFP news shocks' innovations are set at zero).

The choices of the priors of some parameters deserve some comments because they are not usually estimated or calibrated in the literature. The quarterly survival rate of a new product ψ is assumed to follow a normal distribution with mean 0.975 and standard deviation 0.02 (i.e., the mean of the rate of technology depreciation is assumed to be 0.025). α, the parameter related to the elasticity of product development to PD investment, is assumed to follow a normal distribution with mean 0.25 and standard deviation 0.125. $\frac{1}{1+\alpha}$ measures the steady-state elasticity, and $\alpha = 0.25$ implies that the elasticity is equal to 0.8. Branstetter (2001) uses U.S. firm-level data and finds that the elasticity of innovation to R&D is 0.81. Bottazi and Peri (2007) use OECD macro data and find that the elasticity of innovation to R&D is 0.79. Since the parameter α is related to the elasticity to PD investment rather than the elasticity to R&D investment, we allow a relatively large standard deviation of 0.1 for α. φ, the parameter related to the steady-state (desired) markup, is assumed to follow a normal distribution with mean 6 and standard deviation 0.75.

Section 5: Counterfactual simulation for the inflation persistence puzzle

Figure A1 shows the result of a counterfactual simulation in which consumption habit persistence and the elasticity of investment adjustment costs are reduced and set to extremely low levels ($\lambda_h = \xi = 0.0001$). As shown in the figure, shutting the two frictions does not significantly alter the paper's finding.[2]

Section 6: Endogenous PD and persistent impacts of shocks

This section studies whether the shocks modeled in this paper, through their effects on the EPD, can generate persistent changes in output. Because the shocks can affect the EPD and thus TFP, even demand shocks, e.g., a monetary policy shock, can have a long lasting impact on output if their effects on TFP remain for a relatively long period. To see the role of the EPD effect on persistence, we examine theoretical impulse responses of TFP and output. Figures A2 and A3 present the impulse responses of TFP and output both with and without the EPD by type of shock (as in the previous analysis, to shut down the EPD effect, α is set at 500). The figures show that the EPD makes many of the shocks induce persistent impacts on TFP and output. Even demand shocks, e.g., monetary policy and government expenditure shocks, cause some long-lasting changes in TFP and output for the EPD model. Especially, large, persistent effects of the EPD are found for 8-period-ahead news and labor preference shocks.

[2] The corresponding mean t-statistic values for the coefficient estimates, like those shown in Table 3, are available upon request.

The EPD-triggered persistent impact of the shocks is also reflected in the standard deviations of output and TFP, as shown in Table A1.[3] The table presents the percentage standard deviations of the simulated TFP and output (the simulation sample period is 190 quarters, and the modes in Table 1 are used for the simulations). It shows that the EPD model has generally larger standard deviations of TFP and output than the non-EPD-effect model and that the EPD increases the standard deviation of output by 12 percent (0.53 percentage points). Monetary policy and government expenditure shocks in the EPD model generate increases in the standard deviations. The differences in standard deviations between the EPD and non-EPD-effect models are especially large for the news and labor preference shocks. Among the news shocks, an 8-period-ahead news shock gives the largest differ

Although the large estimated standard error of an 8-period-ahead news shock (it is the largest among the news shocks, as shown in Table 1) partly contributes to this result, it is also because an 8-period-ahead news shock generates the largest increase in expected $\widetilde{A}$ among the news shocks. Figure A4 depicts the theoretical impulse responses of $\widetilde{A}$ to news regarding the T-period-ahead future technology, where T is 4, 8, 12 and 16. The shocks correspond to increases of 1 basis point in the news shocks. The figure shows that 12- and 16-period-ahead positive news shocks lead to persistent drops in $\widetilde{A}$ and 4- and 8-period-ahead positive news shocks lead to long-term increases in $\widetilde{A}$. Specifically, an 8-period-ahead positive news shock generates the largest persistent change in $\widetilde{A}$ among the other news shocks. This large effect of an 8-period-ahead news shock on $\widetilde{A}$ contributes to its disinflationary effect shown in Figure 6-(a).

Why does an 8-period-ahead positive news shock generate large increases in $\widetilde{A}$, compared with the other news shocks ? This is because product development is time consuming and firms are assumed to need 8 periods to develop a new product (recall that this assumption of the 8-period PD process is empirically consistent). Firms need to pay interest during their product development periods and can only begin to generate profits after the products are innovated and placed on the market. Thus,

[3] Because non-zero correlations among the news shocks are allowed, the standard variance decomposition exercise cannot be performed.

if the forecast horizon of good news is very short (e.g., a forecast horizon of 4), firms have little incentive to begin developing a new product because at the time they finish developing their product (8 periods later), the demand for the new product induced by the increased output will diminish substantially. Furthermore, if the forecast horizon of good news is too long (e.g., a forecast horizon of 16), firms also have little incentive to begin developing a new product, because the initial interest rate payment is too large compared with the discounted future monopoly profits from selling their new innovative products in the future. This is because at the time when the shock materializes, the demand for the new product will diminish substantially due to product obsolescence.

Given that under the EPD model, a "realized" 8-period-ahead news shock leads to large persistent changes, I also examine that whether an "*unrealized*" 8-period-ahead news shock leads to long-lasting changes in these values. Figure A5 illustrates impulse responses of TFP and output to an unrealized 8-period-ahead news shock (along with impulse responses to a realized 8-period-ahead news shock). According to the figure, due to the existence of EPD, even if (8-period-ahead) TFP news shocks do not materialize, the shocks cause persistent changes in TFP and output.

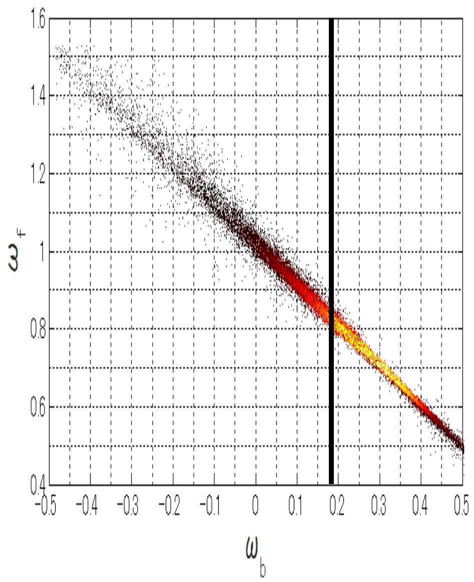
Table A1 : Standard Deviations (percentage deviations from the steady states) by types of shocks: PD and No PD

Variables	TFP			Output		
Types of shocks	EPD	No EPD	Difference (EPD - No EPD)	EPD	No EPD	Difference (EPD - No EPD)
TFP news shocks: all news shocl	2.01	1.89	0.12	2.96	2.64	0.32
4-period-ahead	0.67	0.63	0.04	0.93	0.84	0.09
8-period-ahead	1.17	0.99	0.18	1.57	1.31	0.26
12-period-ahead	0.51	0.57	-0.06	0.77	0.76	0.01
16-period-ahead	0.38	0.42	-0.04	0.57	0.56	0.01
TFP unanticipated shocks	2.38	2.3	0.08	3.08	2.8	0.28
Monetary policy shocks	0.09	0	0.09	0.29	0.26	0.03
Consumption preference shocks	0.02	0	0.02	0.29	0.3	-0.01
Labor preference shocks	0.19	0	0.19	2.44	2.19	0.25
Government expenditure shocks	0.13	0	0.13	0.64	0.6	0.04
All shocks	3.16	3.01	0.15	5.03	4.5	0.53

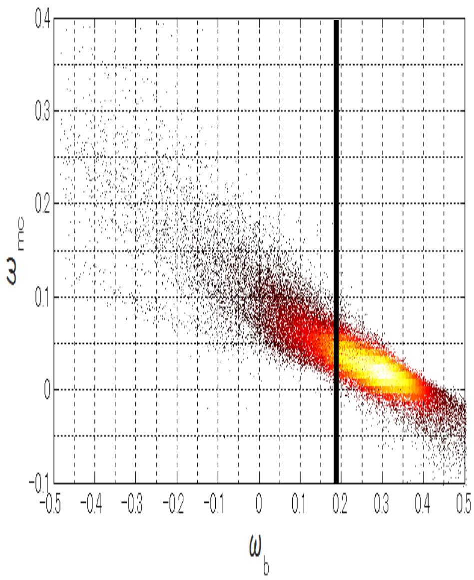
Figure A1 : Counterfactual simulation results of the Phillips curve estimation (no habit persistence and no investment adjustment cost)

Without measurement errors in mc

a1.

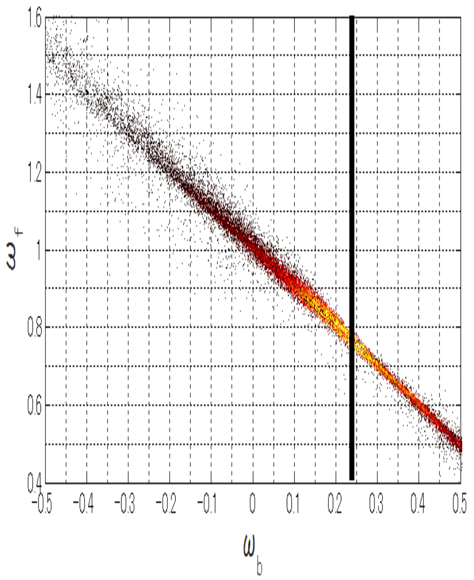


a2.

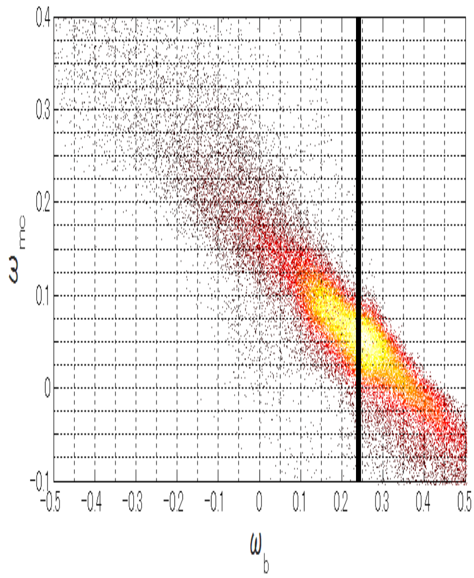


With measurement errors in mc

b1.

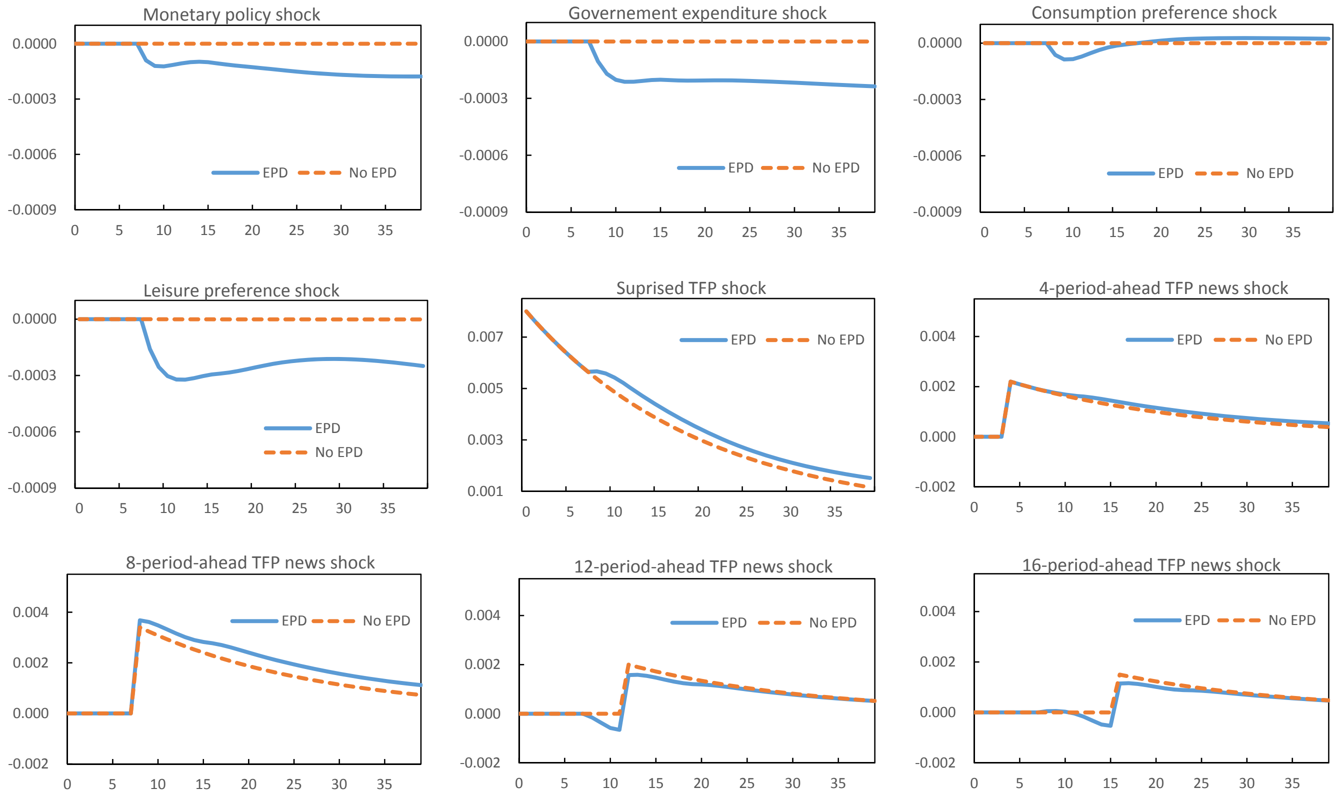


b2.



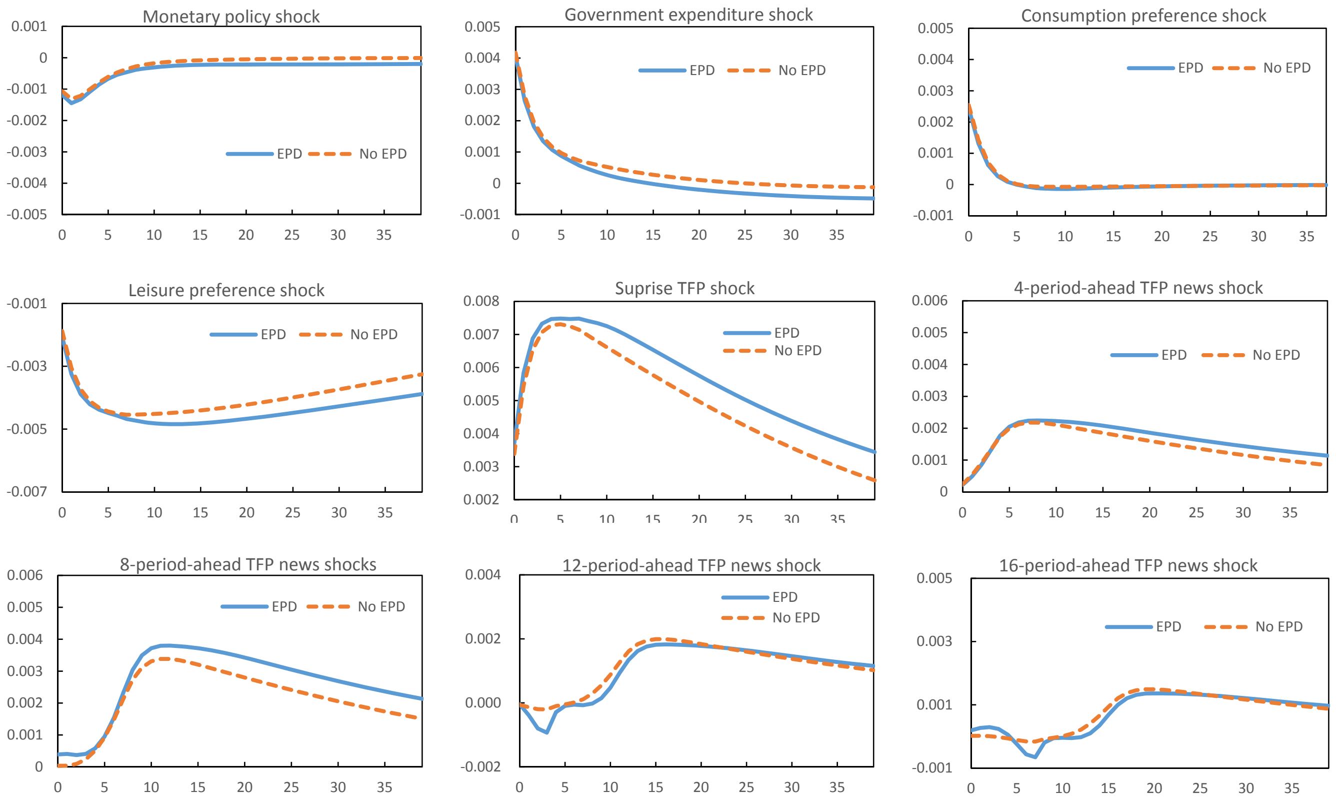
Notes: See the notes in Figure 2

Figure A2 : Estimated impulse resposes of TFP to various shocks



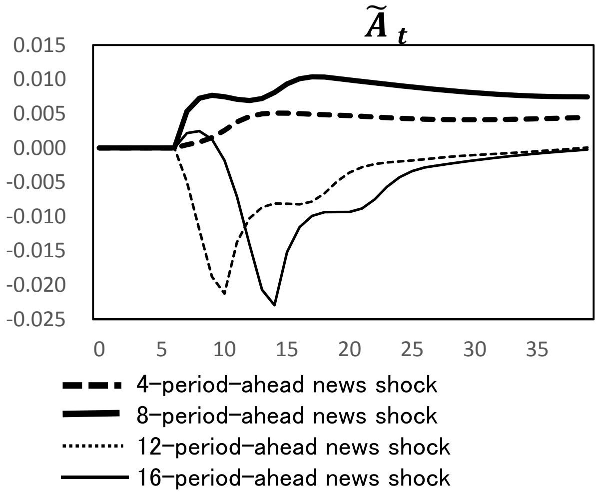
Notes: Each panel shows impulse responses to a one-standard-deviation shock. The impulse reponses are calculated by using the posterior mode shown in Table 1.

Figure A3 : Estimated impulse resposes of output to various shocks



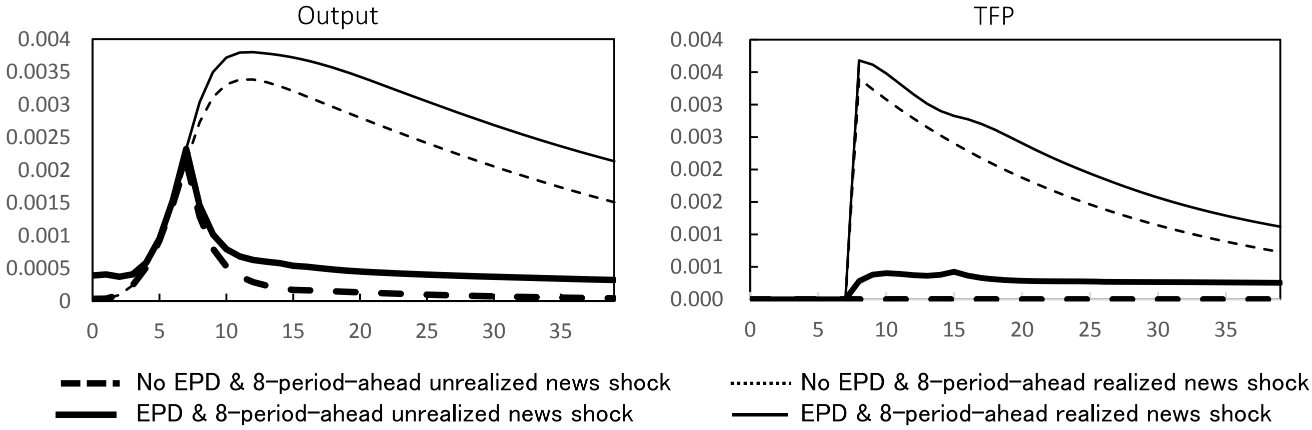
Notes: See the notes in Figure 8.

Figure A4 : Theoretical impulse responses of $\widetilde{A}$ to a news shock



Notes: Impulse responses to a one–basis–point increase in a news shock.

Figure A5: Impulse responses of TFP and output to unrealized news shocks



Notes: Panels show impulse responses of TFP and output to one–standard–deviation shocks of unrealized and realized news. The impulse reponses are calculated by using the posterior mode shown in Table 1.