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THE NEW KEYNESIAN PHILLIPS CURVES IN MULTIPLE QUANTILES AND THE ASYMMETRY OF MONETARY POLICY

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Abstract

This paper empirically explores the New Keynesian Phillips Curve (NKPC) in multiple quantiles and examines the risk structure of the inflation process focusing on the asymmetric monetary policy. The estimation results support the canonical NKPC in upper quantiles while the hybrid version fits better with mid-quantiles. We find evidence of an asymmetric risk such that a decrease in the expected inflation reduces the risk in the sense of dispersive order and vice versa. This result implies that tightening rather than easing money is more effective in reducing risks. Structural break tests detect a break in all quantiles around 1983. Post-break data still support the asymmetric pattern.

Key words: New Keynesian Phillips Curve, multiple quantile estimation, asymmetric monetary policy, and structural break.

JEL classification: C32, E31, E52

1. Introduction

The New Keynesian Phillips Curve (NKPC) has played an important role in recent theoretical work on inflation as well as monetary policy analysis. It explains the inflation dynamics through the relation of expected inflation and marginal cost, and its hybrid version includes lagged inflation as an additional component that shifts the curve. This paper empirically examines the US hybrid NKPC focusing on the roles of forward-looking and backward-looking components and studies the monetary policy implication. However, rather than using the traditional mean relations, we explore the relations in multiple quantiles. Analyzing multiple quantiles has two main purposes. First, using multiple quantiles helps in investigating various aspects of relations between inflation and the components in the NKPC. In general, those factors may influence not only the conditional mean but also many other characteristics of the conditional distribution, such as expanding its dispersion, stretching one tail of the distribution, and even inducing multimodality. Thus, it is possible that the roles of backward-looking and forward-looking components in the NKPC vary across quantiles, so relying only on the mean would not be sufficient to capture the relations. Explicit investigation of these relations via multiple quantile estimation can provide a more nuanced view and, therefore, a more informative empirical analysis.

The other benefit of using multiple quantile model is that it provides a useful inference of the asymmetric monetary policy. The asymmetry can be captured in two ways. First, the monetary authority may respond asymmetrically to different economic circumstances. If the central bank expects inflationary pressure in the near future, it has to focus more on the probability that future inflation will exceed a certain level, such as the target range in the inflation targeting system; thus, the equations for upper quantiles are more interesting. Second, the policy effect on the risk of inflation is asymmetric. If the quantile coefficients are asymmetric in the upper and lower quantiles, then the increase and decrease in the components change the distribution in an asymmetric way, indicating that the changes in the risk structure in expansionary and tightening monetary policies would be different.

The model used in this paper is the hybrid version. The canonical NKPC based on Calvo (1983) does not contain the lagged inflation term, and as Gali, Gertler, and López-Salido (2005) point out, the microfoundation of the lagged term is not clear. However, Fuhrer and Moore (1995) find that the canonical NKPC is not successful in explaining the stylized fact that the monetary policy has a delayed effect on inflation. Thus, many works augment the NKPC with lagged inflation to capture the persistency of inflation, calling it a hybrid NKPC, and thereby improve analysis of the lagged effect (Adam and Padula (2011), Fuhrer and Moore (1995), Gali and Gertler (1999)). On the other hand, Hall et al. (2009) and Kim and Kim (2008) claim that a seemingly significant lagged inflation coefficient is primarily due to the misspecification of the NKPC such as in terms of a structural break and nonlinearity. Examining the backward looking component provides an important monetary policy implication. Without the lagged inflation, the monetary policy effect is generally described by the direct change in expected inflation due to the policy change. The presence of the backward looking component indicates the indirect effect of monetary policy by affecting the real economy, implying that the policy effects are more complicated.

We estimate the model using the multiple quantile version of Chernozhukov and Hansen (2008)'s *instrumental variable quantile regression* and use Fitzenberger (1997)'s *moving blocks bootstrap* to estimate the heteroscedasticity and serial correlation robust (HAC) standard errors. Chortareasa, Magonisa, and Panagiotidisb (2012) estimate a similar model with a different method using the Euro data. But their estimation is not based on the HAC estimation, which generally provides incorrect inference in structural equations such as ours. Considering recent findings of structural breaks in the inflation process by Clak and McCracken (2006), Estrella and Fuhrer (2003), Jouini and Boutahar (2003) and Kim and Kim (2008), we also perform a test for a single structural break of the hybrid NKPC in each quantile level.

The estimation results without a structural break substantially differ across quantile levels. In upper quantiles, the estimated coefficients are close to those of canonical NKPC in that the expected inflation coefficients are higher and the lagged inflation is statistically insignificant. However, the estimation somewhat supports the hybrid version in the mid and lower quantile levels, in which the coefficients for the lagged inflation are significant. Moreover, the inflation becomes larger in the *dispersive order* in the sense of Shaked and Shanthikumar (1998) when increasing expected inflation while decreasing expected inflation makes it smaller. These results indicate that the disinflationary policy would be more efficient in terms of reducing risks.

The structural break tests detect the existence of a break in all quantile levels, and the break point generally ranges between 1982 and 1983. The pattern of non-decreasing expected inflation coefficient with respect to quantile is still present after the break. As for the lagged inflation coefficient, there is a moderate change after the break: The coefficient is statistically insignificant even in lower quantiles. This result indicates that, when there is a change in the monetary policy, it is expected that the risk changes immediately while there is still a lagged effect around the median. The median estimation results coincide with the conditional mean estimation result in that the lagged effect is statistically significant, but is counter to the finding of Kim and Kim (2008).

The remainder of this paper is organized as follows. Section 2 explains the bench mark NKPC used in this paper and introduces multiple quantile models in the NKPC. Section 3 shows the results of the empirical analysis and Section 4 concludes.

2. The New Keynesian Phillips Curve and the Conditional Quantile Model

2.1. **The Hybrid NKPC Model**

The canonical NKPC model, originated from Calvo (1983)'s staggered price setting together with forward-looking economic agents, expresses current inflation as a function of expected inflation and marginal costs. This model has been criticized due to insufficient explanation of the persistence of the US inflation dynamics, and the hybrid version was introduced by economists such as Gali and Gertler (1999). The hybrid NKPC can be derived as follows: The aggregate price level p_t is defined as

$$p_t = \theta p_{t-1} + (1-\theta)p_t^* \tag{2.1}$$

where, p_t^* is the average reset price and $1-\theta$ is a fixed probability that firms set prices at t. p_t^* is defined as a weighted average price set by forward-looking firms and backward-looking firms.

$$p_t^* = (1-\omega)p_t^f + (\omega)p_t^b \tag{2.2}$$

where p_t^f and p_t^b denote the prices set by forward-looking firms and backward-looking firms, respectively, and ω is the fraction of backward-looking firms.

We assume that forward-looking firms follow the canonical NKPC model, but we also assume subjective expectation rather than rational expectation, similar to Adam and Padula (2011) and Zhang, Osborn, and Kim (2009). The forward-looking price is derived from the behavior of forward-looking firms maximizing expected discounted profits and is then transformed into the following log-linear form.

$$\begin{aligned} p_t^f &= (1-\beta\theta)F_t\left[\sum_{j=1}^{\infty}(\beta\theta)^j\left(mc_{t+j}+p_{t+j}\right)\right] \\ &= (1-\beta\theta)(mc_t+p_t)+\beta\theta F_t\left(p_{t+1}^f\right) \end{aligned} \tag{2.3}$$

where F_t is the subjective expectations operator of the firm at time t, $\beta \leq 1$ denotes the discount factor, and mc_t is the marginal cost of production. The backward-looking firms are assumed to follow a rule-of-thumb that allows the last period's reset price to be adjusted by lagged inflation. The backward-looking price is then expressed as follows:

$$p_t^b = p_{t-1}^* + \pi_{t-1}. \tag{2.4}$$

Combining Equations (2.1) through (2.4) gives the following hybrid NKPC.[1]

[1]For detailed derivations, see Gali and Gertler (1999) and Adam and Padula (2011).

$$\pi_t = \gamma_f \pi^e_{t+1} + \gamma_b \pi_{t-1} + \lambda mc_t \tag{2.5}$$

where

$$r_f = \frac{\beta\theta}{\theta + \omega\left[1 - \theta(1-\beta)\right]}, \quad r_b = \frac{\omega}{\theta + \omega\left[1 - \theta(1-\beta)\right]}, \quad \lambda = \frac{(1-\omega)(1-\theta)(1-\theta\beta)}{\theta + \omega\left[1 - \theta(1-\beta)\right]}.$$

Some empirical issues have arisen in the application of the hybrid NKPC. First, the empirical analysis of the forward-looking behavior is affected by what is used as a proxy for the expected inflation. For example, Gali and Gertler (1999) use realized future inflation data as a proxy for expected inflation. On the other hand, Zhang, Osborn, and Kim (2009) and Adam and Padula (2011) use observed inflation expectation data as a proxy for the expected inflation and argue that the introduction of the observed inflation expectation can minimize measurement error, resulting in more accurate estimates.

The second issue is the choice between the canonical model and the hybrid version. Because the observed inflation persistence is difficult to explain using the canonical model, many studies incorporate past inflation into the NKPC model. The presence of lagged inflation in the NKPC indicates the lagged effect of the monetary policy by changing the real economy while the forward-looking term explains the direct effect by changing the economic agent's expectation. Consequently, an important policy implication of the hybrid version is that, if the backward-looking component is not significant, the central bank can control current inflation by managing the expected inflation with little distortion of the real economy. Gali and Gertler (1999), Gali, Gertler, and López-Salido (2001), and Sbordone (2002, 2005) show that expected inflation is an important driving force of current inflation, while Fuhrer and Moore

(1995), Fuhrer (1997), and Roberts (1997) insist that lagged inflation is a more important component than expected inflation in explaining actual inflation.

The third issue is the measure of the marginal cost of firms. Labor income share and output gap have been used as significant proxies for real marginal cost. Gali and Gertler (1999) insist that labor income share is a more suitable measure than output gap for real marginal cost, while Neiss and Nelson (2005) argue that output gap better explains the inflation dynamics of the NKPC when it is estimated in theory-consistent manner.

2.2. **The conditional quantile model and the NKPC**

The main purpose of this paper is to examine the hybrid NKPC at multiple quantile levels. To this end, we introduce the conditional quantile equation to the NKPC. Let $x_t = (1, \pi^e_{t+k}, \pi_{t-1}, mc_t)$ and z_t be the vector of instrumental variables for x_t. In addition, let π_t have the conditional distribution function $F_t(\pi) = Pr(\pi_t \leq \pi | \Omega_t)$, where $\Omega_t = \{\mathfrak{F}_{t-1}, z_t\}$ and $\mathfrak{F}_{t-1}$ is the information set at $t-1$. The αth quantile of π_t conditional on Ω_t, denoted as q^α_t, is defined as

$$q^\alpha_t \equiv \inf_{v \in R} \{v : F_t(v) > \alpha\}$$

$$\text{or if } F_t(\pi) \text{ is continuous,} \quad q^\alpha_t \equiv F^{-1}_t(\alpha) \tag{2.6}$$

That is, conditional quantile q^α_t is that the probability of π_t being less than q^α_t is α. In this paper we restrict our attention to a linear quantile model such that $q^\alpha_t = x'_t \beta^\alpha$, where $\beta^\alpha = (\gamma^\alpha_c, \gamma^\alpha_f, \gamma^\alpha_b, \lambda^\alpha)'$. Then the conditional quantile model can be rewritten in a more familiar formulation as

$$\pi_t = x'_t \beta^\alpha + \epsilon^\alpha_t \quad t = 1, \ldots, T \tag{2.7}$$

where ε_t^α has the following quantile restriction of $Pr(\varepsilon_t^\alpha < 0|\Omega_t) = \alpha$. The data generating process of (2.7) is not truly distinctive to common linear regression models. Indeed, many traditional conditional mean equations can be transformed to (2.7). For example, consider the conventional NKPC model (2.5) with heteroscedastic error.

$$\pi_t \;=\; x_t'\beta + x_t'\gamma\epsilon_t \tag{2.8}$$

where β is the mean parameter, ϵ_t is *iid* with $E[\epsilon_t|\Omega_t] = 0$, and $x_t'\gamma$ represents the heteroscedasticity of the error term. It subsumes many models of systematic heteroscedasticity that have appeared in the econometrics literature: Goldfeld and Quandt (1965)'s model ($\sigma(x) = \sigma x_k$) is a special case where $\gamma = \sigma e$, and Harvey (1976) and Godfrey (1978)'s multiplicative heteroscedasticity model can be considered such a case when $\sigma(x) = x\gamma + o(||\gamma||)$. The conditional quantile of π_t in (2.8) is then simply $q_t^\alpha \;=\; x_t'\beta \;+\; x_t'\gamma \cdot q_t^{\alpha,\epsilon}$, where $q_t^{\alpha,\epsilon}$ is the αth quantile of ϵ_t. Consequently, the αth conditional quantile of π_t can be expressed as $q_t \;=\; x_t'\beta_t^\alpha$, where $\beta^\alpha = \beta + \gamma q_t^{\alpha,\epsilon}$. Thus, the quantile parameter β^α is determined by the mean parameters β, the scale parameters γ, and other parameters that determine the shape of the conditional distribution.

This comparison provides a motivation to consider the quantile model in that the conditional mean model is insufficient to make inferences about the risks of the variable of interest. The measurement and management of uncertainty have been an important issue in macroeconomics. For this reason, many of the central banks prefer density forecasts of inflation, such as the inflation fan chart, to point forecasts in the sense that the former contain the uncertainty structure of the forecasts. Conditional quantiles have more information than simply the conditional mean because they include information about the uncertainty structure of the variable of interest such as skewness, kurtosis, and any other factors determining the shape of the distribution. Consequently, quantile estimation provides a better analysis of risks.

Another strength to consider in using multiple quantiles is that doing so captures the asymmetric monetary policy. The conventional mean equation is based on the symmetric effect. For instance, the effects of inflation on the expected inflation gap and the expected deflation gap are equivalent as long as the size of the gap is the same; thus, the Fed's responses to inflationary and deflationary pressures are identical. However, if a model contains the equations for multiple quantiles, it is possible to capture the asymmetry of the responses in two ways: First, the responses of monetary authorities are asymmetric. It is reasonable to consider that the monetary authorities are interested in different quantiles depending on different economic circumstances. For example, suppose a central bank adopts the inflation targeting system to commit it to stabilizing the inflation in a specific range. Then, if the central bank expects inflationary pressure in the near future, it must focus more on the probability that the future inflation will exceed the upper bound of the target range. Accordingly, the equations for upper quantiles are more useful in implementing a policy reaction. Consequently, if the coefficients for the NKPC are different between lower and upper quantiles, the Fed's reaction should be different according to whether it is an inflationary or a deflationary pressure periods.

Second, the policy effect on the risk of inflation is asymmetric in that having monotonic quantile coefficients with respect to the level of quantile implies that stochastic orders asymmetrically change with a change in the covariates. For example, suppose the coefficient for π^e_{t+1} increases as α increases. Then, an increase in π^e_{t+1} due to the monetary policy change makes the inflation larger in the *dispersive order* in the sense of Shaked and Shanthikumar (1998) while a decrease makes it smaller. That is, an expansionary monetary policy that increases π^e_{t+1} may also increase the uncertainty of inflation while a tightening monetary policy decreases the risks. On the other hand, if the lower and upper quantile coefficients are different, a change in the covariate spreads the tails of distribution in different ways depending on the sign of the change, which alters the risk structure in asymmetric ways.

This asymmetry is also viewed as capturing various types of asymmetric loss function in forecasting. As Granger and Newbold (1986) point out, although an assumption of symmetry about the conditional mean is likely to be an easy one to accept, a symmetry assumption for the loss function is much less acceptable and the corresponding practitioners are more likely to use asymmetric loss functions. In this case, the loss function for forecasting π_{t+i} is generally defined as

$$L(\hat{\epsilon}_{t+i}) = L_1(\hat{\epsilon}_{t+i})1_{\{\hat{\epsilon}_{t+i}>0\}} + L_2(\hat{\epsilon}_{t+i})1_{\{\hat{\epsilon}_{t+i}<0\}} \tag{2.9}$$

where $\hat{\epsilon}_{t+i}$ is the forecast error of π_{t+i}. One popular choice for the asymmetric loss function is the *LinLin* loss function suggested by Granger (1969), in which $L_i = a_i|\hat{\epsilon}_{t+i}|$. On the other hand, using the family of quasi-likelihood functions for consistent estimation of a conditional quantile model, motivated by Komunjer (2005) is defined as

$$\varphi^\alpha_t(y_t|x_t, \beta^\alpha) = \exp\left[-(1-\alpha)a_t(\epsilon^\alpha_t)1_{\{\epsilon^\alpha_t<0\}} + \alpha a_t(\epsilon^\alpha_t)1_{\{\epsilon^\alpha_t\geq 0\}}\right] \tag{2.10}$$

where $a_t(\cdot)$ is continuously differentiable. A specific choice of the likelihood function in (2.10) corresponds to a specific loss function (2.9). For example, when $a(\epsilon_t) = |\epsilon_t|$, which is equivalent to quantile regression, (2.10) is equivalent to the *LinLin* loss function. That is, when the linear quantile model is constructed for forecasting purposes, the conditional quantile model is equivalent to the optimal linear forecasting in which practitioners put more weight on positive/negative forecast error, that is, for $\alpha < 0.5$, they are concerned with the possibilities that the actual process is less than the forecasted value. It is reasonable to assume that central banks are more concern with stabilizing inflation and macroeconomy, while governments are more likely to boost the economy by emphasizing on the growth at the cost of modest inflation. Thus, it is expected that central banks will be more interested in the upper quantile of the inflation process, while governments concern more with the lower quantiles.

3. Empirical Analysis and Discussion

3.1. **Data Description and Issues**

The data used in the estimation span the quarterly period between 1969:I and 2008:II. The GDP deflator is used to calculate the inflation, and the US Survey of Professional Forecast (SPF) is used to account for the expected inflation. As introduced by Croushore (1993), SPF is useful for monetary policy analysis and for measuring the response of expectations to policy change. Two different sets of data are used to calculate the marginal cost: real Gross Domestic Product (GDP) and non-farm unit labor cost (ULC). GDP is detrended using either the CBO's PGDP or Hodrick-Prescott filtering. ULC is detrended using Hodrick-Prescott filtering. Consequently, we estimate NKPC using three different marginal cost data sets. All data are seasonally adjusted. Detailed data descriptions are provided in table 6.

Figure 1 shows the GDP deflator inflation and the GDP gap from CBO, with the GDP gap on the left vertical axis and the right vertical axis indicating inflation. As can be seen from the figure, actual inflation has been stable at a low level since the mid-1980s. On the other hand, the GDP gap has expanded its cycle to about 10

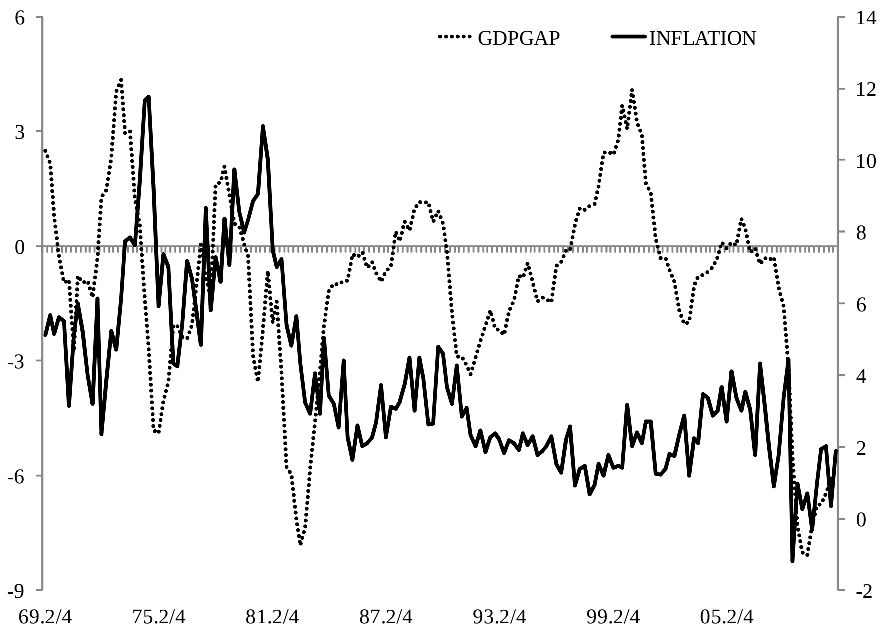


FIGURE 1. **GDP deflator inflation and GDP gap**

years. Clearly, the GDP gap shows a different pattern between the high inflation period, before the mid-1980s, and the low inflation periods, after the mid-1980s, when the second oil shock ended. This result has two possible interpretations. First, the empirical analysis may require structural breaks because of the change in the economic environments. Second, the traditional conditional mean model cannot explain the economic surroundings because the relationship between inflation and the GDP gap appears differently according to the levels of inflationary pressure. This section empirically examines the possibilities of both interpretations.

Figure 2 represents the GDP deflator inflation and SPF inflation forecasts and shows that the actual inflation and the inflation forecasts have very similar patterns. However, when actual inflation increases, the inflation forecasts are usually less than the actual inflation. When the actual inflation decreases, the inflation forecasts are

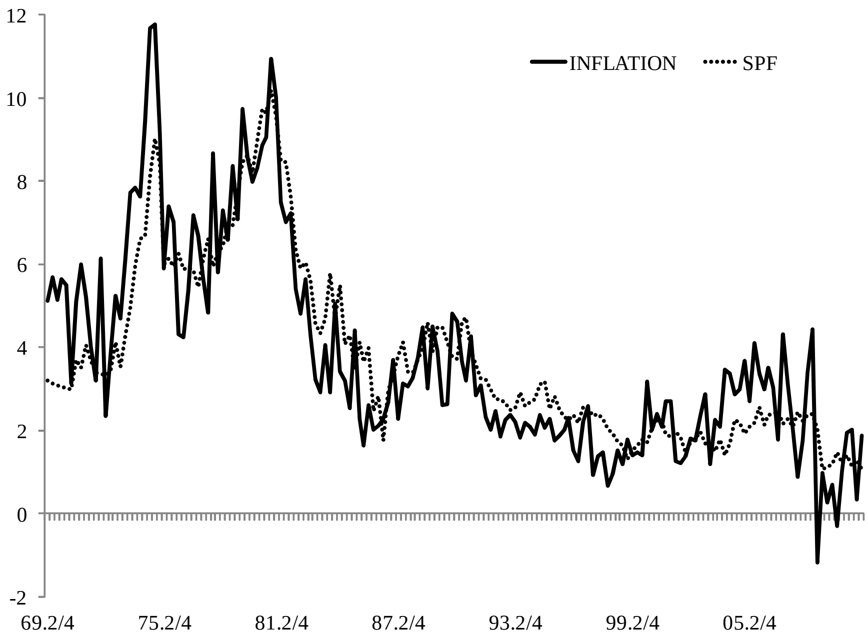


FIGURE 2. **GDP deflator inflation and the SPF inflation forecasts**

greater than the actual inflation. That is, the relation between actual inflation and the inflation forecast differs according to the level of inflationary pressure. Thus, the multiple quantile regression is needed to analyze the various economic situations.

3.2. **Empirical Findings and Discussion**

This section estimates the US NKPC at multiple quantile levels. Using SPF as a proxy for π^e_{t+1} mitigates the endogeneity problem rather than using the actual π_{t+1}. However, as Zhang, Osborn, and Kim (2009) point out, using SPF does not overcome the endogeneity bias because (1) the current output gap is endogenous in that a demand shock causes both GDP and the noise in NKPC, and (2) SPF is possibly correlated with the noise in that one can observe the noise when performing the current forecast. Therefore, we estimate the model using *instrumental variable quantile regression (IVQR)* of Chernozhukov and Hansen (2008) in which the four lags of inflation, interest rate spread (10-year treasury bill rate - 3-month treasury bill rate), the nominal wage growth, and the GDP gap are used as instruments.

The basic idea of the IVQR method is that, from the quantile condition $Pr[\pi_t < c + \gamma_b^\alpha \pi_{t-1} + \gamma_f^\alpha \pi_{t+1}^e + \lambda^\alpha y_t | \Omega_t] = \alpha$, if we regress the quantile of $\pi_t - \bar{\gamma}_f^\alpha \pi_{t+1}^e - \bar{\lambda}^\alpha y_t$ on π_{t-1} and z_t, then $\bar{\gamma}_f^\alpha$ and $\bar{\lambda}^\alpha$ will be close to their true values if the coefficients for z_t are close to zero. Consequently, the estimation is to search for values of $(\gamma_f^\alpha, \lambda^\alpha)$ that minimize the coefficient for z. The estimate procedures are as follows: First, define suitable ranges $\{\gamma_f^{\alpha,i}, i = 1, \ldots, I\}$ and $\{\lambda^{\alpha,j}, j = 1, \ldots, J\}$, and regress the quantile of $\pi_t - \gamma_f^{\alpha,i} \pi_{t+1}^e - \lambda^{\alpha,j} y_t$ on the constants, π_{t-1} and z_t, for each i and j. Second, for each i and j, compute the Wald statistic $W_{i,j}$ for testing that the coefficients for z_t are all zeros. Finally, choose $\gamma_f^{\alpha,i}$ and $\lambda^{\alpha,j}$ that minimize $W_{i,j}$, which are the estimates. We set the range for γ_f^α as $[0,\ 1.5]$, and for λ^α as $[-0.1,\ 1.0]$ with an interval of 0.01, respectively. Because the structural equation contains only the first lag of the inflation, it is reasonable to consider a possible serial correlation of the error process as well as the heteroscedasticity. The covariance estimator suggested by Chernozhukov and Hansen (2008) is robust to heteroscedasticity but is not consistent under the existence of the serial correlation. Thus, it is desirable to seek an alternative estimator that is heteroscedasticity and autocorrelation consistent (HAC). In this paper, we apply Fitzenberger (1997)'s *moving blocks bootstrap (MBB)* which is shown to have a HAC property in quantile regression. Because our framework of IVQR is a generalization of the quantile regression, the MBB standard error will obtain the HAC property. We use 500 bootstrap resampling with the block size of 8 quarters to estimate the standard deviation of the coefficients.

The estimation results using GDP as a proxy for the marginal cost are shown in Table 1. Substantial differences occur in the effect of the expected inflation across

Table 1. **Estimation results using GDP (full sample)**

α	CBO's PGDP				H-P filtered trend			
	π^e_{t+1}	π_{t-1}	y_t	c	π^e_{t+1}	π_{t-1}	y_t	c
0.1	0.530**	0.377**	0.010	-0.788	0.600**	0.328**	0.030	-0.817
	(0.184)	(0.105)	(0.167)	(0.369)	(0.131)	(0.126)	(0.077)	(0.418)
0.2	0.620**	0.339**	0.070	-0.559	0.590**	0.335**	0.100	-0.499
	(0.125)	(0.084)	(0.037)	(0.335)	(0.099)	(0.081)	(0.058)	(0.207)
0.3	0.520**	0.451**	0.100	-0.431	0.560**	0.364**	0.120*	-0.351
	(0.159)	(0.034)	(0.120)	(0.424)	(0.119)	(0.101)	(0.060)	(0.206)
0.4	0.540**	0.458**	0.110	-0.256	0.540**	0.402**	0.180*	-0.151
	(0.201)	(0.156)	(0.120)	(0.607)	(0.131)	(0.116)	(0.086)	(0.235)
0.5	0.500*	0.497**	0.140	0.048	0.480*	0.490**	0.150	0.116
	(0.211)	(0.153)	(0.156)	(0.739)	(0.128)	(0.118)	(0.115)	(0.222)
0.6	0.730**	0.357**	0.230**	0.014	0.700**	0.362*	0.220	-0.022
	(0.136)	(0.117)	(0.071)	(0.227)	(0.146)	(0.138)	(0.117)	(0.253)
0.7	0.810**	0.395**	0.190**	-0.107	0.830**	0.314*	0.210*	0.027
	(0.131)	(0.114)	(0.070)	(0.264)	(0.151)	(0.157)	(0.111)	(0.299)
0.8	1.090**	0.208	0.220*	-0.156	1.220**	0.158	0.230*	-0.057
	(0.118)	(0.168)	(0.074)	(0.347)	(0.107)	(0.209)	(0.117)	(0.576)
0.9	1.370**	0.225	0.220*	0.416	1.220**	0.263	0.020	0.278
	(0.142)	(0.219)	(0.110)	(1.012)	(0.147)	(0.242)	(0.112)	(0.933)
mean eq.	0.694**	0.433**	0.177**	-0.340	0.687**	0.399**	0.178*	-0.255
	(0.089)	(0.075)	(0.028)	(0.157)	(0.092)	(0.082)	(0.056)	(0.147)

Notes: a) Standard errors appear in parentheses.
b) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.
c) The standard deviation is calculated based on MBB with 500 bootstrap resampling and the block size of 8.
d) The mean equation is estimated by GMM with Newey-West covariance estimator.

the lower and upper quantiles: that is, the coefficient for π^e_{t+1} is higher in the upper quantiles compared to the lower quantiles. The coefficient for the lagged inflation is moderately higher in the mid-quantiles, and it is statistically insignificant in the upper quantiles. The results are similar for all the measures of the marginal cost. Consequently, we find different patterns of the inflation dynamics in lower, mid, and upper quantiles. In the upper quantiles, the inflation is more toward the canonical

NKPC in which the backward-looking component is negligible, and the hybrid version fits the mid and lower quantiles better, while the backward-looking component is moderately more important in the mid-quantiles. To examine the monotonic non-decreasing π^e_{t+1} coefficient with respect to quantile level, we also perform the test of $H_1 : \lambda_f^{\alpha_2} - \lambda_f^{\alpha_1} > 0$ for all possible αs. We find no evidence of decreasing coefficient with increasing α, and, in most upper α_2 with mid and lower α_1, the tests indicate $\lambda_f^{\alpha_2}$ is greater. Selected test results are shown in Table 2.

The asymmetry of the NKPC across quantiles indicates an important implication for the Fed's monetary policy. As noted in the previous section, the coefficients for π^e_{t+1} and π_{t-1} explain how the Fed's monetary policy affects the inflation. A high coefficient for π^e_{t+1} indicates that the Fed's announcement of a monetary policy change causes the inflation to change faster so that the monetary policy is more effective. Lower coefficients for π_{t-1} indicates that the lagged effect of the monetary policy via the change in the real economy is relatively weaker so that the monetary policy affects inflation with little distortion of the real economy. Note that, if we assume that the median is the central projection, the upper quantiles indicate the risks of inflation hikes above the central projection. Consequently, higher coefficients for π^e_{t+1} in upper quantiles indicates that the Fed's monetary policy concerning inflationary pressure can quickly decrease the upper risks: that is, the disinflationary monetary policy is more effective in terms of reducing risks. For instance, many central banks adopting inflation targeting system intend for the inflation to stay within a target range. Thus, the risk that the inflation will be outside the range is its primary concern. Our estimate results indicate that, when the economy is currently facing an inflation, the monetary policy effectively eliminates the risk faster than what we expect based on the point path of the inflation.

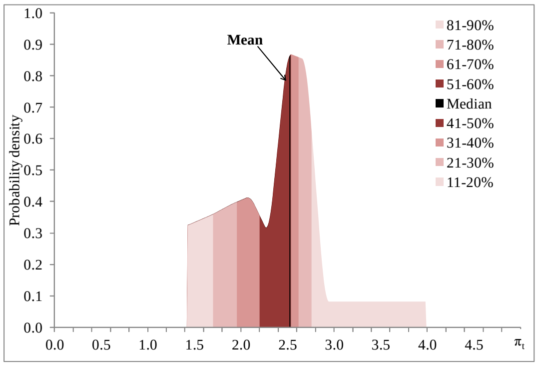
Table 2. **Selected test results for differences in π^e_{t+1} coefficients**

Alt. Hypothesis		$\beta_1^{0.2} > \beta_1^{0.1}$	$\beta_1^{0.6} > \beta_1^{0.5}$	$\beta_1^{0.6} > \beta_1^{0.2}$	$\beta_1^{0.7} > \beta_1^{0.5}$
F-stat	PGDP	0.3758	3.0756*	0.3916	3.4321*
	HP filter	0.3900	2.4569	0.3038	4.1241*
Alt. Hypothesis		$\beta_1^{0.7} > \beta_1^{0.2}$	$\beta_1^{0.8} > \beta_1^{0.5}$	$\beta_1^{0.8} > \beta_1^{0.2}$	$\beta_1^{0.9} > \beta_1^{0.2}$
F-stat	PGDP	1.1074	6.2689**	6.0025*	42.3483**
	HP filter	1.5488	6.9919**	12.8574**	11.2842**

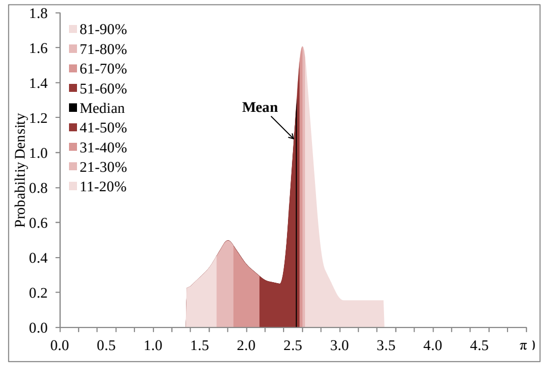
Notes: a) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.

This asymmetry can also be understood in terms of *dispersive order*. A process A is defined to be smaller than B in dispersive order if for all $0 \le \alpha_1 \le \alpha_2 \le 1$, the quantiles for A and B, denoted as $q_t^{A,\alpha}$ and $q_t^{B,\alpha}$, satisfy $q_t^{A,\alpha_2} - q_t^{A,\alpha_1} \ge q_t^{B,\alpha_2} - q_t^{B,\alpha_1}$ and the inequality holds for at least one pair of αs. If the coefficient for π^e_{t+1} is nondecreasing at all $0 \le \alpha \le 1$ and is increasing at one range of α, the quantile difference, $(\beta^{\alpha_2} - \beta^{\alpha_1})\pi^e_{t+1}$, is greater when π^e_{t+1} increases and vice versa. That is, inflation becomes smaller in *dispersive order* when π^e_{t+1} decreases. Table 2 shows that, based on our chosen nine quantiles, a decrease in π^e_{t+1} due to a tightening monetary policy makes inflation smaller in dispersive order while an expansionary policy increases it.

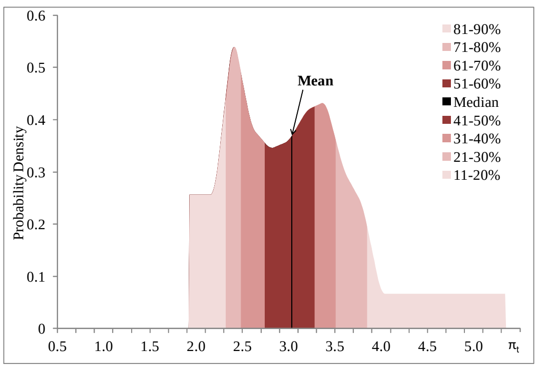
The dependency of the shape of the conditional distribution with respect to the economic condition is clearer if we look at the conditional density functions at the various levels of expected inflation. We draw rough estimates of the conditional densities by transforming nine quantile levels to a density function. Note that a quantile is, by definition, the inverse mapping of the cumulative distribution function. Therefore, we can obtain the density function via inverse mapping if we have sufficient levels of quantiles. Our transformation is a rough estimation in that we have only nine observations in this inverse mapping: that is, our figure is based on nine observations of the density function. In charting the densities, we assume that the inflation at $t-1$



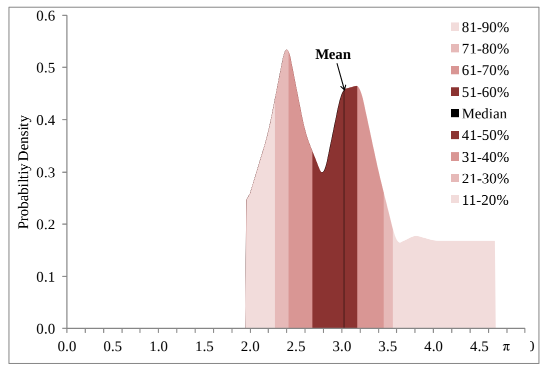
(a) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



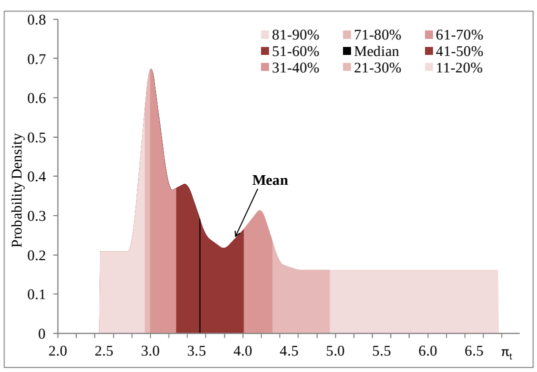
(b) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



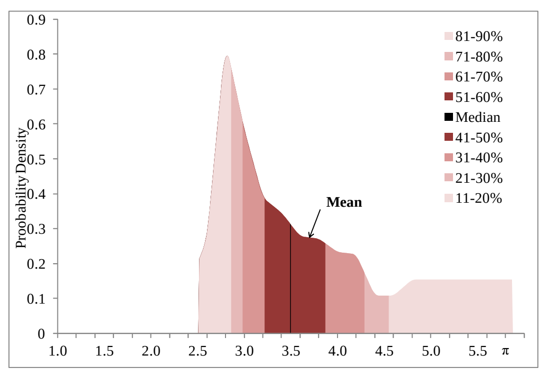
(c) $\pi^e_{t+1} = \pi_{t-1}$



(d) $\pi^e_{t+1} = \pi_{t-1}$



(e) $\pi^e_{t+1} = \pi_{t-1} + 1\%$



(f) $\pi^e_{t+1} = \pi_{t-1} + 1\%$

<CBO's GDP GAP > < HP filtered GDP GAP >

note: 1. π_{t-1} is set at 3%.

2. If the quantiles are overlapped, we set the quantile difference at 0.1%p.

FIGURE 3. **Conditional densities given various π^e_{t+1} using GDP**

is the historical average, 3%, and examine the case when the expected inflation is 1%p above, equivalent to, and 1%p below π_{t-1}, respectively. For simplicity, we disregard the effect of output and focus on the effect of backward-looking and forward-looking components.

Figure 3 shows the conditional densities using the CBO's PGDP, in which the bands with different shades indicate different quantile levels. In each graph, the median is represented with the bold line. The two darkest bands on either side of the median represent equal probability density (10%), resulting in a 20% confidence band around the median. That is, the probability that the inflation lies in this range is 20%. In the same way, adding the next two darkest shades creates a 40% confidence band, and the largest bands indicate an 80% one. The same color bands are not of equal width if the risks are unbalanced. If we regard the median as the central projection, then a wider band on one side indicates that more risks occur to that side in that there is a greater chance that the actual inflation in that direction is far from the central projection. For example, if one is concerned with the 20% confidence band around the median, in Figure 3(a), then one does not have to worry about inflation exceeding the median, but should be concerned with the other direction that is up to 0.3%p below the median.

The figure shows that the shape of the conditional distribution clearly depends on the value of π^e_{t+1}. The density is positively skewed if there is deflationary pressure ($\pi^e_{t+1} < \pi_{t-1}$), and the skewness moves downward as π^e_{t+1} goes up. In addition, there is a substantial change in the upper part of the distribution when π^e_{t+1} shifts, while the downward part is stable. That is, a higher expected inflation than π_{t-1} spreads out the upper tails of the conditional distribution, while a lower one causes little change. This asymmetry in the figure provides useful information about the asymmetric effect of the monetary policy, shifting expected inflation. For example, suppose the Fed reacts to increasing inflationary pressure by announcing a policy change to suppress the inflation. If the announcement affects economics agents' expectation of the future inflation path, the conditional distribution would shift from Figures 3(c) or 3(d) (3(e) or 3(f)) to 3(a) (3(b)), if we disregard the level of π_{t-1} and focus on the change in $\pi^e_{t+1} - \pi_{t-1}$. We can also view 3(e) and 3(f) as the risk effect of the opposite case: easing the monetary policy. The figures show that the upper risks are reduced significantly after the announcement of a tightening monetary policy compared with little change in the lower risk. When comparing 3(c) to 3(a), the 60%-70%, 70%-80% and 80%-90% bands are changed by 0.08, 0.28, and 0.34, respectively. On the other hand, the expansionary policy to overcome recession has little effect on the downside risk while increasing the risk of inflation. Consequently, if we assume that the effect of the monetary policy on expected inflation is symmetric, the monetary policy is more effective in eliminating the risks when tightening rather than easing. The asymmetric pattern is unchanged even if we view the conditional mean as the central projection although the effect is milder. Since the asymmetry is due to the nondecreasing expected inflation coefficient, the results is still valid even when the previous inflation is lower so that an expansionary policy is more reasonable. We chart a distribution when $\pi_{t-1} = 2\%$ as shown in Figure 7, which shows that the asymmetric pattern is unchanged.

In the above estimation, we exclude a possible structural break in each quantile NKPC. However, many researchers have detected structural breaks in the inflation processes. Clak and McCracken (2006) find a break in 1982, while Estrella and Fuhrer (2003) suggest another break in 1984. Furthermore, Kim and Kim (2008) find that the backward-looking component is negligible if structural breaks at 1977 and 1982 are explicitly considered in the hybird NKPC. Accordingly we perform the structural

Table 3. **Test results for structural breaks**

	CBO's PGDP		GDP H-P filter		ULC H-P filter	
α	supF	break point	supF	break point	supF	break point
0.2	56.90**	82:II	81.45**	81:II	33.01**	82:IV
0.3	85.72**	82:III	73.51**	83:IV	23.90**	83:IV
0.4	70.94**	82:II	40.76**	83:III	138.51**	81:IV
0.5	161.81**	82:III	63.15**	83:IV	65.09**	82:I
0.6	157.60**	84:III	54.02**	83:IV	51.57**	82:I
0.7	42.52**	83:II	74.02**	82:II	78.26**	82:I
0.8	34.14**	82:III	49.60**	82:III	64.05**	83:I

Notes: ** and * indicates that the test rejects the hypothesis of no structural break at 1% and 5% levels, respectively.

break test, estimate the break point and finally modify the NKPC including the detected structural breaks. A few studies examined structural break tests in quantile equations. Qu (2008) applies *supF* and *expF* type tests to quantile regressions. Lee (2010) suggests the quantile counterpart of Elliott and Müller (2006)'s point optimal test. This paper uses the *supF* test because it provides a break point estimate as a by-product of the test.

Qu (2008)'s *supF* test does not explicitly consider the instrumental variable case. However, it is not difficult to show that the test is valid for instrumental variable estimation if the coefficient estimators in the split samples are asymptotically normal under the null hypothesis of no structural break, which is proved in Chernozhukov and Hansen (2008). Rather than performing a single Bai-Perron type test in all quantiles, we perform the test independently at each quantile level to examine the specific property of the structural breaks across different quantiles.

Table 3 shows the structural break test results. The tests reject no structural break at most quantile levels regardless of the choice of the measure of the marginal cost. In most cases, the test detects a break between 1982 and 1984. The break point is consistent with the existing tests based on the conditional mean. However, we could

TABLE 4. **Estimation results using GDP (1984:I -)**

α	CBO's PGDP π^e_{t+1}	CBO's PGDP π_{t-1}	CBO's PGDP y_t	CBO's PGDP c	H-P filtered trend π^e_{t+1}	H-P filtered trend π_{t-1}	H-P filtered trend y_t	H-P filtered trend c
0.1	0.405**	0.186	0.060	-0.065	0.360*	0.160	0.050	0.302
	(0.129)	(0.117)	(0.060)	(0.342)	(0.153)	(0.115)	(0.090)	(0.419)
0.2	0.435**	0.178	0.020	0.225	0.540**	0.035	0.100	0.254
	(0.104)	(0.124)	(0.044)	(0.315)	(0.096)	(0.106)	(0.075)	(0.263)
0.3	0.390**	0.301**	0.040	0.439	0.490**	0.148	0.080	0.354
	(0.100)	(0.118)	(0.039)	(0.300)	(0.093)	(0.117)	(0.070)	(0.284)
0.4	0.465**	0.197	0.040	0.476	0.430**	0.241*	0.100	0.432
	(0.103)	(0.121)	(0.048)	(0.277)	(0.092)	(0.110)	(0.081)	(0.256)
0.5	0.420**	0.357**	0.020	0.426	0.350**	0.489**	0.080	0.559
	(0.078)	(0.099)	(0.062)	(0.254)	(0.088)	(0.101)	(0.088)	(0.276)
0.6	0.360**	0.413**	0.040	0.641	0.350**	0.477**	0.060	0.469
	(0.076)	(0.071)	(0.056)	(0.268)	(0.094)	(0.081)	(0.087)	(0.312)
0.7	0.450**	0.414**	0.040	0.548	0.830**	0.363*	0.040	0.231
	(0.128)	(0.091)	(0.060)	(0.342)	(0.156)	(0.119)	(0.093)	(0.353)
0.8	0.990**	0.147	0.100	0.295	1.140**	0.060	0.230*	0.014
	(0.243)	(0.161)	(0.090)	(0.519)	(0.236)	(0.190)	(0.106)	(0.547)
0.9	1.060**	0.090	0.120	1.182	1.180**	-0.127	0.220*	0.831
	(0.208)	(0.218)	(0.109)	(0.959)	(0.209)	(0.245)	(0.108)	(0.953)
mean eq.	0.604**	0.203**	0.049**	0.338	0.618**	0.210**	0.074	0.268
	(0.086)	(0.063)	(0.028)	(0.209)	(0.069)	(0.057)	(0.047)	(0.203)

Notes: a) Standard errors appear in parentheses.
b) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.
c) The standard deviation is calculated based on MBB with 500 bootstrap resampling and the block size of 8.
d) The mean equation is estimated by GMM with Newey-West covariance estimator.

not find a distinctive pattern in the break points across quantiles. Note that a change in the conditional mean indicates a shift in distribution function, thereby a shift in all quantiles. Accordingly, it is natural that we observe a structural break in all quantiles if there is a structural break in the conditional mean.

To examine the effect of the structural break across quantiles, we estimate the model using the data from 1984:I. Roughly, the pre-break period was dominated by

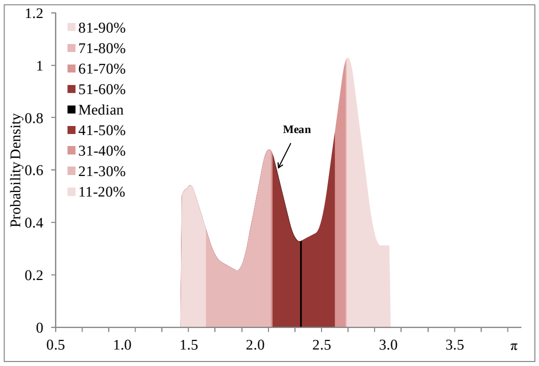
Table 5. **Selected test results for differences in π^e_{t+1} coefficients(1984-)**

Alt. Hypothesis		$\beta_1^{0.2} > \beta_1^{0.3}$	$\beta_1^{0.2} > \beta_1^{0.5}$	$\beta_1^{0.2} > \beta_1^{0.6}$	$\beta_1^{0.3} > \beta_1^{0.5}$
F-stat	PGDP	0.0092	0.0911	0.0074	0.2963*
	HP filter	0.1515	1.1246	1.3622	0.8099
Alt. Hypothesis		$\beta_1^{0.3} > \beta_1^{0.6}$	$\beta_1^{0.7} > \beta_1^{0.6}$	$\beta_1^{0.8} > \beta_1^{0.2}$	$\beta_1^{0.9} > \beta_1^{0.2}$
F-stat	PGDP	0.0094	1.1671	2.8927*	3.5687*
	HP filter	1.5934	7.2000**	3.0769	4.0039*

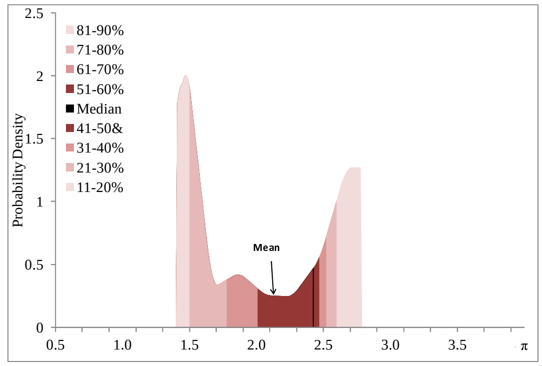
Notes: a) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.

high inflation while stable inflation was common after the break. Table 4 shows the result using the GDP in the post break period. The overall pattern of $\hat{\gamma}_f^\alpha$ is similar to the full sample case, although the monotonic nondecreasingness is less clear. The coefficient for π^e_{t+1} is around 0.5 when q is less than 0.8 while it is substantially higher in the upper quantiles. Consequently, the downside risk is stable with respect to the change in π^e_{t+1}, but there is a substantial asymmetric change in the upside risk in response to a tightening or an expansionary monetary policy. As for the π_{t-1} coefficient, there is a considerable variation across quantiles: The coefficient is greater and statistically significant around the median, supporting the hybrid version of NKPC, and is close to zero and insignificant when the quantile goes further toward the end of the distribution. these results indicate that, when a change in the monetary policy occurs, it is expected that the risk responds more quickly while there is a lagged effect around the median. The median estimation results coincide with the conditional mean estimation results in that the lagged effect is statistically significant, but this finding is is counter to that of Kim and Kim (2008).

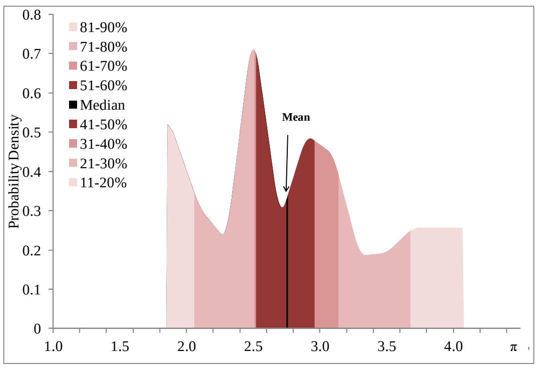
Figure 4 shows the conditional densities for pos-break inflation when the GDP gap is used as a proxy for the marginal cost. There are moderate changes after focusing on post-break data: We find a symmetry or a mild asymmetry in the risk structure



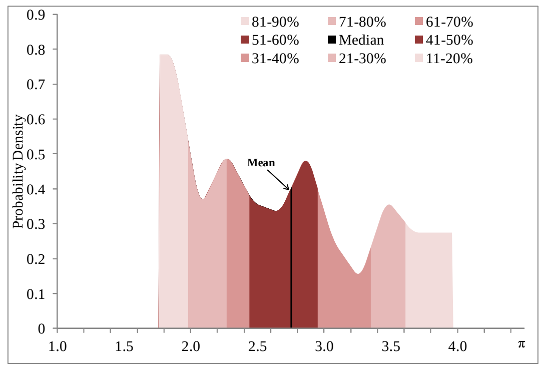
(a) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



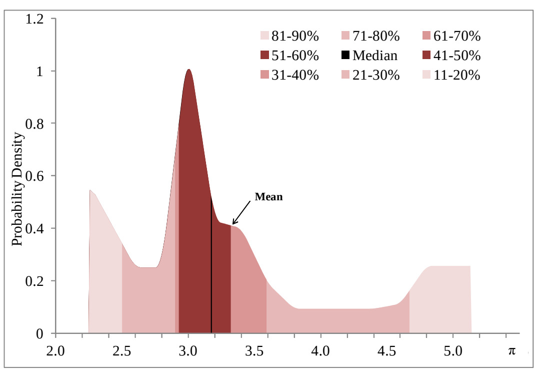
(b) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



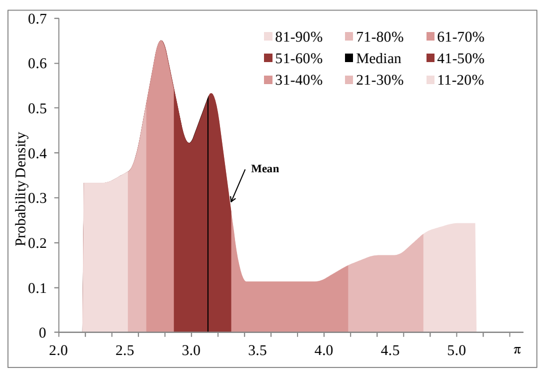
(c) $\pi^e_{t+1} = \pi_{t-1}$



(d) $\pi^e_{t+1} = \pi_{t-1}$



(e) $\pi^e_{t+1} = \pi_{t-1} + 1\%$



(f) $\pi^e_{t+1} = \pi_{t-1} + 1\%$

<CBO's GDP GAP > < HP filtered GDP GAP >

note: 1. π_{t-1} is set at 3%.

2. If the quantiles are overlapped, we set the quantile difference at 0.1%p.

FIGURE 4. **Conditional densities given various π^e_{t+1} using GDP (1984:I -)**

when the confidence bands are 20% and 40%. However, a substantial asymmetry still exists in the larger confidence bands.

4. Conclusion

In this paper, we examine the hybrid NKPC in multiple quantiles. By using the quantile analysis, we find two important features not captured by the traditional conditional mean analysis. First, the response of inflation with respect to the change in expected inflation is asymmetric across quantiles. The lower quantiles are relatively stable for a change in π^e_{t+1} while the upper quantiles are more sensitive to change. An important implication is that a positive shock on π^e_{t+1} increases the risk of inflation in the sense that it spreads out the distribution, while a negative shock decreases the risk. This asymmetry provides an interesting policy implication that tightening monetary policy is more effective in stabilizing the economy in that it reduces uncertainty.

Second, the role of the backward-looking component strongly depends on the level of the quantiles. After considering the structural break at about 1983, we find that the coefficient of the lagged inflation is significant only in the center of the distribution. Because one implication of the existence of the backward-looking component is the indirect and more complicated effect of the monetary policy by affecting the real economy, the result indicates the possibility that the risk structure will shift against a monetary policy shock more quickly while the point path of the inflation shows a relatively gradual change.

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Appendix A. Tables and Figures

Table 6. Data Description

Variables	quarterly average basis[a)]
π_t	Annualized growth rate of GDP deflator
π^e_{t+1}	The quarterly median forecast of the annualized percent change of GDP implicit price deflator(one-quarter ahead forecast)
mc_t	1) Percentage deviation of real GDP from the CBO's PGDP or its Hodrick-Prescott (HP) trend y_t 2) Percentage deviation of Non-farm business sector Unit Labor Costs from the Hodrick-Prescott (HP) trend
Instrumental variables	Constant Four lags of π_t, and mc_t 1) and 2) Four lags of the yield spread between long-term and short-term government bond[b)] Four lags of the wage inflation[c)]

Notes: a) All data are obtained from web-based database (FRED) in Federal Reserve Bank of St. Louis.
b) We use yield spread between 10 year and 3 month U.S. Treasury bonds.
c) We use the growth rate of non-farm business compensation

Table 7. **Estimation results using ULC (full sample)**

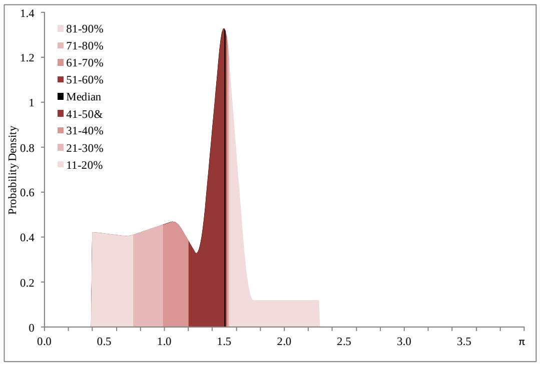
α	π^e_{t+1}	π_{t-1}	y_t	c
0.1	0.700**	0.250	0.140	-0.724
	(0.160)	(0.129)	(0.100)	(0.354)
0.2	0.520**	0.341*	0.120	-0.394
	(0.171)	(0.125)	(0.136)	(0.310)
0.3	0.430*	0.480**	0.120	-0.232
	(0.181)	(0.151)	(0.142)	(0.257)
0.4	0.460**	0.486**	0.220*	-0.063
	(0.190)	(0.163)	(0.127)	(0.229)
0.5	0.380*	0.566**	0.150	0.152
	(0.180)	(0.159)	(0.131)	(0.200)
0.6	0.360**	0.602**	0.150	0.101
	(0.209)	(0.191)	(0.123)	(0.278)
0.7	0.600**	0.557**	0.150	-0.071
	(0.225)	(0.218)	(0.128)	(0.317)
0.8	1.070**	0.195	0.220	0.122
	(0.144)	(0.180)	(0.140)	(0.337)
0.9	1.110**	0.165	0.380*	0.615
	(0.164)	(0.261)	(0.148)	(0.523)
mean eq.	0.605**	0.443**	0.250*	-0.158
	(0.093)	(0.076)	(0.108)	(0.150)

Notes: a) Standard errors appear in parentheses.
b) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.
c) The standard deviation is calculated based on MBB with 500 bootstrap resampling and the block size of 8.
d) The mean equation is estimated by GMM with Newey-West covariance estimator.

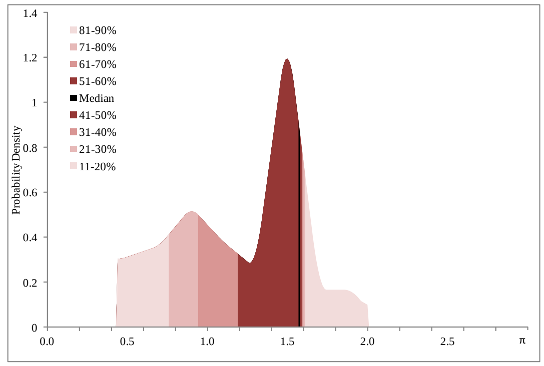
TABLE 8. **Estimation results using ULC (1984:I -)**

α	π^e_{t+1}	π_{t-1}	y_t	c
0.1	0.720**	-0.051	0.240*	-0.266
	(0.140)	(0.121)	(0.106)	(0.440)
0.2	0.510**	0.088	0.180	0.247
	(0.122)	(0.129)	(0.101)	(0.237)
0.3	0.370*	0.210	0.180	0.514
	(0.095)	(0.124)	(0.103)	(0.209)
0.4	0.420	0.294*	0.260**	0.378
	(0.089)	(0.130)	(0.097)	(0.244)
0.5	0.440**	0.426**	0.180*	0.280
	(0.093)	(0.113)	(0.088)	(0.243)
0.6	0.370**	0.460**	0.180*	0.445
	(0.085)	(0.094)	(0.074)	(0.232)
0.7	0.330**	0.512**	0.160	0.518
	(0.139)	(0.104)	(0.085)	(0.306)
0.8	0.990**	0.181	0.160	0.196
	(0.220)	(0.159)	(0.108)	(0.457)
0.9	0.850**	0.029	-0.068	1.385
	(0.217)	(0.219)	(0.120)	(0.987)
mean eq.	0.689**	0.190**	0.266**	0.053
	(0.077)	(0.071)	(0.061)	(0.200)

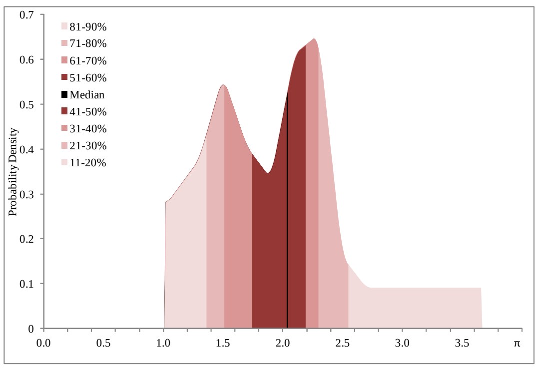
Notes: a) Standard errors appear in parentheses.
b) ** and * in π^e_{t+1}, π_{t-1} and y_t columns indicate statistical significance at 1% and 5% levels, respectively.
c) The standard deviation is calculated based on MBB with 500 bootstrap resampling and the block size of 8.
d) The mean equation is estimated by GMM with Newey-West covariance estimator.



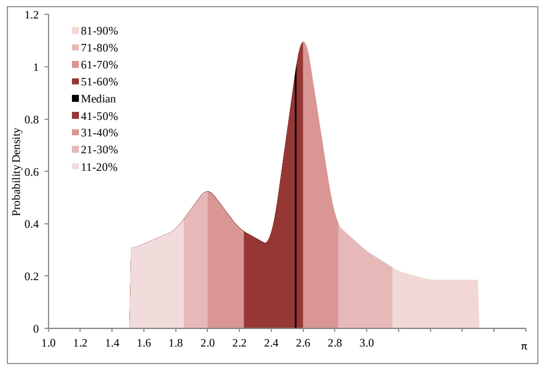
(a) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



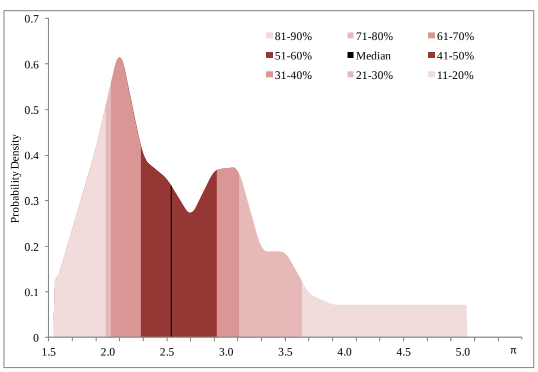
(b) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



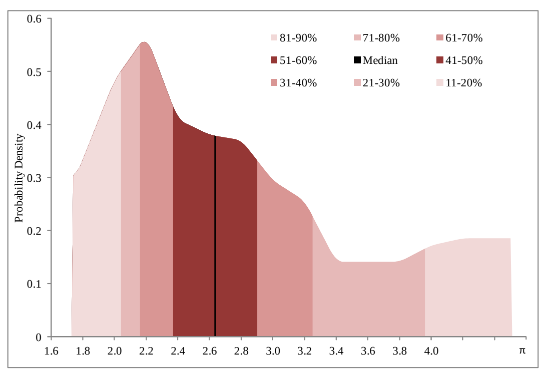
(c) $\pi^e_{t+1} = \pi_{t-1}$



(d) $\pi^e_{t+1} = \pi_{t-1}$



(e) $\pi^e_{t+1} = \pi_{t-1} + 1\%$



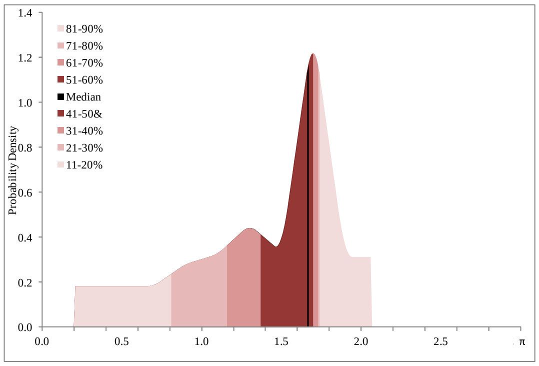
(f) $\pi^e_{t+1} = \pi_{t-1} + 1\%$

<CBO's GDP GAP > < HP filtered GDP GAP >

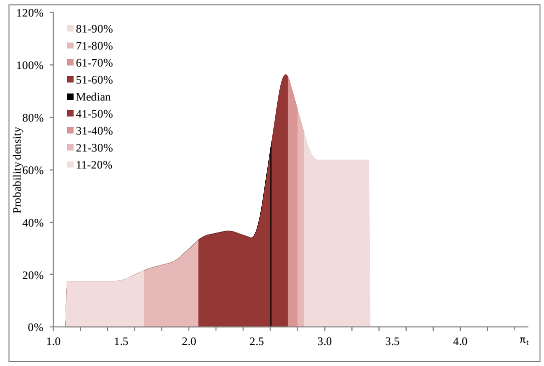
note: 1. π_{t-1} is set at 2%.

2. If the quantiles are overlapped, we set the quantile difference at 0.1%p.

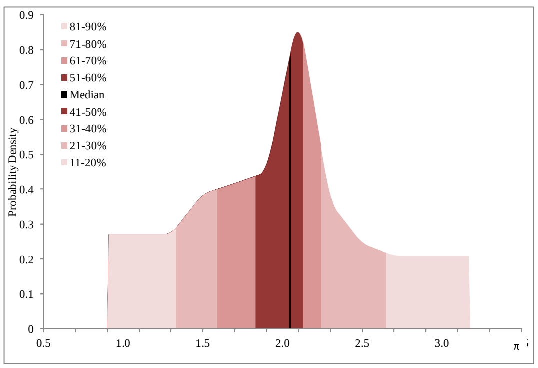
FIGURE 5. **Conditional densities given various π^e_{t+1} using GDP (2)**



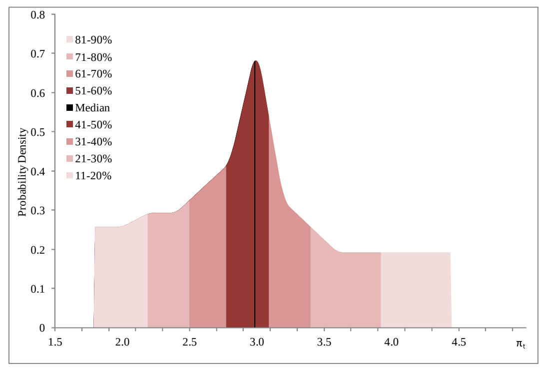
(a) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



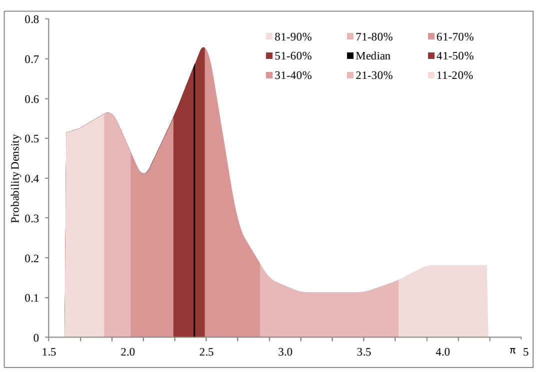
(b) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



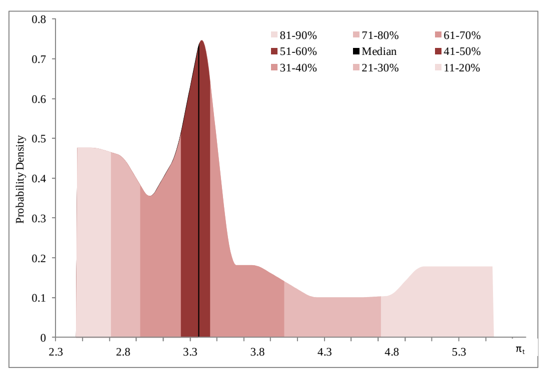
(c) $\pi^e_{t+1} = \pi_{t-1}$



(d) $\pi^e_{t+1} = \pi_{t-1}$



(e) $\pi^e_{t+1} = \pi_{t-1} + 1\%$



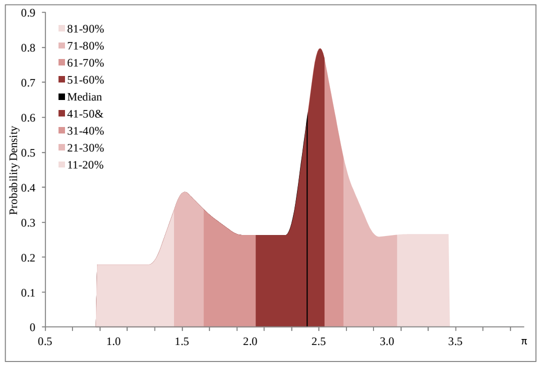
(f) $\pi^e_{t+1} = \pi_{t-1} + 1\%$

$< \pi_{t-1} = 2\% >$ $< \pi_{t-1} = 3\% >$

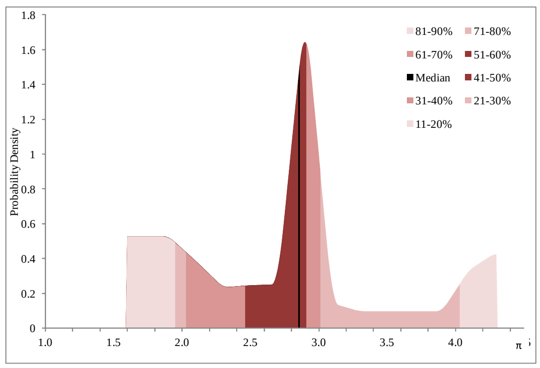
note: 1. π_{t-1} is set at 2%.

2. If the quantiles are overlapped, we set the quantile difference at 0.1%p.

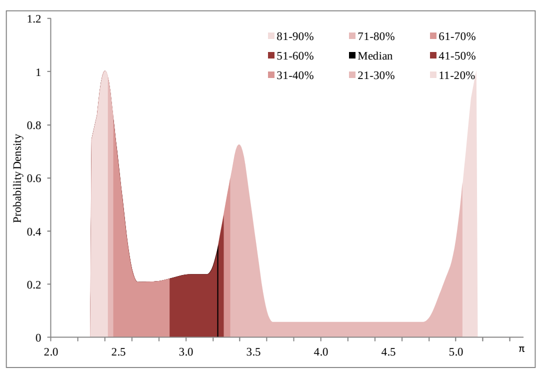
FIGURE 6. **Conditional densities given various π^e_{t+1} using ULC**



(a) $\pi^e_{t+1} = \pi_{t-1} - 1\%$



(b) $\pi^e_{t+1} = \pi_{t-1}$



(c) $\pi^e_{t+1} = \pi_{t-1} + 1\%$

note: 1. π_{t-1} is set at 3%.

2. If the quantiles are overlapped, we set the quantile difference at 0.1%p.

FIGURE 7. **Conditional densities using ULC (1984:I -)**