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Inflation dynamics, the role of inflation at different horizons and inflation uncertainty☆

Yoonseok Choi [a,*]

[a] Department of Economics, Chonnam National University, 77 Yongbong-ro, Buk-gu, Gwangju, 61186, Republic of Korea

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A B S T R A C T

Despite a widespread adoption of the hybrid new Keynesian Phillips curve (NKPC), previous empirical studies deliver conflicting results as to the relative importance of forward- and backward-looking behavior, depending on empirical specifications and econometric methods. This paper contributes to this important issue by showing that the role of expected inflation in the NKPC also hinges on inflation at different horizons (referred to as inflation horizons henceforth). The main result reveals that the quantitative importance of forward-looking behavior becomes smaller as the inflation horizon is long. It comes out of a positive correlation of the inflation horizon with inflation uncertainty. This positive link renders firms more likely to have recourse to a safe way (e.g., the use of information about past prices as a forecasting rule) to set their current prices to avoid greater price uncertainty created by the distant future. The changing role of forward-looking behavior at different inflation horizons implies that the NKPC may embrace both the view of the important role of expected inflation and the opposite view that backward-looking behavior matters, rendering different policy recommendations. Various robustness analyses do not reverse the main finding.

1. Introduction

Understanding inflation dynamics and cyclical interactions between inflation and relevant measures of real economic activity (economic slack) is of crucial importance for monetary policy analyses. Significant advances in models of inflation based on nominal frictions have been made since the early 1980s to capture dynamic properties of inflation behavior (e.g., Calvo, 1983; Rotemberg, 1982; Taylor, 1980), and the resulting models of inflation reduce to what Roberts (1995) calls the "new Keynesian Phillips curve (NKPC)." A key feature of the standard (pure) NKPC is that inflation is primarily a forward-looking process in that it is determined by expected future inflation and a real economic activity.

A vast set of previous studies, however, has demonstrated that the standard NKPC leads to unsatisfactory empirical results as it fails to generate sufficient inflation persistence. This failure has led economists to develop an extended version of the NKPC, which includes a lag of inflation. Since this model is viewed as a combination of new and old Phillips curves, such a model is called the hybrid NKPC (e.g., Christiano et al., 2005; Galí; Gertler 1999; Sbordone, 2006). This newly proposed model has been broadly used to examine inflation

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* Department of Economics, Chonnam National University, 77 Yongbong-ro, Buk-gu, Gwangju, 61186, Republic of Korea.
E-mail address: yoonchoi3@jnu.ac.kr.

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dynamics and monetary policy issues because it is a crucial part of modern macroeconomic models as the price determination equation and is capable of accounting for intrinsic persistence of inflation observed in data.[1]

Despite its widespread adoption as the inflation model, there are still unsettled issues of the empirical validity of the hybrid NKPC. One of the important issues is the relative importance of forward- and backward-looking behavior of inflation.[2] Forward-looking behavior of inflation provides an important role in monetary policy rules and has significant effects on expectations management and communications as a tool of monetary policy. Furthermore, the relative size of forward- and backward-looking behavior translates into different policy implications. For instance, a credible central bank can achieve costless disinflation if an inflation process is completely forward-looking, whereas disinflation can be costly if backward-looking behavior is quantitatively important (e.g., Ball, 1994; Mankiw, 2001).

A number of early studies have empirically tested whether the forward-looking element outweighs the backward-looking component for explaining inflation dynamics but presented mixed empirical results.[3] A strand of literature on this issue finds an important role of expected inflation in the NKPC, resulting in a good description of inflation dynamics (e.g., Galí et al., 2005, 2001; Galí; Gertler 1999; Oinonen et al., 2013; Sbordone, 2002, 2006). Another line of research, however, accentuates an apparent need of backward-looking component to create sufficient inflation inertia shown in data (e.g., Fuhrer, 1997; Fuhrer & Moore, 1995; Jondeau & Le Bihan, 2005; Malikane, 2014; Roberts, 2005; Rudd & Whelan, 2005, 2007).

This paper contributes to this important debate by taking a distinct approach from the early studies: It examines whether the quantitative importance of forward- and backward-looking behavior also hinges on different inflation horizons by estimating the hybrid NKPC á la Galí and Gertler (1999). The set of different inflation horizons comprises quarterly, semi-annual and annual inflation rates.[4] Furthermore, this paper constructs and estimates an econometric model with the NKPC as a mean equation and the generalized autoregressive conditional heteroscedasticity (GARCH) model as a variance equation to obtain conditional variance as a measure of inflation uncertainty. An advantage of using the NKPC-GARCH model is to enable me to analyze a direct link between the changing role of forward-looking behavior and inflation uncertainty. It is an important analysis since understanding different degrees of forward- and backward-looking behavior at different horizons can help policymakers set more accurate policy directions and offer various policy recommendations, which eventually affects credibility of monetary policy.

Several important results stand out. First, the relative share of forward-looking behavior reduces as the inflation horizon increases (i.e., from quarterly to annual inflation), implying that the NKPC depends on the choice of inflation horizon. For instance, the baseline estimate of forward- and backward-looking behavior at the quarterly horizon is 0.692 and 0.309. The degree of forward-looking behavior, however, diminishes as the inflation horizon is long: The annual horizon delivers the estimate of 0.414 for forward-looking behavior and that of 0.585 for backward-looking behavior. It implies that forward-looking behavior matters more at the short horizon than at the long horizon.[5] This finding follows from a positive correlation of the inflation horizon with inflation uncertainty estimated by the NKPC-GARCH model.[6] For example, baseline estimation of the NKPC-GARCH model yields inflation uncertainty of 0.231 at the quarterly horizon, while it rises up to 0.394 at the annual horizon. As inflation uncertainty increases, expected profits in the distant future (e.g., in a year) are more unpredictable than those in the near future (e.g., in three months) because price uncertainty in the future also increases (e.g., Ball & Cecchetti, 1990). It leads firms to be more cautious in setting their prices by resorting to information on past prices as a forecasting rule. This explanation carries over to another finding that the fraction of backward-looking firms in the structural NKPC with longer (semi--annual and annual) inflation horizons is relatively large, compared to that with the short (quarterly) inflation horizon.

Second, the role of expected inflation in the recent period (i.e., the one after the Great Recession) becomes larger than that in the previous period irrespective of inflation horizons as credible central bank policies lead to better-anchored inflation expectations (e.g., Oinonen et al., 2013; Stella & Stock, 2012). Third, the result for the post-Volcker period shows a flattening Phillips curve compared to the pre-Volcker period (e.g., Blanchard et al., 2015; Choi & Kim, 2016; Coibion; Gorodnichenko 2015; Kuttnera & Robinson, 2010; Roberts, 2006), whereas the estimated NKPC in the most recent period reveals that the effect of the real economic activity on inflation has become larger since the Great Recession, implying a steeper Phillips curve (e.g., Oinonen et al., 2013; Stella & Stock, 2012). Finally, inflation uncertainty for the pre-Volcker period is much larger than that for the post-Volcker period due to high and volatile inflation during the 1960s and 1970s.

To the best of my knowledge, none of the early studies have explored the changing role of expected inflation at the different inflation horizons by directly relating it to inflation uncertainty. In this sense, this paper can provide a better understanding of the role of expected inflation in the inflation process at different horizons and the link between inflation horizons and inflation uncertainty, helping guide monetary policy making.

[1] Some studies show that an inclusion of extra lags of inflation can better capture empirically observed persistence of inflation (e.g., Choi & Kim, 2016; Fuhrer, 1997; Fuhrer & Moore, 1995; Jondeau & Le Bihan, 2005; Malikane, 2014; Roberts, 2005; Rudd & Whelan, 2005, 2007).

[2] Another debate over the NKPC is related to a type of forcing variable as a proxy for the real economic activity. Some argue that labor income share (or real unit labor cost) is an appropriate variable for inflation (e.g., Galí & Gertler, 1999; Galí et al., 2001, 2005; Sbordone, 2002, 2006), while others argue that output gap is better than labor income share (e.g., Fuhrer, 1997; Fuhrer & Moore, 1995; Neiss & Nelson, 2005; Rudd & Whelan, 2007).

[3] Galí et al. (2005) and Rudd and Whelan (2005) provoked a fierce debate over the relative importance of forward-looking behavior of inflation. These two articles have received much attention since these two papers were published in the same volume of Journal of Monetary Economics.

[4] Federal Reserve Economic Data (FRED) of St. Louis offers these types of data. Section 3 elaborates on these data.

[5] The GMM-based Wald tests for equality of estimated forward-looking behavior for three different horizons substantiate this main finding. Section 4 elaborates on this result.

[6] Though a simple but broadly used measure of inflation uncertainty in empirical macroeconomics is the standard deviation of inflation rates, it is important to directly relate the NKPC to inflation uncertainty for a more precise analysis. Section 4 lays out not only NKPC-GARCH models but AR-GARCH models used as a complementary specification.

The structure of this paper is as follows. Section 2 briefly describes the empirical model of inflation. Section 3 delineates the estimation method with its possible issues and data. Section 4 discusses baseline estimation results, together with results of various sensitivity analyses. Section 5 concludes.

2. Theoretical framework

The model of inflation used in this paper is the conventional hybrid NKPC developed by Galí and Gertler (1999), and a brief description of the model is as follows.[7] There are firms with the probability $1-\theta$ that are able to update their current prices, and these firms are divided into two types of firms: A fraction $1-\omega$ of firms sets their prices optimally in a forward-looking manner, and these forward-looking firms use the staggered price-setting scheme á la Calvo (1983). The other portion ω of firms, however, uses a backward-looking price-setting rule by using the most recent price (simple rule-of-thumb). The equation based on this assumption is then given by

$$\pi_t = \mu_f E_t \pi_{t+1} + \mu_b \pi_{t-1} + \eta mc_t, \tag{1}$$

$$\mu_f = \frac{\beta\theta}{\Phi}, \quad \mu_b = \frac{\omega}{\Phi}, \quad \eta = \frac{(1-\theta)(1-\omega)(1-\beta\theta)}{\Phi}, \quad \Phi = \theta + \omega[1-\theta(1-\beta)],$$

where π_t is the inflation rate, E_t is the expectation operator conditioned on past available information, and mc_t is the real marginal cost as a forcing variable. The coefficients η, μ_f and μ_b in the reduced-form equation indicate the magnitude of inflation pressure, the degree of forward- and backward-looking behavior of inflation. The structural parameters β, θ and ω with economic interpretations denote the discount factor, the degree of price stickiness and the portion of backward-looking firms, respectively. Note that setting $\omega = 0$ yields the pure forward-looking NKPC that is determined only by expected future inflation and the real marginal cost, implying that the monetary policy on inflation is effective via the management of inflation expectations. Note also that setting $\mu_f = 0$ and $\mu_b = 1$ leads to the traditional old Phillips curve that is characterized by a path-dependent inflation process.

3. Estimation method and data

A glance at (1) reveals an immediate econometric issue: Expected inflation is clearly endogenous, and the driving force of inflation is likely to be correlated with the error term because it may be partially driven by cost-push shocks. The empirical approach used in this paper to resolving this issue is the generalized method of moments (GMM) technique that is widely employed in the NKPC literature.[8] In particular, this paper uses the continuously updating GMM estimator (CUE) proposed by Hansen et al. (1996) because it has better finite sample properties than the typical GMM estimator.[9]

The moment (orthogonality) conditions for the reduced-form and structural NKPC are given by

$$E_t\left[\left(\pi_t - \mu_f E_t \pi_{t+1} - \mu_b \pi_{t-1} - \eta mc_t\right) z_t\right] = 0, \tag{2}$$

$$E_t\left[\left(\pi_t - \frac{\beta\theta}{\Phi} E_t \pi_{t+1} - \frac{\omega}{\Phi}\pi_{t-1} - \frac{(1-\theta)(1-\omega)(1-\beta\theta)}{\Phi} mc_t\right) z_t\right] = 0, \tag{3}$$

where $\Phi = \theta + \omega[1-\theta(1-\beta)]$, and z_t is a set of instruments at *t-1* and earlier.

Though any macroeconomic variables that explain inflation behavior can serve as instruments, various combinations of instruments considered in Galí and Gertler (1999) have been frequently used in early studies. The set of instruments includes inflation, output gap, wage inflation, marginal cost (labor share), spread between long and short interest rates and inflation on commodity price. Most previous studies using the GMM technique, however, tend to use a large number of instruments, which are subject to the pitfalls of many instrument biases (e.g., Hansen et al., 2008) and the low power of *J*-test (e.g., Mavroeidis, 2005).[10] This paper, therefore, uses smaller sets of instruments to avoid the over-instrumenting problem.

[7] Since the derivation of the NKPC is straightforward, I just provide the brief description of the model to reduce space. There are various ways to model the hybrid version of the NKPC. For instance, Christiano et al. (2005) use an assumption of indexation when firms set their prices. Fuhrer and Moore (1995) employ an assumption about staggered wage contracts. Sbordone (2006) assumes partial indexation. Regardless of these different assumptions, the resulting reduced-form equations are qualitatively the same as the hybrid NKPC proposed by Galí and Gertler (1999).

[8] Franses (2019) employs a mixed-data sampling (MIDAS) model as a novel approach to grapple with the problem that arises from the use of future inflation in the NKPC with the U.S. annual data.

[9] Hansen et al. (1996) show that the CUE has the smallest bias and correct inference among IV estimators in small samples. As part of sensitivity analyses, this paper also presents results using the standard iterative GMM estimator. The GMM technique is based on the heteroscedasticity and autocorrelation consistent (HAC) estimator with the Bartlett kernel and automatic lag-selection method proposed by Newey-West (1994). Many of previous studies have used the same method to estimate the NKPC (e.g., Guay; Pelgrin 2004; Nason & Smith, 2008; Scheufele, 2010).

[10] In fact, some of earlier studies have already pointed out this problem. For instance, Tauchen (1986) shows in a simulation study that the use of many instruments increases the bias of estimates, arguing that the number of instruments should be parsimonious. One of the serious problems is that the use of many instruments biases IV estimators towards OLS.

Furthermore, since it is well known that the GMM estimator may be sensitive to the choice of instruments, this paper employs four different sets of instruments to test for its sensitivity of empirical results. IV set 1 includes a lag of inflation, marginal cost, output gap, inflation on commodity price, interest-rate spread and wage inflation. IV set 2 contains a lag of inflation, marginal cost, output gap, wage inflation and inflation on commodity price. IV set 3 consists of a lag of inflation, marginal cost, output gap and inflation on commodity price. IV set 4 includes a lag of inflation, marginal cost, output gap and wage inflation. Table 1 lists these sets of instruments.[11]

To choose the best set of instruments, this paper uses three moment selection criteria (MSC), which are the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and the Hannan-Quinn information criterion (HQIC) proposed by Andrews (1999). The second, third and fourth columns in Table 2 report the GMM-based AIC, BIC and HQIC from the estimated NKPC with all sets of the instruments, respectively. Regardless of any inflation horizon, the fact that the IV set 1 has the smallest values of MSC suggests that the AIC, BIC and HQIC all prefer the IV set 1 over the other three sets of the instruments, implying that it better fits the NKPC to the data. Therefore, this paper uses the IV set 1 as the baseline instruments and the other three sets for sensitivity analyses.

The GMM technique also raises two important econometric issues: Instrument exogeneity and instrument relevance. The instrument exogeneity implies that the moment conditions are correctly specified, and the test for this issue is typically performed by the *J*-test statistic that checks whether over-identifying restrictions in the estimated model are satisfied. Another important issue that arises in IV estimation is instrument relevance (or weak instruments). Recently, many economists who use the IV regression method have paid more attention to this issue because estimates are not reliable if instruments are weakly correlated with regressors. This paper uses the Anderson-Rubin (AR) statistic developed by Anderson and Rubin (1949) and Lagrange multiplier (LM) statistic proposed by Kleibergen (2002).[12] The penultimate and last columns of Table 2 present the AR and LM test results. The AR and LM tests for all IV sets and inflation horizons (except for the IV set 3 for semi-annual inflation) clearly do not reject the null of no weak instruments at 5% significance level, implying that the choice of instrument sets is immune to the weak instrument issue.

Federal Reserve Economic Data (FRED) of St. Louis offers the U.S. quarterly, semi-annual and annual data. The data at relatively long horizons such as semi-annual and annual data are based on the quarterly data with two different computation methods. FRED provides the long-horizon data by using either the average method or the end-of-period method. The average method constructs the semi-annual and annual data by taking averages of quarterly data, whereas the end-of-period method creates these data by increasing the lead of variable (i.e., two-quarter-ahead and four-quarter-ahead data for the semi-annual and annual data, respectively). This paper uses the data constructed by the former method with the range of 1960–2016.

Inflation is defined as the percentage change of the GDP deflator (series ID: GDPDEF). The HP-filtered series of the log of the labor income share of nonfarm business sector (series ID: PRS85006173) is used for the real marginal cost as a proxy variable.[13] Output gap is constructed by the log deviation of real GDP (series ID: GDPC1), which is also measured by the HP-filter. Wage inflation is created by the percentage change of the unit labor cost (ULC) of nonfarm business sector (series ID: ULCNFB). Commodity price inflation is measured by the percentage change of the producer price index of all commodities (series ID: PPIACO). The interest-rate spread is calculated by the difference between long (series ID: IRLTLT01USQ156N) and short (series ID: TB3MS) interest rates.

4. Empirical analysis

4.1. Baseline results

Table 3 reports the estimation results using the baseline set of instruments (IV set 1 in Table 1) for three different horizons. The left (right) panel of Table 1 lists the estimates in the reduced-form (structural) NKPC. The overall results show that all the estimates are highly significant, and the reasonably similar estimates from the different estimators (CUE and GMM) suggest that the results are quite robust to the choice of the estimator. Since the results from the CUE and GMM do not show much difference, this paper uses the average values of estimates to discuss the results unless otherwise mentioned.

Consider first the estimates in the reduced-form NKPC. For all inflation horizons, the slope coefficient ηremains positive and is correctly signed with the average value of 0.029, 0.025 and 0.434 at the quarterly, semi-annual and annual inflation horizons. The positive values of the slope coefficient, in particular a large value at the annual inflation horizon, imply that the labor income share is a valid measure of the real economic activity.[14]

The estimate of forward-looking (μ_f)and backward-looking (μ_b)components is 0.692 and 0.309 for the quarterly inflation horizon, suggesting that expected inflation plays a relatively important role in accounting for inflation dynamics (e.g., Galí & Gertler, 1999; Galí et al., 2001, 2005; Sbordone, 2002, 2006; Oinonen at al. 2013). The result using the semi-annual (annual) horizon, however, gives the value of 0.571 (0.414) for forward-looking behavior and that of 0.425 (0.585) for backward-looking behavior. The overall results suggest that an increase in the inflation horizon reduces the role of expected inflation in explaining inflation dynamics, which also

[11] IV sets 1 and 4 contain the same variables as in Galí and Gertler (1999), Galí et al. (2001) and Nason and Smith (2008) respectively, aside from the number of lags.

[12] The possible endogenous variables are expected inflation and real marginal cost in (1). The AR and LM statistics are particularly useful in testing the weak instruments in a model with multiple endogenous variables.

[13] This paper uses three different smoothing parameters for the HP-filter due to three different horizons. Following Ravn and Uhlig (2002), the value of 1600, 100 and 6.25 is used as the smoothing parameter for the quarterly, semi-annual and annual data, respectively.

[14] As discussed above, some studies using the quarterly data support the use of output gap against the labor income share due to small and insignificant estimates of the latter variable.

Table 1
List of instruments.

IV set	List of instrumental variables
IV set 1	Inflation, marginal cost, output gap, inflation on commodity price, interest rate spread, wage inflation
IV set 2	Inflation, marginal cost, output gap, inflation on commodity price, wage inflation
IV set 3	Inflation, marginal cost, output gap, inflation on commodity price
IV set 4	Inflation, marginal cost, output gap, wage inflation

Table 2
Moment selection criteria and test for weak instruments.

	GMM-AIC	GMM-BIC	GMM-HQIC	AR test	LM test
Quarterly horizon					
IV set 1	−6.450	−20.132	−12.039	0.234	0.011
				(0.948)	(0.917)
IV set 2	−4.437	−14.712	−8.634	0.293	0.016
				(0.883)	(0.900)
IV set 3	−2.640	−9.490	−5.438	0.199	0.000
				(0.897)	(0.995)
IV set 4	−2.453	−9.303	−5.251	0.348	0.009
				(0.790)	(0.924)
Semi-annual horizon					
IV set 1	−5.410	−16.284	−9.884	1.504	0.693
				(0.185)	(0.405)
IV set 2	−4.998	−13.180	−8.365	2.235	0.026
				(0.063)	(0.872)
IV set 3	−3.000	−8.454	−5.244	2.679	0.036
				(0.045)	(0.849)
IV set 4	−3.000	−8.455	−5.244	0.534	0.156
				(0.659)	(0.693)
Annual horizon					
IV set 1	−6.995	−15.029	−10.160	1.201	0.055
				(0.306)	(0.814)
IV set 2	−5.000	−11.076	−7.397	1.576	0.296
				(0.178)	(0.587)
IV set 3	−3.000	−7.050	−4.598	2.092	0.201
				(0.099)	(0.654)
IV set 4	−3.386	−7.437	−4.984	0.051	0.007
				(0.985)	(0.934)

Note: Parenthesis under AR and LM statistics denotes p-value.

implies that the quantitative importance of forward-looking behavior of inflation varies as to the choice of inflation horizon.

Though casual inspection of the changing role of expected inflation at the different inflation horizons may not have its peril, formal statistical tests can help substantiate the main finding. The test procedure used in this paper is the GMM-based Wald test proposed by Newey and West (1987).[15] The three different inflation horizons lead to three different pairwise tests for equality of estimated forward-looking behavior at between (a) quarterly and semi-annual horizons; (b) quarterly and annual horizons; (c) semi-annual and annual horizons. The bottom of Table 3 presents the test results, and they all suggest that the null of equality is rejected at 5% and 10% significance levels, thereby statistically corroborating the main result.

The decline in the role of expected inflation for an increase in the inflation horizon follows from a positive relationship between inflation horizon and inflation uncertainty.[16] As the inflation horizon increases, it is more difficult to accurately predict expected profits in the distant future (e.g., in a year) than in the near future (e.g., in three months), leading firms to resort to a more cautious way to set their prices to avoid greater uncertainty created by the distant future. Hence, the positive correlation of inflation horizon with inflation uncertainty causes price-setters to reduce dependence on the expected discounted sum of profits and adopt a safer method to set the current price (e.g., combination of past prices as a forecasting rule for the current price).[17]

Since statistical evidence on the positive link between inflation horizon and inflation uncertainty can help better understand the discussion above, this paper considers three measures of inflation uncertainty. One of the simple and frequently used measures of

[15] The underlying idea of GMM-based Wald test is analogous to the conventional Wald test. See Newey and West (1987) for more details.
[16] Inflation uncertainty can arise due to a lack of complete information about future prices.
[17] Ball and Cecchetti (1990) explore implications of the inflation-uncertainty link over various horizons, and one of the central findings is that uncertainty about future inflation becomes larger as the horizon is long.

Table 3
Baseline results.

	Reduced- form NKPC				Structural NKPC			
	μ_f	μ_b	η	*J-statistic*	β	θ	ω	*J-statistic*
CUE								
Q-horizon	0.701*** (0.074)	0.300*** (0.073)	0.029** (0.012)	1.550 (0.818)	1.000*** (0.017)	0.779*** (0.043)	0.333*** (0.108)	1.550 (0.818)
SA-horizon	0.577*** (0.031)	0.425*** (0.031)	0.045*** (0.013)	2.590 (0.629)	0.999*** (0.000)	0.759*** (0.001)	0.425*** (0.001)	1.000 (0.910)
A-horizon	0.412*** (0.001)	0.588*** (0.001)	0.444*** (0.002)	1.000 (0.910)	0.990*** (0.001)	0.290*** (0.001)	0.409*** (0.001)	1.000 (0.910)
GMM								
Q-horizon	0.682*** (0.071)	0.317*** (0.070)	0.028** (0.012)	1.593 (0.810)	0.998*** (0.017)	0.778*** (0.045)	0.360*** (0.108)	1.593 (0.810)
SA-horizon	0.565*** (0.067)	0.425*** (0.070)	0.005 (0.029)	1.007 (0.909)	1.007*** (0.012)	0.673*** (0.047)	0.499*** (0.041)	2.435 (0.656)
A-horizon	0.415*** (0.003)	0.581*** (0.003)	0.423*** (0.006)	1.005 (0.909)	0.982*** (0.009)	0.294*** (0.017)	0.406*** (0.012)	1.122 (0.891)
Wald test								
	$H_o: \mu_f^q = \mu_f^{sa}$ *vs.* $H_a: \mu_f^q \neq \mu_f^{sa}$		$H_o: \mu_f^{sa} = \mu_f^a$ *vs.* $H_a: \mu_f^{sa} \neq \mu_f^a$			$H_o: \mu_f^q = \mu_f^a$ *vs.* $H_a: \mu_f^q \neq \mu_f^a$		
CUE	3.148 (0.076)		7.512 (0.006)			15.594 (0.000)		
GMM	3.000 (0.083)		5.345 (0.021)			14.858 (0.000)		

Note: ***, ** and * denote 1%, 5% and 10% significance levels respectively. Parenthesis below the estimate indicates the HAC-robust standard error, whereas parenthesis below (and next to) the statistic indicates p-value. Wald test is a test for equality of estimated coefficients of forward-looking behavior between two models. μ_f^q, μ_f^{sa} and μ_f^a denote the coefficient of forward-looking behavior for the quarterly, semi-annual and annual inflation horizons, respectively. Q-, SA- and A-horizon indicate the quarterly, semi-annual and annual one.

inflation uncertainty in empirical macroeconomics is the standard deviation of inflation series (e.g., Fischer, 1981; Okun, 1971). However, a disadvantage of using the standard deviation as a proxy for inflation uncertainty is that it is more likely to measure inflation volatility rather than future inflation uncertainty. For this reason, GARCH models are often used to obtain inflation uncertainty measured by conditional variance.[18]

Despite the widespread use of GARCH models to measure uncertainty, conditional variance estimated by standard GARCH models (i.e., purely statistical specifications) does not have a direct link to the NKPC used as the main model in this paper. It implies that simultaneous estimation of NKPC (mean equation) and its uncertainty (variance equation) can provide a more precise analysis on whether there is a positive relationship between inflation horizon and inflation uncertainty. Therefore, this paper estimates NKPC-GARCH models to obtain inflation uncertainty measured by conditional standard deviation (square root of conditional variance).[19] Moreover, this paper also computes the standard deviations of inflation rates and conditional standard deviations produced by standard GARCH models. The set of these two different measures of inflation uncertainty can serve as a complementary to the main inflation uncertainty produced by the NKPC-GARCH models.

Various preliminary experiments based on the conventional information criteria such as the AIC, BIC and HQIC result in the most appropriate GARCH models for all inflation horizons: The quarterly, semi-annual and annual inflation horizons all choose the NKPC-GARCH(1,1) model as a sensible variance equation. For the standard GARCH specification, the AR(3)-GARCH(1,1), AR(1)-GARCH(1,1) and AR(1)-GARCH(1,1) models best fit the quarterly, semi-annual and annual inflation horizons, respectively.[20] The second column of Table 4 offers three types of inflation uncertainty over the whole sample period. Inflation uncertainty 1, 2 and 3 indicate conditional standard deviation of inflation created by the NKPC-GARCH models, conditional standard deviation of inflation produced by the AR-GARCH models and standard deviation of the inflation rates, respectively. The baseline uncertainty (inflation uncertainty 1) shows an apparent increase as the inflation horizon is long. For instance, inflation uncertainty 1 for the quarterly horizon has the value of 0.231, whereas it rises up to 0.394 for the annual horizon. This result is confirmed by the other two measures of uncertainty (inflation uncertainty 2 and 3). Overall, all the results suggest that the inflation horizon has a positive relationship with inflation uncertainty as discussed above.

From a policy perspective, a better understanding of different roles of expected inflation at different horizons and the interactions with inflation uncertainty is important for monetary policy making. For example, large uncertainty at the long horizon creates risks for individuals with nominal contracts and firms setting prices, leading to a decrease in efficiency gains from economic activities. Hence, though keeping an appropriately low level of inflation is a primary policy goal of the central bank, reducing variability of inflation over long periods is also crucial to create more stable economic states, enhancing credibility of monetary policy.

Next, turn to the structural NKPC. The average value of price stickiness $\theta$is 0.779, 0.716 and 0.292 for the quarterly, semi-annual and annual inflation horizons, respectively. It implies that the average period in which prices are fixed lies between about 4.5 and 7.0 quarters.[21] This finding is not far off from the values reported in earlier studies.[22] The average portion of backward-looking firms $\omega$is 0.347, 0.462 and 0.408 for the quarterly, semi-annual and annual inflation horizons, suggesting a relatively large role of backward-looking behavior for inflation dynamics at longer horizons than the short horizon. The discount factor $\beta$is close to unity on average for any inflation horizon, which is in line with the theoretical prediction.

Overall performance of the model is evaluated by instrument exogeneity. Both reduced-form and structural NKPCs for all of the inflation horizons work well through the test for instrument exogeneity. The *J*-test clearly does not reject the over-identifying restrictions, implying that the instruments used for baseline estimation are valid.

[18] For instance, the seminal papers by Engle (1982) and Bollerslev (1986) also employ conditional variance of inflation as a measure of inflation uncertainty.

[19] Russell and Chowdhury (2013) use a NKPC-GARCH model to examine the empirical validity of various Phillips curves. Fuest and Schmidt (2017) explicitly use the NKPC as a framework to explore how inflation uncertainty measured by conditional variance is intimately linked to inflation expectations and inflation rates. Since estimation of NKPC-GARCH models involves the possible endogeneity issue that arises from expected inflation and the real economic activity, this paper estimates the NKPC-GARCH models using fitted values of expected inflation and the forcing variable by regressing these two endogenous variables on the IV set 1. Russell and Chowdhury (2013) also employ the same procedure to estimate the NKPC-GARCH model.

[20] The estimation method is the maximum likelihood (ML) technique with the Berndt-Hall-Hall-Hausman (BHHH) optimization algorithm. The test for normality is important to estimate GARCH models. The Jarque-Bera statistic (p-value) for the NKPC-GARCH [AR-GARCH] model with the quarterly, semi-annual and annual data is 4.970 (0.083) [1.206 (0.547)], 11.112 (0.004) [0.264 (0.877)] and 0.066 (0.968) [4.253 (0.119)], respectively. The overall test results suggest that the null of normality is not rejected at conventional level except for two cases. Furthermore, the ARCH LM statistic (p-value) for the NKPC-GARCH [AR-GARCH] model with the quarterly, semi-annual and annual data is 1.792 (0.116) [0.753 (0.585)], 0.358 (0.876) [0.657 (0.657)] and 0.537 (0.747) [0.706 (0.622)] up to the lag at 5, implying that the null of no remaining ARCH effect in the residuals is not rejected and therefore the variance equations are correctly specified.

[21] The fact that θ is the probability that the price does not change means that the average duration in which the previous price level is fixed follows the geometric distribution. Hence, the expected duration of holding the previous price level fixed is $(1-\theta)^{-1}$.

[22] Estimation of structural NKPC with different horizons clearly leads to different values of price stickiness, implying that converting all the values to those with the same horizon (e.g., quarterly horizon) can give correct price durations. A little calculation finally gives the average quarterly duration of 4.514, 7.042 and 5.650 for the quarterly, semi-annual and annual horizons, respectively. Galí and Gertler (1999) and Galí et al. (2001) present the price duration of about 5 quarters on average. Another set of studies also supports the range of price duration reported in this paper. For instance, Blinder et al. (1998) show that the average price duration is about 12 months, and Kashyap (1995) reports the average of 14.7 months.

Table 4
Inflation uncertainty.

	Whole period (1960–2016)	*Pre-Volcker period (1960–1983)*	*Post-Volcker period (1984–2016)*	*Pre-crisis period (1960–2006)*	*Post-crisis period (2007–2016)*
Quarterly horizon					
Inflation uncertainty 1	0.231	0.276	0.198	0.231	0.233
Inflation uncertainty 2	0.244	0.296	0.205	0.244	0.240
Inflation uncertainty 3	0.588	0.706	0.249	0.602	0.232
Semi-annual horizon					
Inflation uncertainty 1	0.331	0.359	0.310	0.327	0.347
Inflation uncertainty 2	0.398	0.494	0.327	0.407	0.353
Inflation uncertainty 3	1.148	1.380	0.438	1.178	0.339
Annual horizon					
Inflation uncertainty 1	0.394	0.441	0.360	0.402	0.350
Inflation uncertainty 2	0.867	1.098	0.700	0.914	0.651
Inflation uncertainty 3	2.296	2.779	0.826	2.360	0.557

Note: Inflation uncertainty 1, 2 and 3 indicate the square root of conditional variance of inflation from the NKPC-GARCH models, square root of conditional variance of inflation from the AR-GARCH models and the standard deviation of inflation series, respectively.

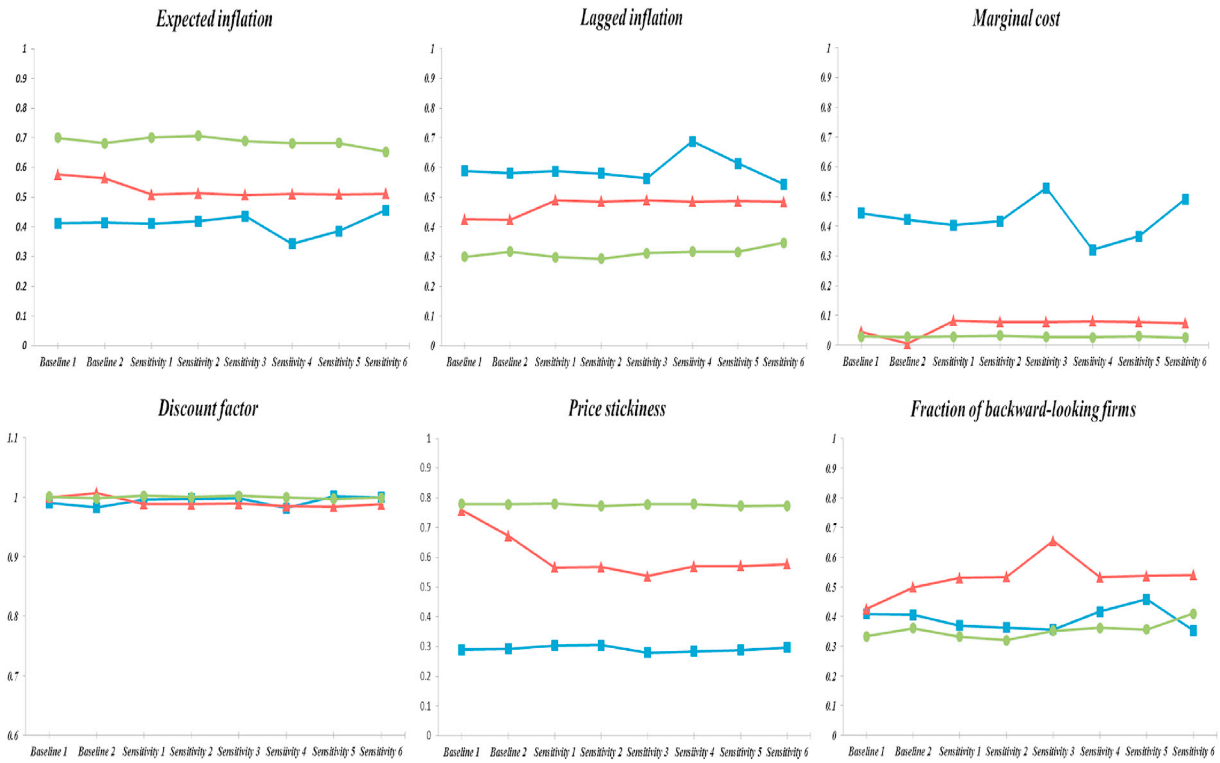

Fig. 1. Robustness analysis using the different sets of instruments and different estimators. *Note:* Baseline 1, Baseline 2, Sensitivity 1, Sensitivity 2, Sensitivity 3, Sensitivity 4, Sensitivity 5 and Sensitivity 6 denote the results from the CUE with IV set 1, GMM with IV set 1, CUE with IV set 2, CUE with IV set 3, CUE with IV set 4, GMM with IV set 2, GMM with IV set 3 and GMM with IV set 4, respectively. The line with circle, triangle and square indicates the results using quarterly, semi-annual and annual inflation horizon, respectively.

4.2. Robustness analyses

Sensitivity of IV estimation may arise due to the choice of instruments and the different estimation periods. Thus, this section focuses on stability analyses on the parameter estimates of the NKPC to see if the different instruments and periods alter the baseline results.

4.2.1. Use of different sets of instruments

Fig. 1 displays the estimates from the different sets of instruments (IV set 2, 3 and 4) listed in Table 1.[23] Baseline 1 and 2 are the baseline estimates from the CUE and the GMM in Table 3. Sensitivity 1, 2 and 3 indicate the estimation results using the CUE with the IV set 2, 3 and 4, whereas the GMM with the IV set 2, 3 and 4 yields Sensitivity 4, 5 and 6. The line with circle, triangle and square denotes the result with the quarterly, semi-annual and annual inflation horizon, respectively.

The average estimate of forward- and backward-looking behavior using the quarterly inflation horizon is about 0.72 and 0.31, implying that the forward-looking component plays an important role in describing inflation behavior. In contrast, the role of backward-looking behavior becomes more important than that of forward-looking behavior as the inflation horizon increases. For instance, the annual inflation horizon shows that the backward-looking component hovers around 0.62, while the forward-looking element remains 0.42 on average. The other estimates of the reduced-form and structural equations are not far off from the baseline results. All of these results, therefore, suggest that the baseline results are quite robust to the different sets of instruments and different estimators.

4.2.2. Sub-sample analysis

It is well known that the U.S. monetary policy has been dramatically changed since the early 1980s. It implies the importance of analysis on inflation dynamics in different sub-periods.[24] Moreover, given that the Great Recession is another important episode, exploring the recent inflation dynamics also merits an analysis. Therefore, this paper splits up the entire sample into four sub-samples: Pre-Volcker period (1960–1983), post-Volcker period (1984–2016), pre-crisis period (1960–2006) and post-crisis period (2007–2016).[25] Table 5 reports the estimation results.[26]

All the sub-sample analyses find that the quantitative importance of forward-looking behavior becomes smaller as the inflation horizon increases. This result is also corroborated by the Wald test presented at the bottom panel of Table 5: All the test results, apart from a few cases, show that the null of equality between estimated parameters for pairwise inflation horizons is rejected at the conventional level, suggesting that the main finding reported in Section 4.1 remains intact. To reinforce the main result, Table 4 reports three measures of uncertainty to investigate the positive link between inflation horizon and inflation uncertainty for all the sub-samples. The third and fourth (penultimate and last) columns show inflation uncertainty for the pre- and post-Volcker eras (pre- and post-crisis periods), respectively. All the results in Table 4 suggest that none of uncertainty measures reverse the baseline result irrespective of any sub-samples, implying the positive correlation between inflation horizon and inflation uncertainty.

In addition to the main finding, several interesting results from the sub-sample analyses deserve mention. First, Table 5 reveals a weak interaction of inflation with the real economic activity in the post-Volcker period, compared to that in the pre-Volcker period, resulting in a flattening Phillips curve (e.g., Roberts, 2006; Kuttnera & Robinson, 2010; Blanchard et al., 2015; Coibion & Gorodnichenko, 2015; Choi & Kim, 2016). However, the link between inflation and the real economic activity in the post-crisis period is slightly stronger than that in the pre-crisis period, leading to a relatively steep Phillips curve (e.g., Stella & Stock, 2012; Oinonen et al., 2013). In particular, this phenomenon is more noticeable at the quarterly inflation horizon. Second, a comparison of empirical results in the pre- and post-Volcker periods in Table 5 shows that the recent period delivers the larger role of forward-looking behavior in accounting for inflation dynamics (e.g., Zhang et al., 2008).[27]

This result is intimately linked to smaller inflation uncertainty in the post-Volcker period than that in the pre-Volcker period in Table 4. In particular, inflation uncertainty 3 (standard deviation of inflation rates) shows more marked differences. The low and stable period of inflation gives rise to smaller uncertainty than the volatile and unstable period (e.g., 1960s and 1970s) of inflation because high inflation makes people hard to predict accurate future prices. It leads real values of future payments and earnings to be more uncertain, thereby inducing distortions of resource allocations.[28] It implies that managing inflation expectations during the stable and tranquil period of inflation is easier than the period in which the inflation rate constantly rises, resulting in better-anchored inflation expectations by credible monetary policy (e.g., Oinonen et al., 2013; Stella & Stock, 2012).

5. Conclusion

The NKPC has gained popularity from its appealing theoretical micro-foundations and achieved empirical success since the early

[23] All the estimates are significant at 1% and 5% levels.

[24] This is an important exercise since the stability analysis using the sub-samples tests whether the estimates of NKPC are immune to the Lucas critique.

[25] This paper sets the starting period at 1984 as in Roberts (2005). Furthermore, many economists argue that a new monetary regime started in 1984, which is characterized by an active monetary and passive fiscal policy. This new policy implemented by Paul Volcker successfully curbed inflation rates and expectations that inflation continues to rise, thereby keeping inflation rates at around 3% after 1984.

[26] The CUE with the IV set 1 is used for the results.

[27] The analysis between the pre- and post-crisis periods also exhibits the similar result.

[28] Some studies demonstrate that high inflation leads to greater uncertainty (e.g., Ball, 1992; Friedman, 1977).

Table 5
Sub-sample analysis.

	Reduced-form NKPC							
	Pre-Volcker period (1960–1983)				*Post-Volcker period (1984–2016)*			
	μ_f	μ_b	η	*J-statistic*	μ_f	μ_b	η	*J-statistic*
Q-horizon	0.690***	0.304***	0.031***	1.843	0.848***	0.161* (0.087)	0.023 (0.018)	0.932
	(0.021)	(0.021)	(0.008)	(0.765)	(0.095)			(0.920)
SA-horizon	0.545***	0.453***	0.098***	1.677	0.552***	0.448***	0.003 (0.014)	1.711
	(0.023)	(0.023)	(0.030)	(0.795)	(0.052)	(0.049)		(0.789)
A-horizon	0.432***	0.566***	0.584***	1.000	0.476***	0.528***	0.395***	1.000
	(0.001)	(0.001)	(0.002)	(0.910)	(0.001)	(0.001)	(0.002)	(0.910)
	Pre-crisis period (1960–2006)				*Post-crisis period (2007–2016)*			
Q-horizon	0.719***	0.277***	0.024* (0.012)	2.824	0.824***	0.197***	0.066***	0.805
	(0.069)	(0.068)		(0.588)	(0.056)	(0.050)	(0.019)	(0.938)
SA-horizon	0.592***	0.408***	0.035 (0.025)	3.541	0.681***	0.322***	0.074* (0.038)	1.000
	(0.039)	(0.043)		(0.472)	(0.071)	(0.065)		(0.910)
A-horizon	0.481***	0.522***	0.480***	1.001	0.565***	0.430***	0.209***	1.000
	(0.002)	(0.002)	(0.004)	(0.910)	(0.001)	(0.001)	(0.001)	(0.910)
Wald test								
	$H_o: \mu_f^q = \mu_f^{sa}$ *vs.* $H_a: \mu_f^q \neq \mu_f^{sa}$			$H_o: \mu_f^{sa} = \mu_f^a$ *vs.* $H_a: \mu_f^{sa} \neq \mu_f^a$			$H_o: \mu_f^q = \mu_f^a$ *vs.* $H_a: \mu_f^q \neq \mu_f^a$	
Pre [Post]-V	3.602 (0.058) [9.809(0.002)]			3.727 (0.054) [2.443 (0.118)]			10.796 (0.001) [15.792 (0.000)]	
Pre [Post]-C	4.665 (0.031) [6.150 (0.013)]			8.219 (0.004) [2.857 (0.091)]			11.985 (0.001) [21.525 (0.000)]	

Note: ***, ** and * denote 1%, 5% and 10% significance levels respectively. Parenthesis below the estimate indicates the HAC-robust standard error, whereas parenthesis below (and next to) the statistic indicates p-value. Wald test is a test for equality of estimated coefficients of forward-looking behavior between two models. μ_f^q, μ_f^{sa} and μ_f^a denote the coefficient of the forward-looking behavior for the quarterly, semi-annual and annual inflation horizons, respectively. Q-, SA- and A-horizon indicate the quarterly, semi-annual and annual one. Pre [Post]-V and –C indicate Pre [Post]-Volcker period and -crisis period.

1980s, leading it to be a cornerstone of mainstream macroeconomic models. Nonetheless, a substantial body of literature has presented mixed empirical evidence in various aspects, in particular in terms of the relative importance of forward- and backward-looking behavior in explaining inflation dynamics.

This paper contributes to this important debate by taking a different approach from previous studies: It examines whether the inflation horizon is also an important determinant of changes in the role of expected inflation by estimating the conventional NKPC using the quarterly, semi-annual and annual inflation horizons.

The baseline result finds that the role of forward-looking behavior reduces as the inflation horizon increases, implying that it also hinges largely on the choice of inflation horizon. For example, the degree of forward-looking behavior is large for the quarterly horizon, whereas the annual horizon shows the large role of backward-looking behavior in accounting for inflation dynamics. This main finding can be explained by the positive link between inflation horizon and inflation uncertainty measured by the conditional standard deviation from NKPC-GARCH models, standard GARCH models and the standard deviation of inflation rates. As the inflation horizon is longer, firms are more likely to have recourse to a safe way (e.g., use of information on the past prices as a forecasting rule for the current price) to set their current price due to an increase in uncertainty of future prices that may negatively affect the expected discounted sum of profits. As a result, the relative size of backward-looking behavior increases as the inflation horizon is long.

In addition to the main empirical result, some interesting results emerge. First, the fraction of backward-looking firms at the longer horizons is larger than that at the short horizon. Second, the role of expected inflation has become larger since the post-Volcker period due to the better-anchored inflation expectations by the central bank, and in particular the recent Phillips curve in the post-crisis period shows the largest role of expected inflation. Third, the Phillips curve flattens in the post-Volcker period, while the post-crisis period shows a relatively steep Phillips curve, suggesting that the forcing variable adds more explanatory power to inflation behavior during this period. Finally, all measures of inflation uncertainty reveal that inflation during the post-Volcker period is more stable and predictable than that during the pre-Volcker period in which inflation shows a rising trend with large volatility, causing future prices to be more uncertain.

The overall lesson from the main empirical result in this paper is that neither the view of essential role of forward-looking behavior nor the opposite view of important role of backward-looking behavior can be disregarded for explaining inflation dynamics. Moreover, since large uncertainty at the long horizons creates risks for economic activities, in particular long-term planned activities, reducing variability of inflation at the long horizons would be the key to an improvement in credibility of monetary policy.

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Author contributions

Yoonseok Choi
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
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Performed the analysis
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Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 2: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 3: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
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Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
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Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 4: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 5: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 6: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 7: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 8: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 9: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

Collected the data
Specify contribution in more detail (optional; no more than one sentence)
Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)
Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)
Other contribution
Specify contribution in more detail (required; no more than one sentence)
Author 10: N/A
Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)
Collected the data
Specify contribution in more detail (optional; no more than one sentence)
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