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The role of forward- and backward-looking information for inflation expectations formation

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Abstract

Assuming that private forecasters learn inflation dynamics to form their inflation expectations and that they believe a hybrid New Keynesian Phillips curve (NKPC) to capture the true data-generating process of inflation, we aim at establishing the role of backward- and forward-looking information in the inflation expectation formation process. We find that longer term expectations are crucial in shaping shorter horizon expectations. While the influence of backward-looking information seems to diminish over time, we do not find evidence of a structural break in the expectation formation process of professional forecasters. Our results further suggest that the weight put on longer term expectations does not solely reflect a mean-reverting process to trend inflation. Rather, it might also capture beliefs about the central bank's long-run inflation target and its credibility to achieve inflation stabilization.

KEYWORDS
inflation, new keynesian phillips curve, survey expectations

1 | INTRODUCTION

Private expectations regarding future economic developments influence current decisions about wages, savings and investments, and concurrently, policy decisions. In recent years there has been an increasing interest in explaining the private inflation expectations formation process by departing from the full information rational expectations hypothesis.[1] Another strand of literature has focused on inflation dynamics and the role of private expectations in estimating New Keynesian Phillips curves (NKPC).[2]

The objective of this paper is to investigate inflation expectation dynamics, not inflation dynamics. We build on the result that the NKPC is a robust representation of how inflation evolves. By bridging these two strands of literature, this paper aims to document the role of backward- and forward-looking information in inflation expectation dynamics and investigates the role of longer term private inflation expectations in determining shorter term inflation expectations. Assuming that professional forecasters learn the dynamics of inflation to form their inflation expectations and that they believe the reduced-form hybrid

[1]Within this literature, Mankiw and Reis (2002) propose a sticky-information model, while Sims (2003), as well as Moscarini (2004) or Mackowiak and Wiederholt (2009) focus on partial and noisy information models. In both types of model, a fraction of the information set used by private agents is backward looking—that is, based on past information. Carroll (2003), Mankiw, Reis, and Wolfers (2003), Pesaran and Weale (2006), Branch (2007), Nunes (2009), Andrade and Le Bihan (2013), Coibion (2010), and Coibion and Gorodnichenko (2012, 2015a) provide empirical evidence based on survey data to characterize and distinguish these types of models.

[2]Roberts (1995, 1997), Galí and Gertler (1999), Rudd and Whelan (2005), Nunes (2010), and Adam and Padula (2011, among others, assess the relative weights of forward- and backward-looking components of inflation. The latter may play a role due to a share of "backward-looking" firms that do not reoptimize their prices but set them according to a rule of thumb (see, e.g., Steinsson, 2003) or index them to lagged inflation as in Galí and Gertler (1999) or Christiano, Eichenbaum, and Evans (2005).

NKPC captures the true data-generating process of inflation dynamics, our contribution to the literature is to propose an NKPC-based inflation expectations formation equation. We then assess whether and by how much professional forecasters' inflation expectations are driven by forward-looking information (i.e., further-ahead expectations) or backward-looking information (i.e., past realized or perceived inflation).

Three papers have opened this line of research. Lanne, Luoma, and Luoto (2009) find that inflation expectations are consistent with a sticky-information model where a proportion of households base their expectations on past inflation. Pfajfar and Santoro (2010) show that the distribution of professional forecasts might be explained by three different expectation formation processes: a static or highly autoregressive process, a nearly rational approach, and adaptive learning and sticky information models. Cornea-Madeira, Hommes, and Massaro (2017) find time variation and heterogeneity in the type of expectations formation with evolutionary switching between backward- and forward-looking behavior.

Estimating these forward- and backward-looking parameters matters for understanding how private expectations are formed and how policymakers can anchor them. Optimal monetary policy is determined by the degree of price stickiness (see, e.g., Erceg, Henderson, & Levin, 2000; Steinsson, 2003) and by the expectations formation process—that is, whether professional forecasters use up-to-date information about the state of the economy or continue using their previous plans and set prices based on outdated information (see, e.g., Ball, Mankiw, & Reis, 2005; Reis, 2009). Therefore, the real effects of monetary policy and policy recommendations depend on the speed of price adjustments, which in turn depend on the (in)completeness of information and/or the degree of backward- and forward-lookingness of price setters and inflation forecasts.

We estimate our NKPC-based inflation expectations formation equation on US data, for which survey expectations of the gross domestic product (GDP) deflator from the Survey of Professional Forecasters (SPF) are fixed-horizon forecasts and available on a long time span—that is, from 1968:Q4. We test the robustness of our results using various variables for marginal costs, including a constructed measure of the output gap. Finally, we also assess whether relative weights have varied across time, differ with the forecasting horizons, and whether longer term expectations could be seen as a proxy for trend inflation.

We provide original evidence that longer term inflation expectations are crucial in determining shorter horizon inflation expectations.[3] First, professional forecasters put relatively more weight on forward-looking information whereas the weight put on past information is significant but quite small. Second, we find that the estimated parameter of forward-looking information tends to increase over time, while there is no structural break. Though still significant, the influence of backward-looking information seems to diminish over time. We also find that these results are stable when the forecasting horizon varies or when we consider further-ahead horizons for forward-looking information. Our results further suggest that longer-term expectations should not be seen as a proxy for trend inflation. Third, the coefficients are similar to those found in the literature estimating the actual NKPC, which suggests that professional forecasters may use this relationship to form their own inflation expectations.[4]

These results are related to Ang, Bekaert, and Wei (2007) and Cecchetti, Hooper, Kasman, Schoenholtz, and Watson (2007). They provide evidence that survey expectations have a good forecasting performance that stems from survey respondents' ability to anticipate structural change. One reason why professional forecasters use further-ahead expectations—information at horizons further ahead than the forecasting horizon—to form their expectations could thus be that further-ahead expectations might be seen as a representation of the long-run beliefs about the central bank inflation target and about the central bank credibility to achieve inflation stabilization. The fact that the weight on forward-looking (backward) information has an upward (downward) dynamic echoes back to Coibion and Gorodnichenko (2015b) and the “anchored expectations” hypothesis of Bernanke (2010), that the credibility of the Federal Reserve is such that neither high inflation nor deflation is seen as a plausible outcome so actual inflation, and short-run inflation expectations remain stable through expectational effects. z The two main implications of these results for policymakers are, first, that anchoring medium- or long-term expectations enables anchoring shorter term expectations and, second, that professional forecasters' expectations still depend (in part) on past information. Importantly, it appears that the expectation formation process is relatively stable over time. Besides, the estimated parameters may serve for calibrating macroeconomic models in which private expectations

[3]This result is found to be robust to specification tests, to the exclusion of the financial crisis and post-2007 data, to the use of real-time data, to generalized method of moments (GMM) estimation, to various measures of marginal costs, and to the inclusion of potentially relevant additional variables.

[4]Mavroeidis, Plagborg-Moller, and Stock (2014) and Coibion, Gorodnichenko, and Kamdar (2018) survey empirical evidence on the actual NKPC and find a vast set of results. Our estimated coefficients for the NKPC-based equation are in the mode region of the distribution of all point estimates they report.

are not solely forward looking. Finally, it appears that professional forecasters form their inflation expectations on the grounds of the hybrid NKPC.

The rest of the paper is organized as follows. Section 2 describes the methodology and data. Section 3 reports the empirical analysis, while Section 4 aims to characterize forward-looking information. Section 5 concludes.

2 | EMPIRICAL STRATEGY

2.1 | Framework

Galí and Gertler (1999) propose a hybrid NKPC of the following form, where π_t is the inflation rate, $\mathbb{E}_t\pi_{t+1}$ is expected future inflation, and mc_t is a measure of marginal costs:

$$\pi_t = \lambda mc_t + \gamma_f \mathbb{E}_t\pi_{t+1} + \gamma_b \pi_{t-1}. \tag{1}$$

The equation derives from a New Keynesian model with staggered price setting á la Calvo, where a fraction of firms set their prices using the lagged aggregate inflation rate, γ_f and γ_b being the weights on the forward-looking and the backward-looking variable, respectively.

Under the assumption of unbiased expectations and in the case of current-quarter expectations, it holds that $\pi_t = \mathbb{E}_t\pi_t + \epsilon_t$, where the error term ϵ_t has zero mean.[5][6] Combining these two equations yields the following NKPC-based inflation expectations formation equation:

$$\mathbb{E}_t\pi_t = \lambda mc_t + \gamma_f \mathbb{E}_t\pi_{t+1} + \gamma_b \pi_{t-1} - \epsilon_t. \tag{2}$$

We use the output gap x_t as a proxy for marginal costs (as is common in the literature; see, for example, Fuhrer & Moore, 1995; Woodford, 2003), and we measure expected inflation by survey expectations, as is often done in the literature on Phillips curve estimations (see; Adam & Padula, 2011; Nunes, 2009) or on monetary policy rules (see, e.g., Orphanides, 2001). We thus estimate the following equation, where $\mathbb{S}_t$ represents inflation expectations collected from a survey of forecasters:

$$\mathbb{S}_t\pi_t = \delta x_t + \beta_f \mathbb{S}_t\pi_{t+1} + \beta_b \pi_{t-1} + \nu_t, \tag{3}$$

and where the error term $\nu_t = u_t - \epsilon_t$ has zero mean, and it is not restricted otherwise such as the estimated measurement error u_t.[7]

This approach is different but related to the study by Smith (2009), which proposes a forecast pooling method that improves statistical fit compared to GMM estimation of the NKPC but not dramatically compared to the use of surveys, whereas Nunes' (2010) different pooling approach gives less weight to surveys, while they still appear as a key ingredient of the information set of price-setters. Finally, Kozicki and Tinsley (2012) develop a model of expected inflation using survey forecasts to capture shifts in structural changes, while Brissimis and Magginas (2008) use survey forecasts to explain inflation dynamics.

Our empirical model is derived from a monopolistic price-setting environment with homogeneous agents as in Adam and Padula (2011), where rational expectations are substituted by the median of forecasters' subjective expectations. We then obtain the dynamics of inflation expectations by combining the process explaining inflation dynamics and the property that the median of forecasters' subjective expectations is unbiased as shown, for example, by Thomas (1999), Croushore (2010), or Smith (2009).

2.2 | Data

We focus on quarterly US data for which GDP deflator forecasts from the SPF are available on a fixed-horizon scheme[8] and for a long time span: 1968;Q4–2017;Q1. We use the median of individual responses as our baseline. Figure 1 plots SPF inflation expectations at the current horizon (nowcast) and the one-quarter-ahead horizon for the GDP deflator. These different measures show similar statistical properties in terms of persistence. Consistent with US inflation history, inflation expectations followed the disinflation path during the 1980s, while they have seemed anchored around 2% ever since.

The output gap is computed based on the Congressional Budget Office (CBO)'s assessment of the real potential GDP. For robustness, we also compute a filtered version of real GDP. We use the one-sided Christiano–Fitzgerald (CF) random walk band-pass filter under the common assumption of a business cycle duration of 6 up to 32

[5] We precede our empirical analysis with tests of the hypothesis that survey expectations are unbiased. The results of these tests are presented in Table A2 in the Appendix. To account for potential bias in expectations, we estimate all models with a constant α, verifying that it is insignificant.

[6] This specification is different from rational expectations, for which three additional assumptions would be required: ϵ_t is normally distributed, not serially correlated, and uncorrelated with all past information (any variable dated t or earlier); see, for example, Andolfatto, Hendry, and Moran (2008) for a discussion of rational expectations.

[7] We later analyze whether endogeneity may be an issue in this specification, so that the error term ν_t would be correlated with the expectation term; see Table A4.

[8] An advantage of fixed-horizon forecasts compared to fixed-event forecasts is that the latter have a decreasing forecasting horizon in each calendar year. One might thus consider this variable as not being drawn from the same stochastic process which introduces heteroskedasticity in the estimation process.

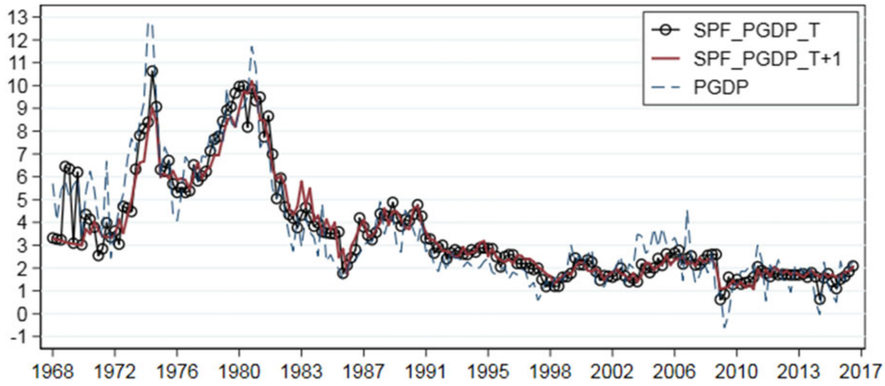

FIGURE 1 Survey expectations and actual PGDP. This figure shows SPF expectations for the GDP deflator and its actual values. SPF_PGDP_T is the nowcast of the GDP deflator, SPF_PGDP_T+1 is the one-quarter-ahead forecast and PGDP is the actual GDP deflator measured with final data [Colour figure can be viewed at wileyonlinelibrary.com]

quarters (see; Christiano & Fitzgerald, 2003).[9] To further check the robustness of the results we also use other marginal cost measures frequently considered in the literature: namely, unit labor costs, labor share, the unemployment gap (also based on the CBO's estimate of the NAIRU), inventories, industrial production index, and capacity utilization.

Further, we evaluate our models with real-time data to examine whether results are different with respect to the use of final revised data. The SPF survey and other real-time data come from the Federal Reserve of Philadelphia, while final data are from the FRED database. See Table A1 in the Data Appendix for more details.

3 | FORWARD VERSUS BACKWARD-LOOKING INFORMATION

3.1 | Baseline results

We present ordinary least squares (OLS) estimates of Equation 3 in Table 1. We compute heteroskedasticity and autocorrelation robust Newey–West standard errors, assuming that the autocorrelation dies out after four quarters.[10] The coefficients on the forward- and backward-looking element of the inflation expectations formation process are estimated to be 0.76 and 0.25, respectively. This means that forward-looking expectations dominate the formation process, while the backward-looking part is still significant. This outcome is consistent with the literature focusing on the expectations formation process, which finds a role—small but significant—for backward-looking behavior as in Lanne et al. (2009) or Pfajfar and Santoro (2010). The resulting coefficients are also similar to those found in the literature on estimations of the actual NKPC (see, e.g., Galí & Gertler, 1999; Mavroeidis et al., 2014; Nunes, 2010; Woodford, 2003). This suggests that forecasters may form their predictions on the grounds of the NKPC assuming that it properly captures inflation dynamics.[11] In line with the NKPC literature we evaluate the hypothesis that the weights on the backward- and the forward-looking element add up to one by means of a partial F test. The null hypothesis cannot be rejected, consistent with other studies findings for the actual NKPC (Galí & Gertler, 1999; Woodford, 2003).

The coefficient on the output gap is negative and significant. The negative sign on the output gap coefficient might be a surprise on theoretical grounds, while it is well documented empirically in the NKPC literature (see ; Nunes, 2010; Woodford, 2003). In the Appendix, we test the robustness of the backward- and forward-looking parameters when using alternative marginal cost measures that yield estimates more in line with the theory.

The high R^2 of 0.94 derives, among other things, from the fact that survey expectations of the GDP deflator at different horizons are highly correlated. Given the high correlation among inflation variables and the survey measure, we test for multicollinearity evaluating the uncentered variance inflation factors, and we reject it for the models we analyze in this paper. We also verify that including a con-

[9]Using a one-sided filter means that the estimated output gap does not contain any information about the future which is not available in real time.

[10]The Breusch–Godfrey test indicates the absence of any serial correlation in the error term at different lag lengths for the baseline model (p-values of 0.14 at four lags). We nevertheless estimate robust Newey–West standard errors. The choice of lag length corresponds to the Stock and Watson (2007) rule of thumb, which suggests setting it equal to $0.75 \times T^{\frac{1}{3}}$ (rounded), T being the number of observations.

[11]Estimating Equation 3 on a sample ending in 2007:Q3, so excluding the global financial crisis, yields extremely similar results and excludes that these outcomes are driven by the most recent data only.

TABLE 1 NKPC-based inflation expectation formation model

	Baseline	Constrained	Forward-looking	Backward-looking
β_f	0.762***	0.748***	1.029***	
	[0.08]	[0.06]	[0.03]	
β_b	0.249***	0.252***		0.826***
	[0.07]	[0.06]		[0.05]
δ	0.032*	0.032*	0.052**	−0.008
	[0.02]	[0.02]	[0.02]	[0.04]
Constant	0.037	0.076	0.022	0.587***
	[0.09]	[0.05]	[0.13]	[0.16]
N	193	193	194	193
R^2	0.94	.	0.93	0.85
$\beta_f + \beta_b = 1$	0.65	.	.	.
$\beta_f = 1$	.	.	0.34	.
$\beta_b = 1$	.	.	.	0.00
LR test	.	.	0.00	0.00

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS. Asymptotic Newey–West four lags robust standard errors are in brackets. The "Constrained" approach enforces the following condition: $\beta_f + \beta_b = 1$. In this case, Huber–White/sandwich robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$. The next two rows show the p-values based on an F test for the hypothesis that the given parameter equals one for the alternative models. The following row gives the p-value corresponding to an LR test of the alternative model relative to the baseline model.

stant does not improve the fit of the model, as the constant is statistically insignificant.

As is common in the NKPC literature, we further evaluate a model where we constrain the sum of the coefficients β_f and β_b to one (see, e.g., Galí & Gertler, 1999). In this case, standard errors are computed with the Huber–White/sandwich robust variance estimates. The results based on this approach are presented in Table 1 and the estimated parameters are very similar.[12]

We implement a model specification test to assess whether our NKPC-based equation is properly specified. More specifically, we test whether the squared fitted values of our baseline regression are a significant determinant of the dependent variable. The intuition behind the *link* test is that if the model is correctly specified the squared fitted values should have no explanatory power. The p-value associated with the squared fitted values is 0.78, suggesting that the present results are not driven by misspecification.

The previous results provide support for our NKPC-based expectations formation model; that is, the fact that the coefficients on the forward- and backward-looking variables are significantly different from zero and in line with NKPC estimates may be interpreted as evidence in favor of this baseline model. As a next step, we compare our baseline model to two major alternative inflation expectations formation processes, namely a purely forward-looking ($\gamma_b = 0$ in Equation 3) and a purely backward-looking model ($\gamma_f = 0$). We present parameter estimates for the alternative models and LR test results in the final columns of Table 1, in order to provide evidence in favor or against these models relative to our baseline. The LR test clearly rejects the reduced models in favor of our baseline NKPC-based inflation expectations formation model.

Turning to the parameter estimates, the purely backward- and the purely forward-looking model perform differently. The latter has an R^2 similar to the baseline case and the coefficient β_f is insignificantly different from one. The former model, on the other hand, has a lower R^2, with the coefficient β_f being significantly smaller than one, while the constant is large and significant. We interpret these results as the purely forward-looking model approximating our baseline model reasonably well, while the backward-looking model is clearly inferior.[13] At the same time it is worth noting that forward-looking expectations may incorporate information on past developments and thus may implicitly capture some degree of backward-lookingness.

[12]Given the constrain put on the estimation, no goodness-of-fit measure is provided as it would have a different interpretation.

[13]We also compare our baseline model to an autoregressive model. Performing two nonnested model tests as suggested by Coibion (2010), we find that both our baseline model and the AR model cannot be rejected statistically, while the former is preferred over the alternative. Results are available upon request.

These findings square well with the evidence by Coibion and Gorodnichenko (2015a). They argue that deviations from the full-information rational expectations hypothesis are unlikely to be driven by departures from rationality and instead are driven by deviations from the assumption of full information. This is consistent with our finding of a significant lagged inflation rate in the forecasters' expectations formation equation suggesting the presence of informational rigidities in the economy which does not preclude rationality of the forecasters.

3.2 | Time variation

In Table 2 we present results for different subsamples that correspond to the monetary regimes in the USA over the last decades: the pre-Volcker disinflation before 1984, the disinflation and Great Moderation from 1984 to 2007, and the post Great Recession after 2007. The forward-looking coefficient is high and significant in the three subsamples but increases over time, from 0.71 to 0.83 and finally 0.88. In contrast to that, the backward-looking coefficient decreases from 0.23 to 0.14. The latter finding could be related to a larger emphasis on backward-looking information when forecasting in the early part of the sample. Studies on the actual NKPC similarly find a larger weight on backward-looking elements in the 1960s and 1970s (see, e.g., Galí & Gertler, 1999).

As shown in the literature, the parameters of the estimated NKPC may display some degree of instability (see, e.g., Inoue & Rossi, 2011) that would not be captured by discrete breaks but through continuous and slow changes. Thus this raises the question whether the dynamics of inflation expectations also exhibit a similar degree of variability. To that end, we estimate Equation 3 with a rolling window of 120 observations. The resulting estimates are reported in Figure 2 along with 68% and 95% confidence interval bands.

TABLE 2 Subsamples

	Pre-1984	1984–2007	Post-2007
β_f	0.729***	0.828***	1.107***
	[0.13]	[0.05]	[0.25]
β_b	0.283***	0.144***	0.136***
	[0.08]	[0.04]	[0.05]
δ	0.072**	−0.011	−0.059*
	[0.03]	[0.02]	[0.03]
Constant	0.078	0.043	−0.608
	[0.42]	[0.14]	[0.51]
N	60	92	41
R^2	0.84	0.88	0.72
$\beta_f + \beta_b = 1$	0.87	0.60	0.32

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$.

The estimated coefficients show some variability consistent with the changes in point estimates reported in Table 2. While the weight put on the forward-looking variable seems to increase slightly, the coefficient on the backward-looking variable exhibits a downward movement over time. However, these differences are not significant. One can thus conclude that there has not been a de-anchoring of expectations during the great recession. Overall, these results provide evidence for the robustness of the estimated parameters of the baseline model in Table 1.[14]

3.3 | Final versus real-time data

We also present estimates based on real-time data since the timing of information is paramount in this context. Orphanides (2001) stresses that the use of final revised data in Taylor rule estimations may cause misleading results given that economic agents can only know the most recent publication of data rather than revisions that would be published in the future. Accordingly, the determinants of inflation and hence inflation expectations should then depend on the information available to professional forecasters at that time. We thus evaluate our model with real-time data stemming from the Real-Time Database from the Federal Reserve Bank of Philadelphia.

In column 1 of Table 3, we replace both the lagged inflation measure as well as the real GDP variable used to construct the output gap by their respective first vintage published. In column 2, the inflation variable considered is the second vintage published. Table 3 shows that the parameter estimates are largely unchanged, while the forward-looking coefficient is somewhat higher and the backward-looking coefficient is somewhat lower than in the baseline approach, but the differences are not significant.

One can also argue that even the first release of real GDP is not yet known at time t, as survey respondents have to provide their answers during a given quarter, while the first vintage of this given quarter will typically not be released before the following quarter. In column 3 of Table 3, we therefore replace the output gap measure by an unemployment gap measure based on the first release of unemployment. The results are very similar to the two previous specifications that use real-time data.

[14] We also estimate the model on a rolling window of only 48 observations (see Figure A1 in the Appendix). While the estimation results are slightly more volatile they still support the main messages from the previous analysis.

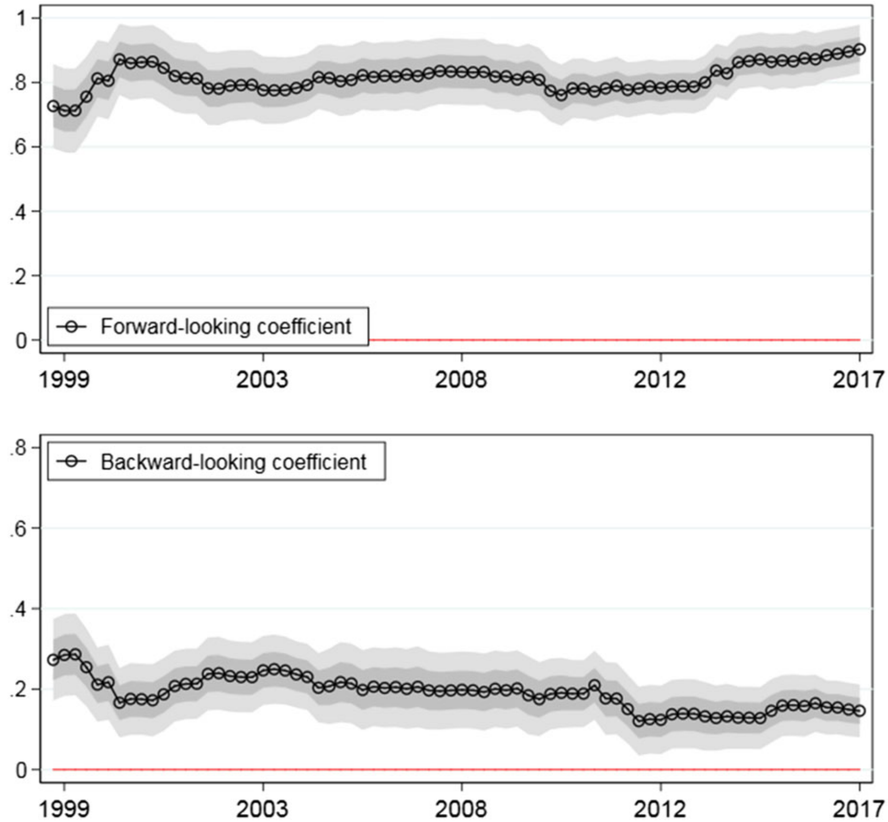

FIGURE 2 Time-varying estimation. These plots show the time series of the forward-looking parameter β_f and the backward-looking parameter β_b in Equation 3. The rolling-window estimation is performed on 48 observations. The gray area around point estimates represent the 1- and 2-standard-error confidence bands [Colour figure can be viewed at wileyonlinelibrary.com]

3.4 | Does different forward-looking information matter?

We also examine whether the lack of some potentially important but omitted variables—the federal funds rate and oil prices, for instance—may bias the baseline estimates. Survey respondents might base their expectations on more information than is incorporated in Equation 3, and one way to test whether forecasters form their expectations on the grounds of the NKPC is to add more variables to the regression to evaluate whether additional information changes our baseline estimates. We also test the effect of including the Chicago Fed National Activity Index (CFNAI), which is a weighted average of 85 existing indicators of economic activity and related inflationary pressures developed by Stock and Watson (1999) and supposed to capture the relevant information set of forecasters. We include a lag of either the federal funds rate, oil price changes or CFNAI, and then all three together.[15] We aim to capture the stance of monetary policy, a potential external price shock or activity shock, and to analyze how these affect the results. Given the high autocorrelation in the interest rate (see, e.g., Galí & Gertler, 1999; Mavroeidis, 2010), the previous stance of monetary policy might give an idea about the present and future stances. Similarly, in light of the fact that an external price shock takes some time to feed through the economy, the shock history tells us something about future developments. The estimation results for Equation 4 below (including a constant) are given in Table 4:

$$\mathbb{S}_t\pi_t = \delta x_t + \beta_f \mathbb{S}_t\pi_{t+1} + \beta_b\pi_{t-1} + \gamma_i X_{i,t-1} + \eta_t. \quad (4)$$

The additional information does not seem to improve the fit of the model. The R^2 is almost the same as in the baseline case and the parameter estimates are essentially unchanged. The conclusions from the baseline model remain unaltered.

3.5 | Robustness

In the following, we discuss various robustness checks. First, we examine the use of other variables for marginal

[15]The additional variables are denoted by $X_{i,t-1}$ with coefficient γ_i, where i may be either o, f or c.

TABLE 3 Real-time data estimation

	First vintage	Second vintage	Unemp.
β_f	0.787***	0.783***	0.773***
	[0.07]	[0.08]	[0.07]
β_b	0.233***	0.230***	0.238***
	[0.06]	[0.06]	[0.06]
δ	0.010***	0.009***	−0.070**
	[0.00]	[0.00]	[0.03]
Constant	0.034	0.037	0.045
	[0.09]	[0.09]	[0.10]
N	193	193	193
R^2	0.94	0.95	0.94
$\beta_f + \beta_b = 1$	0.37	0.61	0.66

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$.

TABLE 4 Including additional forward-looking variables

	Oil	FFR	CFNAI	All
β_f	0.768***	0.703***	0.775***	0.715***
	[0.08]	[0.10]	[0.08]	[0.11]
β_b	0.232***	0.257***	0.236***	0.234***
	[0.07]	[0.07]	[0.07]	[0.07]
δ	0.031*	0.024	0.048**	0.030
	[0.02]	[0.02]	[0.02]	[0.03]
γ_o	0.002*			0.002*
	[0.00]			[0.00]
γ_f		0.036		0.036
		[0.02]		[0.03]
γ_c			−0.071	−0.030
			[0.06]	[0.07]
Constant	0.055	0.012	0.059	0.040
	[0.09]	[0.09]	[0.09]	[0.09]
N	193	193	193	193
R^2	0.94	0.94	0.94	0.94
$\beta_f + \beta_b = 1$	0.98	0.41	0.63	0.33

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017;Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$.

cost measures that are typically used in the NKPC literature. One common approach is to rely on filtered GDP (see, e.g., Nunes, 2010). Therefore, we show how our results change if we use this latter approach to construct the output gap. More importantly, many authors question the usefulness of the output gap to represent marginal costs in estimations of Phillips curves (among them ; Galí & Gertler, 1999; Galí, Gertler, & López-Salido, 2005; Sbordone, 2002). Other variables commonly suggested are unit labor costs, labor share, unemployment rate (as in the original Phillips curve), industrial production, capacity utilization or inventories. Estimation results for our models based on these marginal cost measures, as well as the different output gap, are presented in the Appendix in Table A3.

Second, given potential measurement error due to the use of surveys (for a discussion of this point see ; Adam & Padula, 2011) and potential endogeneity, we also compare our model results with those from using various GMM approaches (see Table A4), where we treat different predictor variables as endogenous. Further, we provide tests for endogeneity of the explanatory variables, so that OLS would be inconsistent. We compute a test based on the difference between two Hansen–Sargan statistics (one for the GMM approach and one for the OLS approach). The null hypothesis is that the tested variables are exogenous. The test yields p-values of 0.47, 0.68, and 0.82 for the three two-step GMM approaches considered, respectively; that is, we test whether the error term ν_t is uncorrelated with only the expectation term, with the latter and the output gap, or with all three explanatory variables. These results provide evidence in favor of OLS consistent estimates. The main conclusions of Section 3.1 are robust to the different approaches presented in the Appendix.

4 | CHARACTERIZING FORWARD-LOOKING INFORMATION

In this section, we depart from our baseline model in two ways to gain a better understanding of the type of forward-looking information that agents rely on. First, we increase the horizon of inflation expectations used by professional forecasters to determine current inflation expectations. Second, we replace the longer term inflation expectations by a measure of trend inflation as the forward-looking variable.

4.1 | Near versus further-ahead forward-looking information

We aim at establishing the role of the horizon of forward-looking information in the expectations formation process, and more precisely whether professional forecasters put relatively more weight on near or further-ahead

TABLE 5 Near versus further-ahead forward-looking information

	$\mathbb{S}_t\boldsymbol{\pi}_t$	$\mathbb{S}_t\boldsymbol{\pi}_t$	$\mathbb{S}_t\boldsymbol{\pi}_t$	$\mathbb{S}_t\boldsymbol{\pi}_t$	$\mathbb{S}_t\boldsymbol{\pi}_t$
$\beta_f(\mathbb{S}_t\pi_{t+1})$	0.762***				
	[0.08]				
$\beta_f(\mathbb{S}_t\pi_{t+2})$		0.746***			
		[0.07]			
$\beta_f(\mathbb{S}_t\pi_{t+3})$			0.632***		
			[0.07]		
$\beta_f(\mathbb{S}_t\pi_{t+4})$				0.439***	
				[0.10]	
$\beta_f(\mathbb{S}_t\tilde{\pi}_{t+4})$					0.702***
					[0.08]
β_b	0.249***	0.321***	0.415***	0.572***	0.359***
	[0.07]	[0.06]	[0.06]	[0.08]	[0.07]
δ	0.032*	0.037**	0.039	0.048**	0.047**
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Constant	0.037	−0.168	−0.103	0.076	−0.114
	[0.09]	[0.11]	[0.12]	[0.15]	[0.12]
N	193	193	193	193	193
R^2	0.94	0.94	0.92	0.91	0.94
$\beta_f + \beta_b = 1$	0.65	0.03**	0.15	0.79	0.05*

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS, where the horizon of the forward-looking component varies. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$.

forward-looking information. On the one hand, one may expect that professional forecasters have a better understanding of the closer economic outlook and thus put more weight on forward-looking information with a shorter horizon; on the other hand, professional forecasters might use forward-looking information as a representation of the long-run of the economy and of the equilibrium value of inflation and therefore put more emphasis on further-ahead forward-looking information.

The results reveal the following pattern, as shown in Table 5. The weight of forward-looking information diminishes with the forecasting horizon relative to the baseline model, from 0.77 at the one-quarter-ahead horizon to 0.46 at the four-quarter-ahead horizon. Accordingly, the weight on the backward-looking variable increases such that the sum of the forward- and backward-looking variable remains insignificantly different from one. A precise assessment of the relative importance of the expectation variable at different horizons in the same model is impeded by the fact the these measures are highly correlated.

Table 5 also features results on a model where the forward-looking component is the average expected inflation rate over the following four quarters ($\mathbb{S}_t\tilde{\pi}_{t+4}$). This model can be justified, as professional forecasters might find it easier to make predictions for an average over some quarters rather than for an individual quarter. They may use this arguably more reliable average in their information set. Parameter estimates, an F test on the sum of the two coefficients of interest and the R^2 are about the same as in the baseline. Thus the results indicate that this model works about as well as the baseline and that the information incorporated in the further-ahead horizon forecasts is also relevant.

Our findings point out that professional forecasters give more weight to their next quarter forecasts than to those for a longer horizon, while the latter may still play an important role in determining expected current inflation. This might be the case as longer horizon inflation expectations are driven by beliefs about the central bank inflation target or incorporate information on the projected trend inflation rate. Such an interpretation of our findings is consistent with the argument by Faust and Wright (2013) that inflation expectations for the following quarters represent forecasters' expectations of how inflation moves from its current value towards the perceived long-term inflation rate.[16]

4.2 | Trend inflation

In theory, because the NKPC is obtained by log-linearization and variables are considered in terms of deviations from steady state, trend inflation should play no role in such a framework. However, Faust and Wright (2013) argue that inflation expectations represent the way forecasters believe inflation takes from its current expected value (nowcast) towards the perceived trend inflation rate. We therefore assess whether longer term inflation expectations can be seen as a proxy for trend inflation. To do so, we compute trend inflation using the CF filter or a 1-year moving average. We find that the weights put on backward- and forward-looking information are different from the baseline model, when using trend inflation instead of expected inflation in the next quarter, as can be seen in Table 6. The backward-looking coefficient is much higher, whereas the forward-looking coefficient is much lower. The latter is even lower than for the 1-year-ahead inflation expectations of Table 5. We

[16]We also assess whether the formation process of inflation expectations for future quarters differs from the formation process of inflation expectations for the current quarter. In this model, we continue to consider that forecasts at the horizon h are determined by forecasts at the horizon $h + 1$ and we vary the value of h. The weight put on backward- and forward-looking information does not differ dramatically from the baseline model when h varies, as can be seen in Table A5 in the Appendix, thus suggesting that the inflation expectations formation process is relatively stable across the horizons that professional forecasters are typically considering.

TABLE 6 Trend inflation

	Trend only	Trend+SPF	Trend-SPF diff.
$\beta_{f,\text{trend}}$	0.332***	0.107**	
	[0.05]	[0.04]	
β_f		0.691***	0.798***
		[0.09]	[0.07]
$\beta_{f,\text{diff}}$			0.107**
			[0.04]
β_b	0.582***	0.224***	0.224***
	[0.04]	[0.06]	[0.06]
δ	−0.026	0.022	0.022
	[0.03]	[0.02]	[0.02]
Constant	0.246	−0.022	−0.022
	[0.16]	[0.08]	[0.08]
N	193	193	193
R^2	0.88	0.94	0.94

Note. Asterisks denote significance at the ***1%, **%5, and *10% level. Estimation of Equation (3) (including a constant) is conducted by OLS. In the first column, the forward-looking variable is the inflation trend as derived from the CF filter. In the second column, the baseline model is augmented by adding the trend inflation variable. Finally, in the third column, the trend inflation variable is replaced by the difference between the CF trend and the SPF one-quarter-ahead inflation forecast. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom two rows report the number of observations and the R^2 of the regression.

further estimate a model where we augment the baseline setting by including first trend inflation and second the difference between the inflation trend and expected inflation in the next quarter. In these specifications, the forward- and backward-looking coefficients are similar, while the coefficient on trend inflation or its difference with SPF forecasts is significant.

These results suggest that the information conveyed by longer term inflation expectations is not to be interpreted as capturing only trend inflation, as the inflation expectations formation process seems to be based on some information beyond this. One natural candidate would be that longer term inflation expectations also capture the credibility professional forecasters put on the ability of the central bank to reach the inflation target.[17]

5 | CONCLUSION

This paper aims at establishing whether longer term inflation expectations play a role in determining shorter term ones. We evaluate the role of backward-looking, present, and forward-looking information in the professional forecasters' inflation expectations formation process using an NKPC-based expectations formation model. We find that longer term inflation expectations are crucial in determining shorter horizon inflation expectations. Professional forecasters put relatively more weight on forward-looking expectations, while lagged inflation remains significant and the contribution of the marginal cost measure is small. The estimated coefficients are similar to those found in the literature estimating the actual NKPC, suggesting that professional forecasters may indeed use this model to form their inflation expectations and rely more on forward-looking information. These results also hold for different subsamples during which inflation has been very volatile or at the opposite extremely stable, suggesting that there has not been any de-anchoring of inflation expectations. We also find that the estimated parameters of the NKPC-based expectations formation model are relatively stable when the forecasting horizon varies. Finally, we show that longer term inflation expectations capture information beyond the current inflation trend. In particular, they may also be influenced by the policy inflation target and the central banks' credibility in achieving inflation stabilization.

[17]This interpretation notwithstanding, the estimated inflation trend may also change over time, which could further drive professional forecasters' expectations of inflation dynamics in coming quarters.

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APPENDIX A

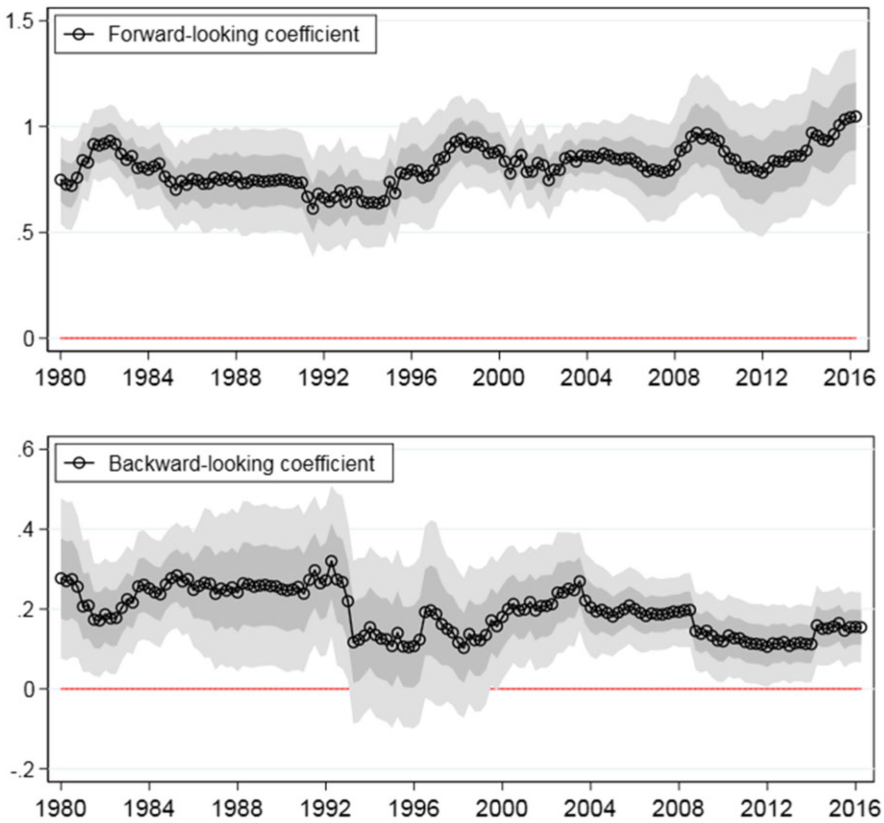

FIGURE A1 Time-varying estimation. These plots show the time series of the forward-looking parameter β_f and the backward-looking parameter β_b in Equation 3. The rolling-window estimation is performed on 120 observations. The gray area around point estimates represent the 1- and 2-standard-error confidence bands [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE A1 Data

Name	Description	Original frequency	Time period
Real-time data first release			
gdp_1st	Real GDP	Quarterly	1968:Q4–2017:Q1
unemp_1st	Unemployment	Quarterly	1968:Q4–2017:Q1
pgdp_1st	GDP deflator	Quarterly	1968:Q4–2017:Q1
pgdp_2nd	GDP deflator	Quarterly	1968:Q4–2016:Q4
Final data			
rgdp	Real GDP	Quarterly	1968:Q4–2017:Q1
pgdp	GDP deflator	Quarterly	1968:Q4–2017:Q1
gdp_cbo	Potential GDP	Quarterly	1968:Q4–2017:Q1
unemp_cbo	(Long-term) NAIRU	Quarterly	1968:Q4–2017:Q1
ulc	Unit labor costs	Quarterly	1968:Q4–2017:Q1
ls	Lab our share	Quarterly	1968:Q4–2017:Q1
unemp	Unemployment rate	Quarterly	1968:Q4–2017:Q1
indpro	Industrial production index	Quarterly	1968:Q4–2017:Q1
cap_uti	Capacity utilization	Quarterly	1968:Q4–2017:Q1
invent	Inventories	Quarterly	1968:Q4–2017:Q1
Survey data (x-quarter-ahead horizon)			
spf_pgdp_0	SPF pgdp expectations (0)	Quarterly	1968:Q4–2017:Q1
spf_pgdp_1	SPF pgdp expectations (1)	Quarterly	1968:Q4–2017:Q1
spf_pgdp_2	SPF pgdp expectations (2)	Quarterly	1968:Q4–2017:Q1
spf_pgdp_3	SPF pgdp expectations (3)	Quarterly	1968:Q4–2017:Q1
spf_pgdp_4	SPF pgdp expectations (4)	Quarterly	1974:Q4–2017:Q1

Note. This table lists the data that we use in the estimation of our models, as well as the respective sources. We use quarterly frequency of the data series, where monthly series are converted to quarterly frequency by taking the 3-month average. The following releases of the data are used: final, first release, and third release. The data series are available for the time periods as indicated in Table the table and come from the following sources: real-time and SPF survey data from the website of the Federal Reserve of Philadelphia and final data from the Federal Reserve of St. Louis FRED database. For all price series annualized quarter-on-quarter growth rates are calculated as: $\pi_t = ((\frac{p(t)}{p(t-1)})^4 - 1) \times 100$.

TABLE A2 Unbiasedness of survey inflation expectations

	Horizons (x quarters ahead)				
	0	**1**	**2**	**3**	**4**
GDP deflator (final)					
α	−0.055	−0.030	−0.114	0.155	0.834
	(0.19)	(0.24)	(0.31)	(0.36)	(0.55)
β_u	1.021***	1.022***	1.038***	0.958***	0.784***
	(0.05)	(0.08)	(0.102)	(0.11)	(0.16)
$\beta_u = 1$	0.70	0.77	0.71	0.72	0.17
GDP deflator (1st release)					
α	−0.220	−0.177	−0.306	−0.075	0.516
	(0.17)	(0.24)	(0.29)	(0.34)	(0.51)
β_u	1.037***	1.036***	1.064***	0.995***	0.847***
	(0.06)	(0.09)	(0.10)	(0.11)	(0.15)
$\beta_u = 1$	0.51	0.67	0.52	0.96	0.31

Note. Asterisks denote significance at the ***1%, **%5, and *10% level, respectively. Estimation of the Equation $\mathbb{S}_t\pi_t = \alpha + \beta_u\pi_t + \eta_t$ is conducted with OLS. Asymptotic Newey–West 4 lags standard errors are in parentheses. The data set goes from 1968:Q4–2017:Q1. The last two categories present the results for final and first release of the GDP deflator on the long sample starting in 1968:Q4, respectively. Below the parameter estimates the p-value corresponding to a t test of $\beta_u = 1$ is presented.

TABLE A3 Other marginal cost measures

GDP deflator	Marginal cost measures GAP-CF	ULC	LS	UNGAP	INDPRO	CAPUTI	INVENT
β_f	0.750***	0.714***	0.756***	0.772***	0.755***	0.757***	0.752***
	[0.08]	[0.08]	[0.07]	[0.07]	[0.08]	[0.08]	[0.08]
β_b	0.262***	0.197***	0.255***	0.239***	0.257***	0.254***	0.260***
	[0.07]	[0.05]	[0.06]	[0.06]	[0.07]	[0.07]	[0.07]
δ	0.041	0.087***	0.061**	−0.068*	−0.003	−0.008	−0.000
	[0.03]	[0.03]	[0.03]	[0.04]	[0.01]	[0.01]	[0.00]
Constant	−0.012	0.070	0.003	0.041	−0.007	−0.011	0.005
	[0.09]	[0.09]	[0.09]	[0.10]	[0.09]	[0.09]	[0.09]
R^2	0.94	0.94	0.94	0.94	0.94	0.94	0.94
$\beta_f + \beta_b = 1$	0.62	0.03	0.68	0.64	0.63	0.66	0.66
Obs.	193	193	193	193	193	193	193

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant), is conducted by OLS. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$. The following abbreviations for the marginal cost measures are used: GAP-CF, Christiano–Fitzgerald filter-based output gap; ULC, unit labor costs; LS, labor share; UNGAP, unemployment gap based on CBO's NAIRU; INDPRO, industrial production; CAPUTI, capacity utilization; INVENT, inventories.

TABLE A4 GMM estimation

	GMM1	GMM2	GMM3
β_f	0.822***	0.827***	0.645***
	[0.04]	[0.04]	[0.07]
β_b	0.202***	0.196***	0.372***
	[0.03]	[0.04]	[0.06]
δ	0.021	0.035**	0.025
	[0.01]	[0.02]	[0.02]
const	-0.025	0.003	0.015
	[0.04]	[0.06]	[0.06]
R^2	0.95	0.95	0.95
$\beta_f + \beta_b = 1$	0.05	0.08	0.24
Hansen *J*	0.82	0.75	0.73
Kleibergen–Paap	0.77	0.69	0.62
Endog.	0.64	0.86	0.95
Obs.	190	190	190

Note. Asterisks denote significance at the ***1%, **5%, and *10% level, respectively. Estimation of Equation 3 (including a constant) is conducted by GMM, where the covariance matrix is corrected by the Newey–West approach with automatic bandwidth selection. Standard errors are in parentheses. The sample is 1968:Q4–2017:Q1. The instrument set consists of four lags of inflation, and two lags each of SPF expected inflation one quarter ahead, unit labor costs, the output gap, and wage inflation. The output gap is computed based on CBO's potential GDP. Under GMM1 only the forward-looking variable is instrumented; in GMM2 the output gap is treated as endogenous as well; while in GMM3 the lagged inflation rate is also treated as endogenous. Below the parameter estimates the R^2 of the regression, as well as the *p*-value of an *F* test for the hypothesis that $\beta_f + \beta_b = 1$ are presented. Further, the *p*-value corresponding to the Hansen *J* statistic, as well as the Kleibergen–Paap statistic, are given. Maximal IV relative bias critical values for the latter come from Stock and Yogo (2005) and are 20.90, 11.51, and 6.56 for GMM1, 19.12, 10.69, and 6.23 for GMM2, and 17.35, 9.85, and 5.87 for GMM3 at the 5%, 10%, and 20% level, respectively. The penultimate row presents *p*-values for an endogeneity test based on the difference between the Sargan–Hansen statistic of the GMM approach and the baseline model, and the final row reports the number of observations.

TABLE A5 The formation process of expectations at longer horizons

	$\mathbb{S}_t \boldsymbol{\pi}_t$	$\mathbb{S}_t \boldsymbol{\pi}_{t+1}$	$\mathbb{S}_t \boldsymbol{\pi}_{t+2}$	$\mathbb{S}_t \boldsymbol{\pi}_{t+3}$
$\beta_f(\mathbb{S}_t\pi_{t+1})$	0.762***			
	[0.08]			
$\beta_f(\mathbb{S}_t\pi_{t+2})$		0.888***		
		[0.04]		
$\beta_f(\mathbb{S}_t\pi_{t+3})$			0.834***	
			[0.06]	
$\beta_f(\mathbb{S}_t\pi_{t+4})$				0.607***
				[0.08]
β_b	0.249***	0.155***	0.136***	0.298***
	[0.07]	[0.03]	[0.04]	[0.06]
δ	0.032*	0.002	0.001	0.003
	[0.02]	[0.01]	[0.01]	[0.03]
Constant	0.037	-0.178***	0.103	0.384***
	[0.09]	[0.07]	[0.09]	[0.14]
N	193	193	193	193
R^2	0.94	0.96	0.96	0.90
$\beta_f + \beta_b = 1$	0.65	0.02	0.16	0.01

Note. Asterisks denote significance at the ***1%, **5%, and *10% level. Estimation of Equation 3 (including a constant) is conducted by OLS, where the horizon of the forward-looking component varies. Asymptotic Newey–West four lags robust standard errors are in brackets. The sample is 1968:Q4–2017:Q1. The bottom three rows report the number of observations, the R^2 of the regression, as well as the *p*-value of an *F* test for the hypothesis that $\beta_f + \beta_b = 1$.