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Inflation Expectation Dynamics : The Role of Past, Present and Forward-Looking Information

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Abstract

Assuming that private agents need to learn inflation dynamics to form their inflation expectations and that they believe a hybrid New-Keynesian Phillips Curve (NKPC) is the true data generating process of inflation, we aim at establishing the role of forward-looking information in inflation expectation dynamics. We find that longer-term expectations are crucial in shaping shorter-horizon expectations. Professional forecasters put a greater weight on forward-looking information – presumably capturing beliefs about the central bank inflation target or trend inflation –, while lagged inflation remains significant. Finally, the NKPC-based inflation expectations model fits well for professional forecasts in contrast to consumers'.

Keywords: Survey expectations, Inflation, New Keynesian Phillips Curve

JEL-Codes: E31

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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 estimating New Keynesian Phillips Curves (NKPC).[2]

By bridging these two strands of literature, this paper investigates whether longer-term private inflation expectations play a role in determining shorter-term inflation expectations, and aims at establishing the role of past, present and forward-looking information in inflation expectation dynamics. In a setting with homogeneous agents, assuming that private agents need to learn the dynamics of inflation to form their inflation expectations and that they believe the reduced-form hybrid NKPC is the true data generating process of inflation dynamics –so the agents' estimated perceived law of motion–, our contribution to the literature is to propose an NKPC-based inflation expectations formation equation. We thus assess whether and by how much private inflation expectations are driven by forward-looking information (i.e. further-ahead expectations), current information (e.g. the current output gap), or backward-looking information (i.e. past realised 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, while Pfajfar and Santoro (2010) show that the distribution of private forecasts might be explained by three different

[1] Within this literature, Mankiw and Reis (2002) propose a sticky-information model where private agents may form rational expectations, but only update their information set each period with a certain probability as they face costs of absorbing and processing information. Sims (2003) as well as Mackowiak and Wiederholt (2009) focus on partial and noisy information models. Albeit updating continuously in this framework, it is an optimal choice for private agents - internalising their information processing capacity constraints - to remain inattentive to some part of the available information because incorporating all signals is impossible (see also Moscarini, 2004, for a similar idea). In both types of models, a fraction of the information set used by private agents is backward-looking, i.e. based on past information. Carroll (2003), Mankiw, Reis, and Wolfers (2003), Pesaran and Weale (2006), Branch (2007), Nunes (2009), Andrade and Le Bihan (2010), Coibion (2010) and Coibion and Gorodnichenko (2010, 2012) provide empirical evidence based on survey data to characterise 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 re-optimise their prices but set them according to a rule of thumb (see e.g. Steinsson, 2003) or index their prices completely to lagged inflation as in Galí and Gertler (1999) or Christiano, Eichenbaum, and Evans (2005).

expectation formation processes: a static or highly auto-regressive process, a nearly rational approach, and adaptive learning and sticky information models. Cornea, Hommes, and Massaro (2012) find time-variation and heterogeneity in the type of expectations formation with evolutionary switching between backward- and forward-looking behaviour.

Estimating the parameters of our proposed model 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, and Levin, 2000; Steinsson, 2003) and by the expectations formation process, i.e. whether private agents 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, and 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 from the Survey of Professional Forecasters are fixed-horizon forecasts and available on a long time span: 1981Q3-2012Q3. We use both GDP deflator and CPI to measure inflation as well as various variables for marginal costs including a constructed measure of the output gap. In addition, we also assess whether relative weights vary for different forecasting horizons and if expectations of consumers differ from those of professional forecasters.

We provide original evidence that longer-term inflation expectations are crucial in determining shorter-horizon inflation expectations. More precisely, our results are threefold. First, professional forecasters put relatively more weight on forward-looking information, while past information is significant and the contribution of the marginal cost measure is small and often insignificantly different from zero.[3] Second, the coefficients are similar to those found in the literature estimating the actual NKPC which suggests that professional forecasters may indeed use this approach to form their own inflation expectations.[4]

[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 GMM estimation, to various measures of marginal costs, to the use of the mean of individual responses, and to the inclusion of potentially relevant additional variables.

[4] Mavroeidis, Plagborg-Moller, and Stock (2014) 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.

Consumers seem to differ from professionals in that their inflation forecasts do not follow the NKPC-based formation process. Third, we also find that the estimated parameters of this NKPC-based expectations formation model are relatively stable when the forecasting horizon varies or when we consider further-ahead horizons for forward-looking information.

While it might appear circular to explain expectations formation by further-ahead survey expectations, Ang, Bekaert, and Wei (2007) and Cecchetti, Hooper, Kasman, Schoenholtz, and Watson (2007) provide evidence that survey inflation expectations have a good forecasting performance which stems from survey respondents' ability to anticipate structural change. One reason why private agents 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 equilibrium value of inflation, and are therefore driven by beliefs about the central bank inflation target or are projections of the trend inflation rate, which would in turn depend, on the central bank credibility to achieve inflation stabilisation. This is in line with the argument by Faust and Wright (2012) that inflation expectations represent the way forecasters believe inflation takes from its current expected value (nowcast) towards the perceived trend inflation rate.

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 private expectations still depend (in part) on past information. Besides, the estimated parameters may serve for calibrating macroeconomic models in which private expectations are not solely forward-looking. Finally, another implication for future research is that professional forecasters appear to form their inflation expectations on the grounds of the hybrid NKPC.

The rest of the paper is organised as follows. Section 2 describes the methodology. Section 3 reports the empirical analysis, while sections 4 and 5 focus on the effect of forecasting horizons and on a comparison with consumers' forecasts respectively. Section 6 concludes.

2 Methodology

Galí and Gertler (1999) propose a hybrid New Keynesian Phillips Curve of the following form, where π_t is the inflation rate, $\mathbb{E}_t\pi_{t+1}$ expected future inflation, and mc_t 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 a 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] It is worth mentioning that 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). 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 e.g. Fuhrer and Moore, 1995; Woodford, 2003) and we measure expected inflation by survey expectations as is recently done in the literature on Phillips curve estimations (see Nunes, 2009; Adam and Padula, 2011) 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.[6]

This approach is different but related to the study by Smith (2009) that proposes a forecast pooling method which improves statistical fit compared to GMM estimation of the

[5] We precede our empirical analysis with tests of the assumption that the survey value is an unbiased predictor in section 2.2 and explain what a departure from it would imply for our estimations.

[6] We also precede our empirical analysis with tests (in section 2.2) that the error term ν_t is uncorrelated with the expectation term. We thus analyse whether endogeneity may be an issue in this specification, so that ordinary least squares would be inconsistent.

NKPC but not dramatically compared to the use of surveys, while 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. It is worth adding that Kozicki and Tinsley (2012) develop a model of expected inflation linking realised inflation rates to SPF forecasts, while Brissimis and Magginas (2008) provide a similar method using the hybrid NKPC.[7]

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 e.g. by Thomas (1999), Croushore (2010) or Smith (2009). One can therefore view this NKPC-based inflation expectation formation equation as the forecasting function of an adaptive learning model in which private agents learn about inflation dynamics by estimating the hybrid NKPC in its reduced form as their perceived law of motion of inflation.

3 Empirical Analysis

3.1 Data

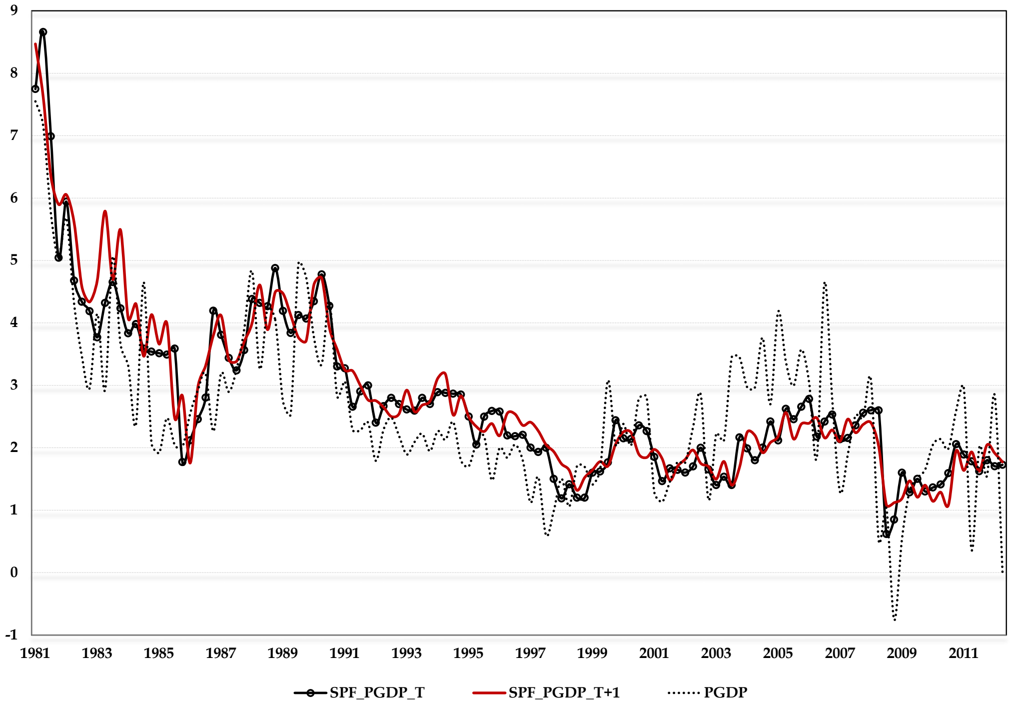
We focus on quarterly US data for which survey forecasts from the Survey of Professional Forecasters (SPF) are available on a fixed-horizon scheme[8] and for a long time span: 1981Q3-2012Q3. SPF expectations for the GDP deflator are actually available as of 1968Q4, however, we present our main results for the above-mentioned period in order to fulfil stationarity requirements and to be consistent with respect to CPI inflation for which survey data does not exist before 1981.[9] We use the median of individual responses as our baseline, and propose robustness tests with the mean. SPF inflation forecasts for

[7]The objective of our study is not directly related to the ones of the just mentioned papers, its focus being on inflation expectation dynamics – crucial for understanding how inflation expectations evolve – rather than on inflation dynamics per se. We build on this abundant literature and borrow the result that the NKPC is a robust representation of how inflation evolves.

[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 heteroscedasticity in the estimation process.

[9]For a discussion on stationarity in the context of survey expectations see Adam and Padula (2011). We verify the consistency of our main results with the alternative longer sample for the GDP deflator.

Figure 1: Survey PGDP Inflation Expectations and Actual PGDP



Note: This figure shows SPF survey expectations for the GDP deflator (PGDP), as well as its realised values. The following abbreviations are used: 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.

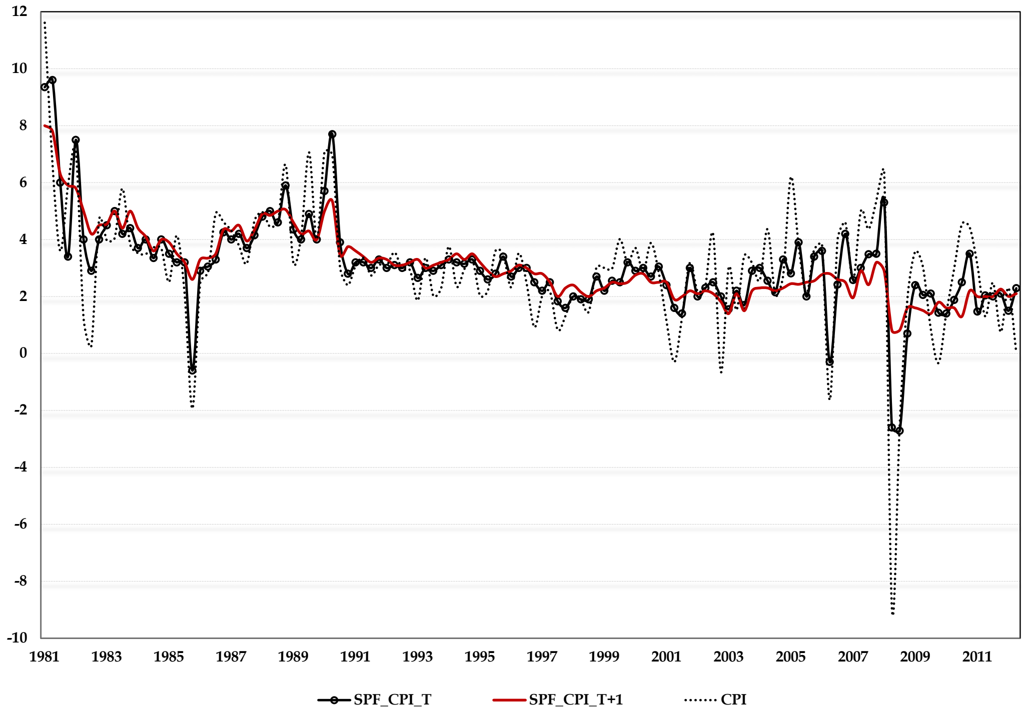
both the GDP deflator and CPI inflation fulfil stationary requirements.[10] We also analyse how consumer expectations differ from those of professionals making use of the University of Michigan's Survey of Consumers.

Figures 1 and 2 plot SPF inflation expectations at the current horizon (nowcast) and the one-quarter ahead horizon for the GDP deflator and CPI inflation. Consistent with US inflation history, inflation expectations followed the disinflation path during the eighties while they have been anchored around 2% ever since. An exception to that is the considerable volatility in the nowcast of CPI inflation around the financial crisis.

As the output gap we employ the filtered version of real GDP growth. 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 quarters (see Christiano and Fitzger-

[10]Stationarity tests are available from the authors upon request. We find that the null hypothesis of a unit root can be rejected for both the GDP deflator and CPI inflation survey variables at all horizons except for three-quarter-ahead expectations of the former inflation measure on the sample starting in 1981Q3. On the sample starting in 1968Q4 a unit root though cannot be rejected for the GDP deflator at all horizons.

Figure 2: Survey CPI Inflation Expectations and Actual CPI



Note: This figure shows SPF survey expectations for CPI inflation, as well as its realised values. The following abbreviations are used: spf_cpi_t is the nowcast of CPI inflation, spf_cpi_t+1 is the one-quarter ahead forecast and cpi is the actual CPI inflation measured with final data.

ald, 2003).[11] To check the robustness of the results we also use the output gap based on the Hodrick-Prescott filter.

We also employ other marginal cost measures frequently considered in the literature namely unit labour costs, labour share, unemployment rate, inventories, industrial production index and capacity utilisation. 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 and the University of Michigan's Survey of Consumers (UMSC) are from the FRED database. See the Data Appendix for more details.

3.2 Pre-Tests

First, we evaluate the assumption of unbiased expectations. To test for unbiasedness, we estimate a model: $\pi_{t+h} = \alpha_u + \beta_u \mathbb{S}_t \pi_{t+h} + \eta_t$, as is common in the literature (see e.g. Smith,

[11] 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. We also use non-filtered measures in the robustness section.

2009; Adam and Padula, 2011). Unbiasedness requires the constant α to be equal to zero and β_u to equal 1. If this is not the case a constant enters equation 2 and accordingly equation 3, and/or the coefficients are divided by a coefficient β_u which, however, would not require a different estimation technique.

The results of these tests are presented in Table 10 in the Appendix. As shown by Smith (2009), SPF forecast unbiasedness cannot be rejected at any horizon for both final and real-time data for the GDP deflator over the extended sample starting in 1968Q4; however, it can be easily rejected in sub-samples. On the sample starting in 1981Q3, unbiasedness cannot be rejected for GDP deflator current-quarter forecast using real-time data, whereas it can be for final data. CPI inflation current quarter forecasts are unbiased for both real-time and final data. To account for potential bias in expectations, we estimate all models with a constant α verifying that it is insignificant.

Second, we precede our empirical analysis with tests for endogeneity of the explanatory variables, so that ordinary least squares 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).[12] The null hypothesis is that the tested variables are exogenous. For the GDP deflator variable the test yields p-values of 0.24, 0.39 and 0.14 for the three GMM approaches considered, respectively: i.e. we test whether the error term ν_t is uncorrelated with only the expectation term, with the latter and the output gap, and with all three explanatory variables. For the CPI inflation variable, the test gives p-values of 0.72, 0.93 and 0.88 for the three cases, respectively. This provides evidence in favour of OLS consistent estimates. In order to further assess this issue, we estimate our empirical model using GMM as a robustness check and show that any potential endogeneity does not affect the main results of this paper.

3.3 Baseline Results

We present OLS estimates of equation 3 for both inflation measures in Table 1. We compute heteroskedasticity and autocorrelation robust Newey-West standard errors assuming that the autocorrelation dies out after four quarters.[13]

[12] These tests are based on the GMM specifications and instrument set detailed in the Appendix and in the robustness subsection 3.8.

[13] This choice corresponds to the Stock and Watson (2007) rule of thumb where the Newey-West lag length is set equal to $0.75 \times T^{\frac{1}{3}}$ (rounded), T being the number of observations used in the regression.

Table 1: NKPC-Based Inflation Expectations Formation Model

	Baseline		Constrained		Extended Sample	
	GDP deflator	CPI inflation	GDP deflator	CPI inflation	Baseline	Constrained
δ	-0.04^{*}	0.08	-0.03	0.07	-0.06^{***}	-0.06^{***}
	(0.02)	(0.05)	(0.02)	(0.07)	(0.02)	(0.02)
β_f	0.82^{***}	0.88^{***}	0.84^{***}	0.81^{***}	0.76^{***}	0.76^{***}
	(0.04)	(0.11)	(0.04)	(0.07)	(0.08)	(0.06)
β_b	0.14^{***}	0.19^{***}	0.16^{***}	0.19^{***}	0.24^{***}	0.24^{***}
	(0.04)	(0.04)	(0.04)	(0.07)	(0.06)	(0.06)
const	0.10	-0.28	-0.03	-0.05	0.05	0.05
	(0.12)	(0.29)	(0.03)	(0.08)	(0.09)	(0.04)
R^2	0.92	0.73	-	-	0.94	-
$\beta_f + \beta_b = 1$	0.31	0.41	-	-	0.97	-
Obs	124	124	124	124	175	175

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 3 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses in the 'Baseline' models. The 'Constrained' approach enforces the following condition: $\beta_f + \beta_b = 1$. In this case the variance estimates of the standard errors are the Huber/White/sandwich robust variance estimates. The data set comprises 1981Q3-2012Q3 for the first four columns; the last two columns present the 'Baseline' and 'Constrained' results for the GDP deflator for the sample starting in 1968Q4. In the last two rows 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 for the 'Baseline' estimations. The final row reports the number of observations. The output gap is derived by means of the CF filter.

The coefficients on the forward- and backward-looking element of the inflation expectations formation process are estimated to be $(0.82, 0.14)$ and $(0.88, 0.19)$ for the GDP deflator and CPI inflation, respectively. This is, forward-looking dynamics dominate the formation process for both inflation expectation measures, while the backward-looking part is still significant in either case. This outcome is consistent with the literature focusing on the expectations formation process which finds a role, small but significant, for backward-looking behaviour as in Lanne, Luoma, and Luoto (2009) or Pfajfar and Santoro (2010). The resulting coefficients are also similar to those found in the literature on estimations of the actual New Keynesian Phillips Curve (see e.g. Galí and Gertler, 1999; Woodford, 2003; Nunes, 2010; Mavroeidis, Plagborg-Moller, and Stock, 2014). It suggests that forecasters may form their predictions on the grounds of the NKPC assuming that it properly captures inflation dynamics.[14]

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.

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

For both inflation measures the null hypothesis cannot be rejected. This is what other studies find in evaluations of the actual NKPC (Galí and Gertler, 1999; Woodford, 2003).

As far as the marginal cost measure is concerned the results for the two inflation variables differ. Whereas the coefficient on the output gap is negative and marginally significant, i.e. at the 10% level, for the GDP deflator, it is positive and insignificant for CPI inflation. The negative sign on the output gap coefficient for the GDP deflator model might be a surprise on theoretical grounds, while it is well documented empirically in the NKPC literature (see Woodford, 2003; Nunes, 2010).

The high R^2 of 0.92 for the GDP deflator model, among other things, derives 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 analyse in this paper and thus do not discuss this issue further. We also verify that including a constant does not improve the fit of the model, as the constant is statistically insignificant in both models.

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 and Gertler, 1999). In this case the variance estimates of the standard errors are the Huber-White/sandwich robust variance estimates. The results based on this approach are also presented in Table 1. For the GDP deflator the estimates are very similar, while the ouput gap is now completely insignificant. For CPI inflation the constrained approach yields similar coefficients. Given that the estimation of the constrained model involves a change in the dependent variable, no goodness-of-fit measure is provided as it would have a different interpretation.

We implement a model specification test to assess whether our NKPC-based equation is properly specified. If this is the case, one should not be able to find any additional independent variables that are significant except by chance. 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. For the GDP deflator and CPI inflation, the p-values associated with the squared fitted values are 0.50 and 0.88, respectively, suggesting that the present results are not driven by misspecification.

These findings square well with the evidence by Coibion and Gorodnichenko (2010).

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.

In the last two columns of Table 1, we present results for the extended sample for the GDP deflator.[15] They are similar to those found for the shorter sample. A few notable exceptions are a relatively higher weight on backward-looking expectations (now at 0.24) and a significant output gap. The first 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 and Gertler (1999)). The second finding can be explained by a steeper Phillips Curve consistently with the literature on the actual NKPC.[16]

3.4 Model Comparisons

The previous results provide support for our NKPC-based expectations formation model, i.e. 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 favour 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 to provide evidence in favour or against the alternative models relative to our baseline.

The LR test clearly rejects the reduced models in favour of our baseline NKPC-based inflation expectations formation model for both the GDP deflator and CPI inflation.

[15] SPF inflation expectations are found to be not stationary over this sample in the US which potentially affects the reliability of the respective results. Inflation itself is also found to be non-stationary in the US and accordingly many forecasting studies make use of models with inflation in first differences, see e.g. Stock and Watson (1999). For a discussion of stationarity of SPF inflation expectations see Adam and Padula (2011).

[16] Given the non-stationarity issue and the similarity of estimates found, we focus from here onwards on the shorter sample. An exception is the section on subsamples, where we consider it relevant to analyse how inflation expectations where formed in the early part of the long sample. We verified that the results do not differ between the longer and the shorter sample for the other specifications discussed in this paper. Results are available from the authors upon request.

Table 2: Model Comparisons

	Forward-looking model		Backward-looking model	
	GDP deflator	CPI inflation	GDP deflator	CPI inflation
$\delta_{(a)}$	-0.05*	0.08	-0.02	0.02
	(0.02)	(0.07)	(0.05)	(0.10)
β_f	0.92***	1.08***		
	(0.05)	(0.11)		
β_b			0.78***	0.46***
			(0.08)	(0.07)
const	0.16	-0.29	0.69***	1.62***
	(0.12)	(0.36	(0.19))	(0.16)
R^2	0.91	0.67	0.65	0.41
$\beta_f = 1$	0.11	0.48	-	-
$\beta_b = 1$	-	-	0.01***	0.00***
LR test	0.00***	0.00***	0.00***	0.00***
Obs	124	124	124	124

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of the forward-looking and the backward-looking model is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3. In the rows below the parameter estimates the R^2 of the regression and the p-value of an F test for the hypothesis that the given parameter equals one are presented. Further, the p-value corresponding to an LR test of the alternative model relative to the baseline model and the number of observations are given.

Note, however, that the LR test is based on the assumption of homoskedastic and non-autocorrelated errors. We thus ask the reader to interpret these results with caution. It stands out though that both LR test results and the t-statistics in Table 1 point in the same direction, i.e. our baseline model performs better than the alternatives.

Turning to the parameter estimates, the purely backward- and the purely forward-looking model perform very 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 significantly 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. In either case though it seems that our baseline model performs better.[17]

[17]We also compare our model to an autoregressive model. Performing two non-nested model tests 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. The same conclusion can be drawn from comparing our baseline model to an alternative in which inflation expectations are explained by shorter-horizon inflation expectations. Results are available upon request.

3.5 Final versus Real-Time Data

We also present estimates based on real-time data since in our context the timing of information is paramount and calls for carefulness. Orphanides (2001) stresses that the use of final revised data in Taylor rule estimations may cause misleading results given that 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 agents at that time. We thus also evaluate our models with real-time data stemming from the Real-Time Database from the Federal Reserve Bank of Philadelphia.

We replace both the inflation measure as well as the real GDP growth variable used to construct the output gap by their first vintage published. The results for both the GDP deflator and CPI inflation are presented in Table 3. The parameter estimates are qualitatively unchanged. While the forward-looking coefficient is somewhat lower and the backward-looking coefficient is somewhat higher than before in the GDP deflator model, both are higher in the CPI model. Note, however, that in the latter model the standard errors are larger which is related to the fact that real-time data for CPI inflation is not available before 1994Q1 and thus 52 observations less are used. Based on real-time data, the coefficient on the output gap becomes insignificant in the GDP deflator model, in the CPI model it is marginally significant.

One can also argue that even the first release of real GDP growth 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. Therefore we replace the output gap measure based on this first release by the output gap measure based on the nowcast for real GDP growth from the SPF. The results are very similar to our baseline estimates as can be seen in Table 3.

3.6 Subsamples

One might ask whether the apparent fit of the NKPC model in explaining inflation expectation dynamics stems from the stability of inflation during the Great Moderation. In other words, for a very high degree of autocorrelation in inflation and accordingly in inflation expectations, a hybrid model, a forward-looking and a backward-looking model would

Table 3: Real-Time Data Estimation

	First vintage		Nowcast	
	GDP deflator	CPI inflation	GDP deflator	CPI inflation
δ	-0.04	0.13^{*}	-0.04	0.16^{*}
	(0.03)	(0.08)	(0.03)	(0.08)
β_f	0.77^{***}	1.02^{***}	0.76^{***}	1.00^{***}
	(0.05)	(0.29)	(0.05)	(0.28)
β_b	0.17^{***}	0.21^{***}	0.18^{***}	0.21^{***}
	(0.04)	(0.03)	(0.04)	(0.03)
const	0.14	-0.52	0.15	-0.46
	(0.10)	(0.63)	(0.10)	(0.61)
R^2	0.93	0.70	0.93	0.70
$\beta_f + \beta_b = 1$	0.15	0.39	0.16	0.43
Obs	124	72	124	72

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 3 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3 for the GDP deflator and 1994Q3-2012Q3 for the CPI model. In the last two rows 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. The final row reports the number of observations. The results for 'First vintage' are based on the first release of both the inflation and the real GDP growth variable. The results for 'Nowcast' rely on the first release of the inflation variable and the nowcast of real GDP growth from the SPF. The output gap is derived by means of the CF filter.

all fit the data well. We have shown earlier that our NKPC-based model fits the data better than some alternatives over the whole sample and we now want to examine whether our results are robust to the choice of the (sub)sample. Similar estimates would support the idea that the relative weights on past inflation and inflation expectations are not due to particular inflation dynamics such as e.g. in the Great Moderation, but capture well a stable inflation expectation formation process independently of whether inflation itself is stable or decelerating. Subsample discrepancies in parameter estimates would indicate a shift across time in the weight professional forecasters put on different information.

Table 4 provides estimates of our NKPC-based model before and after 1992Q3 when inflation came back to the target range of typically around 2%. Although the starting date of the Great Moderation is normally set earlier, as of 1992 inflation followed an even more stable path (estimates are immune to the choice of this specific break date and are similar for all break dates tested between 1987 and 1995). Finally, setting the break date that late allows us to have a reasonably large first subsample (43 observations). We also present results for dividing the longer sample before and after the Great Disinflation; here we set the break date at 1984Q1. This is the latest candidate break date found in the

Table 4: Subsample Estimates

	GDP deflator		CPI inflation		Extended sample	
	Pre 1992Q3	Post 1992Q3	Pre 1992Q3	Post 1992Q3	Pre 1984Q1	Post 1984Q1
δ	-0.06	-0.02	0.05	0.15*	-0.10**	-0.02
	(0.04)	(0.02)	(0.06)	(0.07)	(0.04)	(0.02)
β_f	0.79***	0.83***	1.15***	1.07***	0.71***	0.83***
	(0.10)	(0.06)	(0.19)	(0.29)	(0.11)	(0.04)
β_b	0.12	0.14***	0.18*	0.16***	0.22***	0.13***
	(0.10)	(0.04)	(0.09)	(0.04)	(0.08)	(0.03)
const	0.31	0.06	-1.58***	-0.57	0.47	0.10
	(0.39)	(0.13)	(0.53)	(0.66)	(0.45)	(0.10)
R^2	0.82	0.79	0.75	0.56	0.85	0.89
$\beta_f + \beta_b = 1$	0.37	0.57	0.01**	0.39	0.37	0.33
Obs	43	81	43	81	60	115

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 3 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3 for the first four columns; the last two columns present different subsample results for the GDP deflator with the sample starting in 1968Q4. In the last two rows 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. The final row reports the number of observations. The output gap is derived by means of the CF filter. The first break date corresponds to the date when inflation came back to the 2% inflation target; the second break date is the latest candidate break date found in the study by Inoue and Rossi (2011), who estimate a representative New Keynesian model.

study by Inoue and Rossi (2011). Using this latest break date, once more allows us to have a reasonably long first subsample, while it does not influence the results significantly (as compared to setting an earlier break e.g. around 1980).

On the shorter sample, for both the GDP deflator and CPI inflation, the coefficient on further-ahead expectations is similar before and after the break date and also corresponds to our estimate for the whole sample. Parameter estimates on past inflation are alike and significant for CPI inflation before and after 1992Q3, while they are similar for the GDP deflator but past inflation only becomes significant after the break date. This, however, could be explained by the relatively small sample size in the first subsample. These results provide evidence that our model fits the data well along the whole sample and that our findings are not influenced by the choice of a particular sample. They are not driven by the relatively stable inflation rates between 1992 and 2007 and are robust to the Great Disinflation.

On the extended sample, subsample results are somewhat different, consistent with the literature, showing that the emphasis on backward-looking information was relatively higher before the Great Moderation (0.22 versus 0.13). Also, the output gap is significant (but negative) pre-1984, becoming insignificant thereafter. This squares well with evidence from the literature of a flattening in the Phillips Curve in the more recent period.

3.7 Does More Information Matter?

We also examine whether the lack of some potentially important but omitted variables – the federal funds rate and oil prices – 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.[18] We include a lag of the federal funds rate - denoted i - to represent the stance of monetary policy, as well as of the oil price growth rate - denoted oil - which can be interpreted as an external price shock, and analyse how these affect the results. Given the high autocorrelation in the interest rate (see e.g. Galí and 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 5:

$$\mathbb{S}_t\pi_t = \delta x_t + \beta_f \mathbb{S}_t\pi_{t+1} + \beta_b\pi_{t-1} + \gamma_i\, i_{t-1} + \gamma_o\, oil_{t-1} + \eta_t. \tag{4}$$

The additional information does not seem to improve the fit of the GDP deflator model. The R^2 is almost the same as in the baseline case and the parameter estimates are essentially unchanged. The coefficient on the interest rate is insignificant, while the oil price coefficient is significant but very small. The conclusions from the baseline model remain unaltered and it seems that omitted variable bias in not an issue for the GDP deflator model.

The results for the CPI inflation model differ slightly. The coefficient on the oil price is insignificant, while the one on the interest rate is marginally significant, at the 10% level. γ_i is about -0.10, thus a 100 basis points increase in the lagged federal funds rate would

[18] 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. Neither the lagged nor the current value is significant or affects the main parameter estimates.

Table 5: Omitted Variable Bias

	GDP deflator	CPI inflation
δ	-0.04^{**}	0.05
	(0.02)	(0.05)
β_f	0.78^{***}	1.17^{***}
	(0.07)	(0.23)
β_b	0.11^{***}	0.17^{***}
	(0.04)	(0.05)
γ_i	0.03	-0.10^{*}
	(0.02)	(0.05)
γ_o	0.002^{**}	0.003
	(0.001)	(0.002)
const	0.11	-0.59
	(0.13)	(0.40)
R^2	0.92	0.75
$\beta_f + \beta_b = 1$	0.14	0.10*
Obs	124	124

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 4 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3. In the last two rows 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. The final row reports the number of observations. The output gap is derived by means of the CF filter.

- as expected - decrease the nowcast of CPI inflation by 0.1% above the indirect effect it has through expected inflation for the following period. At the same time the R^2 increases slightly from around 0.73 to around 0.75 relative to the baseline case. The output gap still has an insignificant coefficient. Finally, the coefficient on the forward-looking variable, γ_f, increases to 1.17. Given the relatively high standard error on the forward-looking variable, the hypothesis that the backward- and forward-looking coefficients add up to one cannot be rejected. It thus seems that in either case omitted variable bias is not present for our baseline NKPC-based inflation expectations formation process.[19]

3.8 Robustness

In the following, we discuss various robustness checks. First, we examine other variables for marginal cost measures such as unit labor costs that are typically used in the NKPC

[19] We implement the same model specification test than previously and find no evidence that our results are misspecified (p-values of the squared fitted values for the GDP deflator and CPI inflation are 0.29 and 0.87, respectively).

literature. The ouput gap we use so far is constructed by means of the CF filter. Another filter that is commonly used in the literature is the Hodrick-Prescott (HP) filter (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 and Gertler, 1999; Sbordone, 2002; Galí, Gertler, and López-Salido, 2005). Other variables commonly suggested are unit labor costs, labor share, unemployment rate (as in the original Phillips curve), industrial production, capacity utilisation 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 11. Given potential measurement error due to the use of surveys (for a discussion of this point see Adam and Padula, 2011) and potential endogeneity we also review our model results with the use of GMM.[20] Finally, we analyse whether results differ for the mean versus the median of individual responses for expected inflation; see Table 12 and 13 for GMM based results and those based on the mean rather than the median, respectively. The main conclusions of Section 3.3 are robust to the different approaches presented in the Appendix.

4 The Effect of Forecasting Horizons

In this section, we depart from our baseline model in two ways. First, we increase the horizon of inflation expectations used by private agents to determine current inflation expectations. Second, we assess whether the formation process of inflation expectations for future quarters differs from the formation process of inflation expectations for the current quarter.

4.1 Near vs. 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 private forecasters put relatively more weight on near or further-ahead forward-looking information. On the one hand one may expect that private agents have a better understanding of the closer economic outlook and thus put more weight on forward-looking information with a shorter horizon; on the

[20]We also test the LIML and CUE estimators and they yield similar results.

other hand private agents 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 for both GDP deflator and CPI models have a similar pattern given in Table 6. The weight of forward-looking information decreases with the forecasting horizon, from 0.82 at the one-quarter-ahead horizon to 0.68 at the four-quarter-ahead horizon for the GDP deflator model and from 0.88 to 0.64 for the CPI model. 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. The R-square decreases as the horizon increases, however not by much. It thus seems that private agents rely more on their assessment of the near economic outlook rather than on further-ahead perspectives, while the latter still has significant information for the nowcast.

Table 6 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 agents might find it easier to make predictions for an average over some quarters rather than for an individual quarter. They thus use this arguably more reliable average in their information set when forming their nowcast. The results indicate that this model works about as well as the benchmark for the GDP deflator, i.e. parameter estimates, an F-test on the sum of the two coefficients of interest and the R^2 are about the same. For the CPI model the R^2 is somewhat lower and the backward-looking variable receives a higher weight as in the benchmark case.

In addition, it is worth noting that for the CPI model, we also have 10-year-ahead expectations (on a smaller subsample starting in 1991Q4) and that the coefficient estimated is 0.63, very close to the 1-year-ahead estimate. Beyond this latter horizon, private forecasters give a similar weight to forward-looking information which suggests that these expectations capture the private agents' view on the long-run equilibrium value of inflation.

Our findings point out that private forecasters give more weight to their next quarter forecasts than to the ones for a longer horizon, while the latter 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 are projections of the trend inflation rate. Such an interpretation of our findings is in line with the argument by Faust and Wright (2012) 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.

Table 6: Near vs. Further-Ahead Forward-Looking Information

	GDP deflator				CPI inflation				
	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$	$\mathbb{S}_t\pi_t$
δ	-0.02	-0.04*	-0.05**	-0.04*	0.08	0.07	0.07	0.08	0.12
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.07)	(0.07)	(0.06)	(0.12)
$\beta_f(\mathbb{S}_t\pi_{t+2})$	0.74***				0.73***				
	(0.04)				(0.09)				
$\beta_f(\mathbb{S}_t\pi_{t+3})$		0.68***				0.68***			
		(0.04)				(0.08)			
$\beta_f(\mathbb{S}_t\pi_{t+4})$			0.68***				0.64***		
			(0.04)				(0.08)		
$\beta_f(\mathbb{S}_t\tilde{\pi}_{t+4})$				0.79***				0.75***	
				(0.04)				(0.09)	
$\beta_f(\mathbb{S}_t\pi_{t+10y})$									0.63***
									(0.17)
β_b	0.23***	0.24***	0.29***	0.18***	0.26***	0.28***	0.29***	0.25***	0.26***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
const	-0.02	0.08	-0.03	-0.03	-0.07	-0.02	0.04	-0.13	0.07
	(0.11)	(0.13)	(0.12)	(0.12)	(0.26)	(0.24)	(0.26)	(0.27)	(0.48)
R^2	0.90	0.89	0.89	0.92	0.64	0.62	0.61	0.65	0.35
$\beta_f + \beta_b = 1$	0.46	0.12	0.45	0.48	0.91	0.57	0.36	1.00	0.48
Obs	124	124	124	124	124	124	124	124	84

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation (3), is conducted by OLS, where the horizon of the forward-looking component varies. $\mathbb{S}_t\tilde{\pi}_{t+4}$ represents the average expected inflation rate over the following four quarters. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3, except for 10-year-ahead CPI expectations which start in 1991Q4. In the rows below the parameter estimates the R^2 of the regression, the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$ and the number of observations are presented.

4.2 Different Expectation Pairs

We now 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.

For the GDP deflator model, 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 7. One exception is the β_b coefficient for $h = 2$ which is insignificant while the constant is significant. For the CPI model, the coefficient on forward-looking information is slightly higher than in the baseline estimation when h varies, but most importantly the backward coefficient becomes null for $h = 2$ and 3. Finally, we estimate the effect of 10-year-ahead expectations on four-quarter-ahead expectations for the CPI model, and find an even larger and highly significant weight on forward-looking information.

Table 7: The Formation Process of Expectations at Longer Horizons

	GDP deflator			CPI inflation			
	$\mathbb{S}_t\pi_{t+1}$	$\mathbb{S}_t\pi_{t+2}$	$\mathbb{S}_t\pi_{t+3}$	$\mathbb{S}_t\pi_{t+1}$	$\mathbb{S}_t\pi_{t+2}$	$\mathbb{S}_t\pi_{t+3}$	$\mathbb{S}_t\pi_{t+4}$
δ	0.02	-0.03*	-0.002	0.01	0.001	-0.01	-0.03
	(0.02)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.02)
$\beta_f(\mathbb{S}_t\pi_{t+2})$	0.84***			0.95***			
	(0.04)			(0.02)			
$\beta_f(\mathbb{S}_t\pi_{t+3})$		0.87***			0.98***		
		(0.04)			(0.01)		
$\beta_f(\mathbb{S}_t\pi_{t+4})$			0.86***			0.95***	
			(0.06)			(0.01)	
$\beta_f(\mathbb{S}_t\pi_{t+10y})$							1.04***
							(0.07)
β_b	0.16***	0.06	0.17**	0.04***	0.01*	0.01	0.03***
	(0.03)	(0.04)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)
const	-0.09	0.18**	-0.01	-0.02	-0.06	0.06	-0.32*
	(0.07)	(0.07)	(0.12)	(0.06)	(0.04)	(0.05)	(0.19)
R^2	0.93	0.93	0.89	0.96	0.98	0.98	0.88
$\beta_f + \beta_b = 1$	0.92	0.01***	0.57	0.56	0.62	0.03**	0.33
Obs	124	124	124	124	124	124	84

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation (3), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3, except for 10-year-ahead CPI expectations which start in 1991Q4. In the rows below the parameter estimates the R^2 of the regression, the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$ and the number of observations are presented.

These results suggest that the inflation expectations formation process and the relationship between inflation expectations and both backward- and forward-looking information are relatively stable across the horizons that private agents are typically considering.

5 Consumers vs. Professionals

Carroll (2003) compares professional and consumer forecasts and finds that household expectations are not rational and that professional forecasts, which may be considered rational, spread epidemiologically to the public. We aim here at shedding light on the potential discrepancy between the expectations formation process of professionals and consumers in order to assess whether consumers use the same relative weights on backward-and forward-looking information and whether the NKPC-based expectations model also fits their expectations.

Table 8: Consumers vs. Professionals

	SPF $\mathbb{S}_t\pi_{t+4}$	UMSCI $\mathbb{S}_t\pi_{t+4}$	UMSCI $\mathbb{S}_t\pi_{t+4}$
δ	-0.03	-0.05	-0.04
	(0.02)	(0.03)	(0.04)
$\beta_f(\mathbb{S}_t^{SPF}\pi_{t+10y})$	1.04***		-0.09
	(0.07)		(0.10)
$\beta_f(\mathbb{S}_t^{UMSCI}\pi_{t+5y})$		0.30**	
		(0.14)	
β_b	0.03***	0.12***	0.12***
	(0.01)	(0.03)	(0.03)
const	-0.32*	1.78***	2.91***
	(0.19)	(0.44)	(0.33)
R^2	0.88	0.35	0.23
$\beta_f + \beta_b = 1$	0.33	0.00***	0.00***
Obs	84	90	84

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 3 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1990Q2-2012Q3 for the University of Michigan's Survey of Consumers: Inflation, and 1991Q4-2012Q3 for the SPF CPI series. In the last two rows 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. The final row reports the number of observations. The output gap is derived by means of the CF filter.

We use the University of Michigan's Survey of Consumers to measure consumers' inflation expectations, available since 1991Q4 with a regular quarterly frequency. The survey collects forecasts at the 4-quarter horizon and at the 5-year horizon and we estimate the effect of the latter in setting the former. We compare this model to the closest available pairs of professional expectations, i.e. the effect of 10-year-ahead forecasts on 4-quarter-ahead forecasts for CPI inflation. Estimates are given in Table 8.

Estimates show a clear difference in the expectations formation process of professionals and consumers. The coefficient on forward-looking information for consumers is 0.30, very low compared to professionals: 1.04 while the coefficient on backward-looking information is higher: 0.12 compared to 0.03. The coefficients do not add up to one in the case of consumers, the constant is large, 1.78, and strongly significant and the R^2 is remarkably lower as in the SPF model. As far as this specific expectation pair is concerned (10-year-ahead and 4-quarter-ahead expectations) we can thus reject the hypothesis that consumers form their forecasts on the grounds of the NKPC. We also reject this hypothesis when considering that consumers form their forecasts based on professional forecasts (column 3). Given a lack of consumer expectations in the Michigan survey for other horizons we leave the important question of how consumer expectations are formed at different horizons for future research.[21]

6 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-, present and forward-looking information in the private inflation expectations formation process using a NKPC-based expectations formation model. We find that longer-term inflation expectations – possibly representing the policy inflation target or the expected long-term trend – are crucial in determining shorter-horizon inflation expectations. Professional forecasters put relatively more weight on forward-looking information, while lagged inflation remains significant and the contribution of the marginal cost measure is small and often insignificant. These findings are robust to the use of real-time data, to various measures of marginal costs, to the use of the mean of individual responses, to another estimation procedure namely GMM, and to the inclusion of potentially relevant additional variables. 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. This result also holds for two different subsamples where during one inflation decreases rapidly while during the other it is relatively stable. We also find that the estimated parameters of the NKPC-based expectations formation model are relatively stable when the forecasting horizon varies or when we consider further-ahead horizons for forward-looking information. Finally, consumers differ from professional forecasters in that their expectations formation process is not well-captured by this NKPC-based equation.

[21] The fact that parameter estimates for consumers stand in contrast to our findings for professional forecasters can be related to evidence by Carroll (2003) showing that households update their expectations only with a certain probability as news from professionals spread to them. Similarly, Dräger, Lamla, and Pfajfar (2013) show that only 25% of consumers behave consistently with theory, i.e. a Phillips Curve.

7 Appendix

7.1 Data Appendix

Table 9: Data

Name	Description	Original frequency	Time period
	Real-time data first release		
rgdp_1st	Real GDP growth	Quarterly	1968Q4-2012Q3
pgdp_1st	GDP deflator	Quarterly	1968Q4-2012Q3
cpi_1st	Consumer price index	Quarterly	1994Q3-2012Q3
	Final data		
rgdp	Real GDP growth	Quarterly	1968Q4-2012Q3
pgdp	GDP deflator	Quarterly	1968Q4-2012Q3
cpi	Consumer price index	Quarterly	1968Q4-2012Q3
ulc	Unit labour costs	Quarterly	1968Q4-2012Q3
ls	Labour share	Quarterly	1968Q4-2012Q3
unemp	Unemployment rate	Quarterly	1968Q4-2012Q3
indpro	Industrial production index	Quarterly	1968Q4-2012Q3
cap_uti	Capacity utilisation	Quarterly	1968Q4-2012Q3
invent	Inventories	Quarterly	1968Q4-2012Q3
	Survey data (x-quarters-ahead horizon)		
spf_pgdp_0	SPF median pgdp expectations (0)	Quarterly	1968Q4-2012Q3
spf_pgdp_1	SPF median pgdp expectations (1)	Quarterly	1968Q4-2012Q3
spf_pgdp_2	SPF median pgdp expectations (2)	Quarterly	1968Q4-2012Q3
spf_pgdp_3	SPF median pgdp expectations (3)	Quarterly	1968Q4-2012Q3
spf_pgdp_4	SPF median pgdp expectations (4)	Quarterly	1974Q4-2012Q3
spf_pgdpm_0	SPF mean pgdp expectations (0)	Quarterly	1968Q4-2012Q3
spf_pgdpm_1	SPF mean pgdp expectations (1)	Quarterly	1968Q4-2012Q3
spf_pgdpm_2	SPF mean pgdp expectations (2)	Quarterly	1968Q4-2012Q3
spf_pgdpm_3	SPF mean pgdp expectations (3)	Quarterly	1968Q4-2012Q3
spf_pgdpm_4	SPF mean pgdp expectations (4)	Quarterly	1974Q4-2012Q3
spf_cpi_0	SPF cpi expectations (0)	Quarterly	1981Q3-2012Q3
spf_cpi_1	SPF cpi expectations (1)	Quarterly	1981Q3-2012Q3
spf_cpi_2	SPF cpi expectations (2)	Quarterly	1981Q3-2012Q3
spf_cpi_3	SPF cpi expectations (3)	Quarterly	1981Q3-2012Q3
spf_cpi_4	SPF cpi expectations (4)	Quarterly	1981Q3-2012Q3
spf_cpi_10	SPF cpi expectations (10 years)	Quarterly	1991Q4-2012Q3
msi_1	UMSC cpi expectations (1 year)	Quarterly	1978Q1-2012Q3
msi_5	UMSC cpi expectations (5 years)	Quarterly	1990Q2-2012Q3

This appendix 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 three-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 9 below and come from the following sources: Real-time and SPF survey data from the website of the Federal Reserve of Philadelphia and final data and the University of Michigan's Survey of Consumers (UMSC) from the Federal Reserve of St. Louis FRED database. For all price series annualised quarter on quarter growth rates are calculated as: $\pi_t = ((\frac{p(t)}{p(t-1)})^4 - 1) \times 100$.

7.2 Preliminary Tests

Table 10: Unbiasedness of survey inflation expectations

	Horizons (x quarters ahead)				
GDP deflator (1st release)	0	1	2	3	4
α	0.02	0.35*	0.43*	0.54**	0.71***
	(0.18)	(0.19)	(0.23)	(0.24)	(0.24)
β_u	0.92***	0.76***	0.69***	0.63***	0.56***
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
$\beta_u = 1$	0.17	0.00***	0.00***	0.00***	0.00***
GDP deflator (final)	0	1	2	3	4
α	0.50**	0.80***	0.92***	1.18***	1.28***
	(0.22)	(0.26)	(0.30)	(0.30)	(0.29)
β_u	0.77***	0.63***	0.55***	0.44***	0.40***
	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)
$\beta_u = 1$	0.00***	0.00***	0.00***	0.00***	0.00***
CPI inflation (1st release)	0	1	2	3	4
α	0.13	3.12***	2.50***	2.40**	2.36*
	(0.88)	(0.87)	(0.76)	(1.13)	(1.35)
β_u	1.00***	−0.26	−0.00	0.04	0.06
	(0.34)	(0.40)	(0.31)	(0.40)	(0.48)
$\beta_u = 1$	0.99	0.00***	0.00***	0.02**	0.05*
CPI inflation (final)	0	1	2	3	4
α	−0.29	1.07**	1.43***	1.35**	1.55**
	(0.38)	(0.42)	(0.45)	(0.55)	(0.59)
β_u	1.09***	0.62***	0.49***	0.49***	0.42**
	(0.12)	(0.12)	(0.13)	(0.16)	(0.17)
$\beta_u = 1$	0.45	0.00***	0.00***	0.00***	0.00***
Extended sample (1st release)	0	1	2	3	4
α	−0.18	−0.09	−0.20	0.07	−0.15
	(0.19)	(0.26)	(0.31)	(0.39)	(0.42)
β_u	1.03***	1.02***	1.04***	0.97***	0.92***
	(0.06)	(0.09)	(0.10)	(0.11)	(0.15)
$\beta_u = 1$	0.60	0.79	0.66	0.79	0.60
Extended sample (final data)	0	1	2	3	4
α	−0.04	0.02	−0.03	0.27	0.00
	(0.22)	(0.27)	(0.35)	(0.41)	(0.46)
β_u	1.02***	1.01***	1.02***	0.94***	0.89***
	(0.06)	(0.08)	(0.10)	(0.12)	(0.15)
$\beta_u = 1$	0.75	0.85	0.82	0.61	0.46

***, **, and * 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 for each PGDP and CPI inflation and with both real-time data (1st release) and final revised data. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set goes from 1981Q3-2012Q3, for the first three inflation measures, while it does not start before 1994Q3 for the first release of CPI inflation. The last two categories present the results for final and first release of the GDP deflator on the long sample starting in 1968Q4, respectively. Below the parameter estimates the p-value corresponding to a t test of $\beta_u = 1$ is presented.

7.3 Robustness Tests

7.3.1 Other Marginal Cost Measures

Table 11: Other Marginal Cost Measures

	Marginal cost measure						
GDP deflator	HP-GAP	ULC	LS	UNEMP	INDPRO	CAPUTI	INVENT
δ	−0.04**	0.04*	0.00	−0.01	−0.01	0.01	−0.00
	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
β_f	0.81***	0.80***	0.80***	0.82***	0.81***	0.80***	0.81***
	(0.04)	(0.05)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
β_b	0.14***	0.12***	0.16***	0.15***	0.15***	0.16***	0.16***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
const	0.09	0.11	−0.40	0.13	0.08	−0.70	0.07
	(0.11)	(0.14)	(1.22)	(0.19)	(0.13)	(0.67)	(0.13)
R^2	0.92	0.92	0.91	0.91	0.91	0.91	0.91
$\beta_f + \beta_b = 1$	0.32	0.23	0.55	0.57	0.51	0.51	0.53
Obs	124	124	124	124	124	124	124
CPI inflation	HP-GAP	ULC	LS	UNEMP	INDPRO	CAPUTI	INVENT
δ	0.04	−0.06	−0.07*	−0.06	0.02	0.01	0.00
	(0.06)	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)	(0.00)
β_f	0.86***	0.91***	0.99***	0.88***	0.86***	0.85***	0.87***
	(0.10)	(0.14)	(0.16)	(0.12)	(0.10)	(0.10)	(0.11)
β_b	0.20***	0.20***	0.18***	0.19***	0.19***	0.19***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
const	−0.23	−0.28	6.45*	0.11	−0.24	−1.35	−0.25
	(0.29)	(0.33)	(3.77)	(0.26)	(0.28)	(1.60)	(0.28)
R^2	0.73	0.72	0.73	0.72	0.73	0.72	0.73
$\beta_f + \beta_b = 1$	0.49	0.38	0.21	0.46	0.54	0.66	0.53
Obs	124	124	124	124	124	124	124

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation (3), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3. In the rows below the parameter estimates the R^2 of the regression, the p-value of an F test for the hypothesis that $\beta_f + \beta_b = 1$ and the number of observations are presented. The following abbreviations for the marginal cost measures are used: HP-GAP=HP filter-based output gap, ULC=Unit labour costs, LS=Labour share, UNEMP=Unemployment, INDPRO=Industrial production, CAPUTI= Capacity utilisation, INVENT=Inventories.

Results with the HP-filtered output gap are very similar to the benchmark with the exception that the output gap is now significant at the 5% level in the GDP deflator model, though the coefficient is the same. The output gap measure remains insignificant for the CPI model. Thus, the results for the output gap coefficient are not sensitive to the choice of the filtering method.

Using unit labour costs as is common in many studies (e.g. Adam and Padula, 2011), we find a positive coefficient for the GDP deflator model as would be predicted by theory.

The coefficient is only marginally significant, i.e. at the 10% level. For all other marginal cost measures the coefficient δ is very close to and statistically insignificantly different from zero in the GDP deflator case. The estimates for β_f and β_b are very similar to those presented in Table 1 and 3.

For the CPI inflation models all marginal cost measures result in an insignificant coefficient except for the labor share. For the latter we find a negative and marginally significant coefficient. In this model also the constant is marginally significant unlike in the other models, where it is always insignificant. The results for the backward- and the forward-looking coefficients are similar as before. The null hypothesis of the two coefficients adding up to one cannot be rejected in any case.

7.3.2 GMM

As argued by Adam and Padula (2011), analyses based on survey data might be subject to measurement errors, i.e. it is not clear that expectations are adequately measured nor that survey expectations respresent actual expectations. Further, it is not clear *ex ante* whether expectations of future inflation influence the nowcast or vice versa. Thus endogeneity issues might be present. For these reasons we estimate the model by GMM instrumenting the forward-looking variable; see GMM1 in Table 12. Given that the output gap is potentially unobserved, we also estimate a version, where the output gap is instrumented as well; see GMM2 in the same table. Finally, we also estimate a model, where we treat all three variables, expected future inflation, the ouput gap and the lagged inflation rate as endogenous; see the GMM3 results [22]

[22] We use the same instrument set as Nunes (2010), namely four lags of inflation and two lags each of unit labor costs, wage inflation, output gap and SPF expected inflation one-quarter ahead. This instrument set is based on Galí, Gertler, and López-Salido (2005), while the survey data has been added given that surveys are used as the endogenous variable rather than actual future inflation.

Table 12: GMM estimation

	GDP deflator			CPI inflation		
	GMM1	GMM2	GMM3	GMM1	GMM2	GMM3
δ	-0.03^{**}	-0.03^{**}	-0.03^{**}	0.04	0.05	0.04
	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)
β_f	0.87^{***}	0.87^{***}	0.82^{***}	0.79^{***}	0.79^{***}	0.84^{***}
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
β_b	0.08^{**}	0.08^{**}	0.14^{***}	0.21^{***}	0.21^{***}	0.14^{***}
	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
$const$	0.11	0.11	0.08	-0.04	-0.03	0.00
	(0.07)	(0.07)	(0.08)	(0.10)	(0.10)	(0.12)
R^2	0.90	0.90	0.90	0.68	0.68	0.68
$\beta_f + \beta_b = 1$	0.06^{*}	0.06^{*}	0.24	0.88	0.86	0.67
$Hansen\ J$	0.72	0.66	0.71	0.87	0.80	0.78
$Kleibergen - Paap$	81.51	72.20	6.12	418.28	396.95	5.46
$Endog$	0.24	0.39	0.14	0.72	0.93	0.88
Obs	121	121	121	121	121	121

***, **, and * 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 bandwith selection. Standard errors are in parentheses. 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. Under GMM1 the results for the model where only the forward-looking variable is instrumented are given, for GMM2 also the output gap is treated as endgenous, while for GMM3 the lagged inflation rate is further treated as endogenous. The output gap is derived by means of the CF filter. The data set comprises 1981Q3-2012Q3. 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 two Sargan-Hansen statistics and the final row reports the number of observations.

The results for the first two GMM approaches are almost identical, while in the third case they differ slightly. For the GDP deflator the GMM1 and GMM2 approaches yield a significant output gap coefficient with a similar value as before. However, compared to the benchmark model, the weights on the forward- and backward-looking variables change. While the former increases to around 0.87, the latter is smaller around 0.08. In any case the two remain significant and the hypothesis of these adding to one can still not be rejected at the conventional 5% level. The R^2 is almost not affected. For the GMM3 approach the results are very close to the baseline results with the difference of a significant coefficient on the output gap.

For CPI inflation the GMM results follow a similar pattern. For GMM1 and GMM2 the estimated γ_f is somewhat smaller than in the benchmark at around 0.79, while the rest of the results remain almost unchanged. For GMM3 the parameter estimates come once again closer to the benchmark results.

We perform some tests to examine the validity of the GMM approach. First, we present the p-value corresponding to the Hansen J statistic. The p-value, above 0.60 in all cases, shows that the null hypothesis of valid overidentifiying restrictions cannot be rejected. Second, we report the Kleibergen-Paap rank statistic that corresponds to the first-stage F statistic allowing for heteroskedastic and autocorrelated errors. As shown in Table 12, for GMM1 and GMM2 it exceeds the critical values by far and thus allows us to reject the null hypothesis of weak instruments. In the GMM3 case, however, the evidence is not sufficient to reject weak instruments which is related to the fact that we there have more endogenous variables and less (included) instruments. Third, we test for endogeneity of the variables instrumented in the GMM approaches. We present the p-value corresponding to a test based on the difference between two Hansen-Sargan statistics (one for the GMM approach and one for the OLS approach). In all three case and for both variables, i.e. the GDP deflator and CPI inflation, this test provides evidence in favour of the validity of our OLS benchmark approach.

7.3.3 Mean vs. Median Expectations

Table 13: SPF Mean Expectations

	GDP deflator	CPI inflation
δ	-0.01	0.07
	(0.02)	(0.05)
β_f	0.90***	0.85***
	(0.03)	(0.10)
β_b	0.06**	0.20***
	(0.03)	(0.03)
const	0.03	-0.19
	(0.06)	(0.27)
R^2	0.95	0.76
$\beta_f + \beta_b = 1$	0.07*	0.56
Obs	124	124

***, **, and * denote significance at the 1, 5 and 10% level, respectively. Estimation of equation 3 (including a constant), is conducted by OLS. Asymptotic Newey-West 4 lags standard errors are in parentheses. The data set comprises 1981Q3-2012Q3. In the last two rows 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. The final row reports the number of observations. The output gap is derived by means of the CF filter.

The Survey of Professional Forecasters also reports the mean of all respondents' expectations. Although the mean might be influenced by potential outliers, it seems worthwile to examine whether our conclusions so far hold for this expectation measure. Table 13 contains estimation results for SPF mean expectations.

The results for the GDP deflator are comparable to the benchmark, however, they differ in a few points. First, the output gap measure is statistically insignificant. Second, the forward-looking coefficient is somewhat larger around 0.90, while the backward-looking coefficient is below 0.10, both being significant in all cases. However, the hypothesis of these two adding up to one still cannot be rejected at the 5% level. Finally, the R^2 is slightly larger than before at around 0.95.

For CPI inflation the results are even closer to the benchmark. Apart from a slightly smaller forward-looking coefficient and a slightly higher R^2 no differences can be detected.

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