Is inflation driven by survey-based, VAR-based or myopic expectations?

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An empirical assessment from US real-time data*

Frédérique Bec[†] Patrick Kanda[‡]

Abstract

The relative importance of survey-based, VAR-based or myopic expectations is evaluated in accounting for US inflation dynamics in a New Keynesian Phillips Curve (NKPC) setting. Our contribution is three-fold. First, we estimate the NKPC with both final and real-time vintage data in order to control for large revisions in the real GDP data. Second, we distinguish between two different series for VAR-based inflation forecasts — derived by a recursive or rolling-window method — to account for changes in the conduct and transmission mechanisms of US monetary policy after World War II. Third, joint restrictions are tested in the NKPC to assess whether one of the expectational variables is able, on its own, to capture inflation dynamics. On a statistical basis, we find that there is no clear-cut winner between VAR- and survey-based inflation expectations. Most of our estimated NKPC variants conclude that survey inflation expectations tend to have the largest numerical weight. Nevertheless, the difference between VAR- and survey-based expectations' estimated coefficients is not statistically significant. Moreover, myopic expectations do not play any significant role in the majority of the estimated NKPC variants.

Keywords: VAR-based expectations, Myopic expectations, Survey forecasts, New Keynesian Phillips Curve.

JEL Classification: E27, E31.

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1 Introduction

Expectations play a fundamental role in the study of inflation dynamics in the New Keynesian framework (see for instance Roberts, 1995; Gali and Gertler, 1999). According to this strand of research, inflation depends on a measure of economic activity (usually marginal costs or the output gap) as well as expected inflation. That said, the nature of expected inflation remains a contentious issue. Typically, New Keynesian models are based on the rational expectation hypothesis which posits that economic agents' expectations correspond to the model-implied forecasts.[1].

Despite the popularity and theoretical appeal of the rational expectations hypothesis, some studies[2] challenge its relevance because New Keynesian models based on this assumption cannot replicate key inflation dynamics such as persistence and the cost of disinflation. A number of papers, such as Roberts (1997) or Mavroeidis et al. (2014), show that rational expectations-based New Keynesian monetary models require *ad hoc* extensions such as consumption habit formation, investment adjustment costs, variable capital utilization, autocorrelated shocks as well as wage and price-setting decisions indexation to past inflation to capture key inflation dynamics properties. Yet, there seems to be no microeconomic relevance to these extensions, as extensively documented in Milani (2012). Similarly, the rational expectations hypothesis suggests that all economic agents share the same information set and have the same model-consistent expectations. However, this assumption is at odds with studies from e.g. Mankiw et al. (2003) or more recently Andrade and Le Bihan (2013) and Coibion et al. (2017), which all point out that economic agents form (HAVE ?) heterogeneous expectations.

In the following, rational expectations will in general refer to theoretical model-based expectations. Nevertheless, it is worth noticing that some authors, like for instance Fuhrer (2012); Fuhrer and Olivei (2010), use the same terminology to designate a PAS DE TIRET theoretical model-based — typically VAR-based — expectation. Indeed, as advocated by Fuhrer (2012), " (...) vector autoregressive equations allow us to form rational expectations of inflation without imposing further structure on the model." (p.146)

Some studies show that once the rational expectations hypothesis is replaced by an alternative expectations scheme such as adaptive learning by economic agents, as in Milani

[1] See among others Gali and Gertler (1999), Sbordone (2002), Smets and Wouters (2003), Christiano et al. (2005) or the survey by Milani (2012).

[2] See for instance Fuhrer and Moore (1995), Roberts (1998), Estrella and Fuhrer (2002), Milani (2005) or Milani (2007) *inter alia*.

(2007), or by inflation forecasts from surveys as in Fuhrer (2017), *ad hoc* extensions become redundant and the resulting model closely emulates empirical inflation properties.

It is against this backdrop that a line of research seeks to evaluate the relative contribution of various expectations formation schemes, such as rational or VAR-based, survey-based and myopic schemes, in explaining US inflation dynamics, within the New Keynesian Philips Curve (NKPC hereafter) framework. As will be seen in the next section, the conclusions are at best mitigated, if not contradictory. Our paper contributes to this strand of research, but departs from existing work in three directions.

Firstly, to our knowledge, our paper is the first one to use real-time data in this empirical literature. Secondly, special care is taken for the computation of VAR-based proxy of rational inflation expectations so as to accommodate the major changes which occurred since World War II in the conduct and propagation mechanisms of the U.S. monetary policy. More specifically, our empirical analysis will be conducted using both rolling and recursive computations of these expectations. Thirdly, by contrast with previous empirical studies, we proceed with systematic joint hypothesis tests to assess whether a mix of the VAR-based, survey and/or myopic expectations is needed or if only one of them is enough to capture inflation dynamics.

Our main finding is that VAR-based *and* survey inflation expectations contribute significantly to inflation dynamics. Using final vintage data, their relative contributions to inflation dynamics depends on whether recursive or rolling-window VAR-based inflation forecasts are used. On the contrary, estimations using real-time data consistently show that survey inflation expectations have the largest weight. However, estimates of VAR-based and survey-based inflation expectations contributions are not significantly different from each other: Our tests generally cannot reject the null hypothesis that both expectation variables estimated weights are equal. Hence, contrary to the conflicting outcome of existing studies[3], we cannot conclude that any one of the two types of forward-looking inflation expectations is enough on its own to capture inflation dynamics in the NKPC framework. Finally, myopic (i.e. backward-looking) inflation expectations mostly do not play any significant role in explaining US inflation dynamics.

The remainder of the paper is structured as follows: Section 2 offers a short overview of the recent related literature. Section 3 discusses the data and methodology while Section 4 presents the results. Section 5 concludes.

[3]See next section.

2 Related literature

A few decades ago, studies seeking to compare the relevance of different types of inflation expectations schemes used to consider separately the various types of forward-looking expectations — one at a time — in the NKPC inflation equation and assessed the ability of the corresponding model to capture inflation dynamics (see for example Roberts, 1995).

The strand of research investigating the relative contributions of various expectations schemes to US inflations dynamics is relatively new. It aims at bringing together different practices of benchmarking various measures of inflation expectations in the NKPC literature. Basically, the following hybrid formulation of the NKPC equation featuring heterogeneous inflation expectations is considered:

$$\pi_t = \beta_e E_t \pi_{t+1} + \beta_s S_t \pi_{t+1} + \beta_m \pi_{t-1} + \gamma mc_t + u_t \tag{1}$$

where π_t is the inflation rate, $E_t \pi_{t+1}$ is the model-consistent (i.e. rational or VAR-based) expectation of inflation in period $t + 1$, formed in period t, $S_t \pi_{t+1}$ is the one-period-ahead inflation survey forecast as reported in period t, mc_t is a measure of marginal costs and u_t is a disturbance term.

Given that forward-looking inflation expectations are unobservable, different studies use different proxies. Mainly, three ways are used to circumvent the non-observability of expectations: (1) substitute inflation expectations for realized inflation and use instruments — the so-called Generalized Instrumental Variables (GIV) approach; (2) use a Vector Auto-Regression (VAR hereafter) model to derive inflation expectations; (3) use direct measures of inflation expectations obtained from surveys (Mavroeidis et al., 2014). These three methods are featured in studies that investigate the relative contributions of different expectations schemes (*e.g.* rational, survey and myopic) in explaining US inflation dynamics in the NKPC framework (see for example Nunes, 2010; Fuhrer and Olivei, 2010; Fuhrer, 2012).

In this literature, forward-looking inflation expectations are composed of both rational inflation expectations — which are not observable — and survey counterparts. To deal with unobservable expectations, Nunes (2010) uses the GIV approach. On the other hand, Fuhrer and Olivei (2010) and Fuhrer (2012) derive rational inflation expectations from a reduced-form VAR model. These studies methods, data and results are summarized in Table 1.

Table 1: Relative weights of lagged inflation, rational and survey inflation expectations in a New Keynesian Phillips Curve

Paper	Country	Sample	π_t	$E_t\pi_{t+1}$	Model	$\hat{\beta}_e$	$\hat{\beta}_s$	$\hat{\beta}'_s$	$\hat{\beta}_m$	$\hat{\beta}'_m$
Nunes (2010)	US	1968Q4 - 2007Q4	GDP deflator	GIV	Detrended GDP	**0.82**	**0.22**	–	–	–
						(0.08)	(0.09)			
						0.76	–	0.24	–	–
						(0.09)		(0.09)		
						0.74	**0.19**	–	0.10	–
						(0.10)	(0.09)		(0.11)	
						0.56	**0.18**	–	–	**0.25**
						(0.09)	(0.09)			(0.09)
					Marginal cost	**0.96**	0.07	–	–	–
						(0.05)	(0.06)			
						0.96	–	0.04	–	–
						(0.05)		(0.05)		
						0.88	0.05	–	0.09	–
						(0.09)	(0.06)		(0.12)	
						0.81	0.02	–	–	0.17
						(0.08)	(0.05)			(0.11)
Fuhrer and Olivei (2010)	US	1983 - 2009	Core CPI	VAR	Core CPI, output gap					
					1983 - 1992	0.20	0.40	–	0.30	–
						(n.a)	(n.a)		(n.a)	
					1990 - 1999	0.20	0.30	–	0.40	–
						(n.a)	(n.a)		(n.a)	
					1999 - 2008	0.20	0.20	–	0.20	–
						(n.a)	(n.a)		(n.a)	
Fuhrer (2012)	US	1990Q1 - 2010Q3	CPI	VAR	SPF TI / ML	0.00	**0.75**	–	–	**0.25**
						(n.a)	(0.25)			(0.10)
					CS TI / ML	0.00	**0.73**	–	–	**0.36**
						(n.a)	(0.17)			(0.11)
					SPF TI / ML (including 1980s)	0.03	**0.87**	–	–	0.10
						(0.14)	(0.30)			(0.06)
				GIV	TI / Optimal GMM	0.11	**0.57**	–	–	**0.25**
						(0.21)	(0.28)			(0.09)
					TI / GMM	**0.77**	0.22	–	–	-0.04
						(0.33)	(0.56)			(0.13)

Notes: Figures in **bold** denote significant coefficients at the 5%. π_t: inflation rate; $E_t\pi_{t+1}$: inflation rational expectations; β_e and β_s: coefficients pre-multiplying the rational and survey expectations variables, respectively; β_m: lagged inflation parameter. $\beta'_s = 1 - \beta_e$ and $\beta'_m = 1 - \beta_e - \beta_s$. Standard errors are in ( ). "SPF": Survey of Professional Forecasters; "TI": trend inflation; "CS": Cogley-Sbodorne; "n.a": not available.

Based on NKPC estimations featuring both rational and survey expectations, Nunes (2010) finds weak evidence in favor of survey expectations but strong evidence in favor of rational expectations in explaining inflation dynamics: while the maximum estimated weight found for the former ($\hat{\beta}_s$) is 0.22, it ranges from 0.56 to 0.96 for the latter ($\hat{\beta}_e$), depending on the model and on the proxy chosen for the marginal cost in the NKPC, Equation (1). However, this argument clashes with Fuhrer and Olivei (2010)'s finding that the role of survey expectations slightly dominates that of rational counterparts: Depending on the period considered, these authors find a contribution of survey expectations ranging from 0.2 to 0.4 while the one of rational expectations is always 0.2. In the same perspective, Fuhrer (2012) finds overwhelming evidence that survey expectations play a more important role than (VAR-based) rational counterparts in inflation dynamics explanation. The myopic expectations contribute significantly in half the cases. All in all, columns labelled $\hat{\beta}_e$ and $\hat{\beta}_s$ in Table 1 emphasize that the relative contributions of rational and survey-based inflation expectations in explaining inflation dynamics is still debated. Furthermore, the column labelled $E_t\pi_{t+1}$ denoting inflation rational expectations, reveals that there is no consensus in this literature regarding the ideal proxy for rational inflation expectations.

3 Data and Methodology

In the NKPC Equation (1), the model-consistent inflation expectations and the marginal cost variables are not directly observable. Hence, they need to be proxied. There are almost as many different flavors of NKPC estimated equations as empirical contributions to this literature, since the latter use different proxies for the marginal cost and/or model-consistent inflation expectations. In this section, we first describe the data used to build these proxies and then present the methodology retained for the NKPC estimation.

3.1 Data

Real-time output gap: In this study, the output gap is used as a proxy for marginal costs in the NKPC Eq.(1). Our benchmark analysis relies on final vintage (FV hereafter) data, that is, the most up-to-date data for the real GDP. However, real GDP data are submitted to large revision every quarters for years. Hence, using final vintage of observations to compute the output gap used in the VAR and the NKPC equation could be misleading. To compute the inflation expectations recursively from 1981Q3 on, one would rather use the observations that were available back then. Indeed, Koenig et al. (2003) and Clements and Galvão (2013) argue that the use of the latest available vintage data leads to an overestimation of independent variables' power to predict the dependent variable. As such, the authors advocate the use of real-time data. Furthermore, data revisions have been shown to have an impact on economic agents' expectation formation as well as the conduct of monetary policy and the response of policy to uncertainty (see Croushore and Stark, 2001, for a review). Hence, the Philadelphia Fed's real-time database is used to extract real-time data for the real GDP. This database consists of quarterly snapshots or "vintages" of key macroeconomic variables. A vintage refers to data series on a variable as it appeared to an analyst at a specific point in time. For any given vintage date, the series are exactly those an analyst would have observed in published sources at that particular date (see Table A1 in the Appendix). To illustrate this, for each vintage at time t (in quarters), the series runs from 1947Q1 to time $t-1$. The combination of different vintages forms a real-time dataset. The first vintage date in the real-time database is 1965Q4. The Philadelphia Fed's real-time dataset comprises data as they appeared in the middle of each quarter. In fact, the timing of the real-time dataset was set so as to match the timing of the Survey of Professional Forecasters (Croushore and Stark, 2001). Hence, at every date within the sample, we use the most up-to-date available estimate for the variable. For instance, in 1981Q4, the most up-to-date estimate is the first release of the 1981Q3 value of real GDP. This entails using the vector of diagonal elements of the real-time database as the real-time vintage (RTV hereafter) series for a variable.

For different vintages of output would correspond different vintages of the output gap. In other words, the final vintage output gap data does not correspond with the ones forecasters used in forming expectations in the past. Unfortunately, the potential output is not observable and no real-time measure of it is available to our knowledge. Hence, it needs to be estimated. There exists a number of estimation approaches for the potential output in the academic literature, but there is still no consensus on which approach yields the best estimate of it. Here, inspired by the paper of Guisinger et al. (2018), we have compared two methods for extracting the potential output: the quadratic trend and the Hodrick and Prescott filter. Then, using final vintage data, we have compared these series based on both methods to the Congressional Budget Office (CBO) official measure of the potential output which is not available in real-time vintage to our knowledge. As a result, it turned out that the HP filter was more correlated to the CBO measure than the nonlinear trend measure. Consequently, we have carried out all the subsequent estimations using the HP-filtered measure of potential output.

Model-consistent expectations: As a matter of fact, the computation of the empirical counterpart of the so-called rational expectations is far from reaching a consensus among macro-economists. As stressed in the Introduction, even the terminology regarding expectations computation is still unsettled: Fuhrer (2012) proxies the rational expectations by VAR-based forecasts while, for instance, the Federal Reserve Bank's model of the US economy clearly distinguishes rational expectations from VAR-based expectations (see Brayton et al., 1997).

Yet, Nason and Smith (2008b) argue that the many difficulties in estimating and testing the NKPC can be traced back to the fact that inflation expectations are unobservable. Morever, Fuhrer and Olivei (2010) point out that the model-consistent nature of rational expectations poses a difficulty when the model does not match key features of the economy.

Given the significant costs of accessing all the information as well as elaborating a model that mimics the economy's complex structure, agents may opt for limited information (a small set of key macroeconomic variables) and a forecasting model that closely represents the economic environment but does not capture the complexity of the economy. This approach motivates the use of VAR-based expectations (Brayton et al., 1997; Branch, 2004; Fanelli, 2008b,a; Fanelli and Palomba, 2011; Tulip, 2014). Here, following the Fed's model of the US economy described in Brayton et al. (1997), a small unrestricted VAR model is used, consisting of an equation for each of the output gap, the inflation rate and the Federal Funds rate. Let $X_t = (\tilde{y}_t, \pi_t, i_t)$, where $\tilde{y}_t$ is the output gap, π_t is the inflation rate and i_t is the Federal Funds rate (nominal interest rate). The following VAR system is considered:

$$X_t = \mu + \sum_{j=1}^{\ell} P_j X_{t-j} + \xi_t, \quad \xi_t \sim WN\left(0_{N\times 1}, \Sigma_\xi\right) \tag{2}$$

where $P_j \ \ (j = 1, \ldots, \ell)$ are $n \times n$ matrices of parameters, ℓ is the lag length, and ξ_t is a white-noise error with covariance matrix Σ_ξ. All the data in X_t come from the Federal Reserve Bank of St. Louis' FRED online database. The sample starts in 1954Q3 due to the effective Federal Funds rate (i_t) availability and ends in 2017Q4. Using quarterly US data, we compute the output gap as $\tilde{y} = 100 \times (y_t - \bar{y}_t)$; where y_t and $\bar{y}_t$ are the logs of real GDP and potential GDP, respectively. The inflation rate is given by $\pi_t = 400 \times (p_t - p_{t-1})$, where p_t is the log of the consumer price index (CPI). The output gap is stationary by construction and Augmented Dickey-Fuller tests applied to π_t and i_t reject the unit root null at the 5%-level in both cases[4]. Hence, the vector X_t is stationary.

First, the VAR model given in Equation (2) is estimated over the full sample, that is 1954Q3-2017Q4. In order to choose the number of lags, ℓ, the Lagrange Multiplier test for no serial correlation in residuals is sequentially implemented for the VAR(ℓ)'s residuals, $\forall \ell = 1, 2, \ldots 8$): the smallest lag order for which the residuals are serially uncorrelated up to order 8 is selected. The chosen lag order, say $\hat{\ell}$, is kept as a key feature of the DGP. Next, the VAR($\hat{\ell}$) model is estimated over the period 1954Q3-1981Q2 (i.e. the quarter just before the survey inflation forecasts data is available).

The one-step-ahead VAR inflation expectations are computed recursively over the remaining part of the sample (1981Q3-2017Q4). By doing so, our measure of inflation expectations begins exactly at the same quarter as the survey forecasts. Given the possibility of major changes in the monetary policy over our sample, for instance moving from the Great Inflation period to the Great Moderation one, VAR-based inflation forecasts computed on a rolling window basis are also considered. Each window spans 134 quarters, starting from 1954Q3-1981Q2 and ending in 1991Q1-2017Q4.

Survey-based expectations: The survey-based expectations data used in this paper come from the Federal Reserve Bank of Philadelphia Survey of Professional Forecasters (SPF) which is available online. This quarterly survey is conducted among private-sector economists who share the specificity that forecasting macroeconomic variables is a key part of their work. Its outcomes are released at the end of the middle month of a given quarter. A key feature of the survey is that it is anonymous so as to ensure that forecasters do not feel compelled to adapt to the consensus forecast (see Croushore, 1993). We use the median CPI inflation survey forecasts.[5] Following e.g. Fuhrer (2012), the four-quarter-ahead inflation survey forecasts are used in the NKPC. As emphasized by this author, theoretical models of inflation do not explicitly consider relative price variation. However, in practice, forecasters usually take into consideration relative price variations (food, energy and import prices) when forecasting one-quarter-ahead inflation. Hence, using the four-quarter-ahead inflation expectations rather than one-period-ahead inflation forecasts addresses this issue to some extent. Indeed the four-quarter-ahead inflation forecasts series is smoother than its one-quarter-ahead analogue (see Figure A1d in the Appendix). Although the starting date

[4] These tests were conducted with an intercept only and with respectively 2 and 5 lags in first differences so as to eliminate residuals serial correlation up to order 8. The resulting tests statistics are respectively -3.61 and -2.87.

[5] These are median CPI values across forecasters, over time.

of the SPF is 1968, the CPI forecasts are included in the survey only since 1981Q3. This explains why the estimation of the NKPC equation featuring survey inflation expectations cannot start before this date.

3.2 Estimation of the NKPC

To assess the relative importance of different schemes of inflation expectations in explaining inflation dynamics, we consider a specification of the NKPC featuring heterogeneous expectations, that is, a combination of survey, VAR-based as well as myopic (i.e. lagged) inflation expectations. The various specifications of the NKPC considered are nested in the following version of Equation (1):

$$\pi_t = \beta_{var} E_t \pi_{t+1} + \beta_s S_t \pi_{t+4} + \beta_m \pi_{t-1} + \gamma \tilde{y}_t + u_t \tag{3}$$

where $E_t\pi_{t+1}$ is time t VAR-based forecast of inflation in period $t+1$ and $S_t\pi_{t+4}$ is the $t+4$ inflation survey forecast as reported in period t.

We restrict parameters pre-multiplying expectational variables to sum up to one, such that $\beta_{var} + \beta_s + \beta_m = 1$ throughout the empirical analysis. This restriction is in the spirit of a strand of the literature where a fraction of firms sets prices by relying on either model-consistent, survey or myopic inflation expectations (Nunes, 2010). In addition, we consider two versions of the NKPC model: (1) the purely forward-looking model where β_m is set to zero, and (2) the so-called hybrid one where β_m can be different from zero, allowing for a fraction of firms to form myopic expectations.

Given that there are endogeneity issues as well as measurement errors due to the estimation of unobservable variables (VAR-based expectations and output gap) in the NKPC equation, it will be estimated using the method of Generalized Instrumental Variables, a special case[6] of the Generalized Method of Moments (GMM). According to this method:

$$E\left[\left(\pi_t - \beta_{var} E_t \pi_{t+1} - \beta_s S_t \pi_{t+4} - \beta_m \pi_{t-1} - \gamma \tilde{y}_t\right) Z_t\right] = 0, \tag{4}$$

which means that its residuals should have a zero mean and be orthogonal to the instruments contained in Z_t. The instruments set used here is in the spirit of Gali et al. (2005) and Nunes (2010). It consists of four lags of inflation, two lags of each regressor as well as wage inflation

[6] See for instance Mavroeidis et al. (2014), pages 133–134.

and labor share[7]. The estimation method is the continuously-updated GMM (here equivalent to GIV) with Newey-West weight matrix and Bartlett bandwidth selection. The estimation sample period is 1982Q3-2017Q4.

Mavroeidis et al. (2014) (and references therein) argue that weak identification is prevalent in the NKPC since it is difficult to forecast changes in inflation. Hence, lagged instruments would be close to irrelevant. As such, inference relying on the J-test for overidentifying restrictions may be misleading. Therefore, weak identification of the NKPC has to be handled with robust inference methods, which remain valid under weak identification, (Dufour et al., 2006; Nason and Smith, 2008a,b; Mavroeidis et al., 2014). One such method is the Anderson and Rubin (1949) test.

Following Nason and Smith (2008b), we illustrate how inference on a given parameter of the NKPC can be carried out. For this purpose, let us consider the parameter pre-multiplying the survey inflation forecast (β_s), and rewrite Equation (3) as:

$$\pi_t - \beta_s S_t \pi_{t+4} = \beta_{var} E_t \pi_{t+1} + \beta_m \pi_{t-1} + \gamma \tilde{y}_t + \Gamma V_t + u_t \tag{5}$$

where V_t represent a list of v supplementary variables and γ is a $(1 \times v)$ vector of parameters. In our case, V_t contains the same variables as the instrument set. To compute the left-hand side variable of the equation, we should pick a value β_{s0} for β_s. Testing the hypothesis that $\beta_s = \beta_{s0}$ involves performing the standard F-test of the hypothesis that the variables in V_t are all insignificant, that is, $\Gamma = 0$. The reasoning is that if β_{s0} is the true value for β_s, then *(i)* the main regressors in the NKPC will generate the dynamics of π_t and *(ii)* the residuals will not exhibit any systematic pattern due to the inclusion of supplementary variables V_t in the regression (Nason and Smith, 2008b). Using a range of values between 0 and 1 for β_{s0}, Equation (5) is estimated.[8] For each round of estimation, both the F-statistic of the null that the parameters pre-multiplying the supplementary variables are zero, and its associated p-value are collected. All values of β_{s0} associated with p-values greater than 5% do not reject the null. Consequently, the boundaries of the interval over which these p-values are greater than 5% define the 95% confidence interval for the estimated value of β_s in the above example. Of course, the same applies to all estimated coefficients of the NKPC equation.

[7] For real-time data estimations, the instrument set includes two lags of the inflation rate, survey inflation expectations, VAR-based inflation expectations and the real-time vintage output gap, in the spirit of Mavroeidis et al. (2014)

[8] In practice, we have used a grid of 100 evenly spaced values between 0 and 1 for inflation expectation variables. For the output gap variable, the grid spans from -0.25 and 0.25 as in Mavroeidis et al. (2014).

4 Results

Following the lines described in subsection 3.1, a lag order of six is retained for the VAR model given in Equation (2). Figure A2 in the Appendix shows the VAR-based inflation expectations series. Figures A2a and A2b show the VAR-based inflation expectations obtained by the recursive forecasting approach using final and real-time vintage data, respectively. Similarly, Figures A2c and A2d plot VAR-based inflation expectations from the rolling-widow forecasting approach. Next, Figure A3 in the Appendix displays the HP filter-based real time vintage output gap series, along with the final vintage measure obtained using official data on potential output from the CBO.

Given the choice between *(i)* final and real-time vintage data, *(ii)* recursive and rolling-window estimation for the VAR-based forecasts, and *(iii)* hybrid and purely forward-looking (i.e. without myopic inflation expectations) model, eight variants of the NKPC are estimated.

Table 2: Estimates of the NKPC model

	Final vintage				Real-time vintage			
	Recursive $E_t\pi_{t+1}$		Rolling $E_t\pi_{t+1}$		Recursive $E_t\pi_{t+1}$		Rolling $E_t\pi_{t+1}$	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\hat{\beta}_{var}$	0.37	0.42	0.60	0.54	0.07	0.32	0.12	0.40
	(0.15)	(0.11)	(0.15)	(0.12)	(0.17)	(0.12)	(0.31)	(0.16)
	[0.00, 0.65]	[0.00, 0.65]	[0.00, 1.00]	[0.00, 1.00]	[0.00,0.50]	[0.00,0.50]	[0.00,1.00]	[0.00,1.00]
$hat\beta_s$	0.59	0.58	0.43	0.46	0.70	0.68	0.66	0.60
	(0.11)	(0.11)	(0.13)	(0.12)	(0.13)	(0.12)	(0.20)	(0.16)
	[0.09, 1.00]	[0.09, 1.00]	[0.14, 1.00]	[0.14, 1.00]	[0.10,0.81]	[0.10,0.81]	[0.00,0.86]	[0.00,0.86]
$hat\beta_m$	0.04	—	-0.03	—	0.23	—	0.22	—
	(0.08)		(0.08)		(0.09)		(0.14)	
	[0.00, 0.50]		[0.00, 0.45]		[0.00,0.36]		[0.00,0.36]	
$hat\gamma$	0.09	0.08	0.00	0.01	-0.09	-0.20	-0.08	-0.14
	(0.07)	(0.07)	(0.07)	(0.07)	(0.11)	(0.11)	(0.09)	(0.10)
	[-0.17,0.25]	[-0.17,0.25]	[-0.09,0.25]	[-0.09,0.25]	[-0.25,0.25]	[-0.25,0.25]	[-0.25,0.25]	[-0.25,0.25]
J	70%	78%	83%	88%	64%	63%	72%	68%

Notes: Standard errors are in ( ); Anderson and Rubin (1949)-based robust 95% confidence intervals are in [ ]; J gives the p-value for the GMM overidentifying restrictions test.

Table 2 presents the results. The first (respectively last) four columns correspond to final (resp. real-time) vintage data. Columns (a), (c), (e) and (g) report the estimated parameters for hybrid NKPC models while columns (b), (d), (f) and (h) show purely forward-looking NKPC models' estimates.

For all models, the J-test for over-identifying restrictions, bottom line of Table 2, is associated with a large p-value. Hence, the restrictions are valid. However, in this framework of the NKPC estimated by GIV, inference may be misleading due to prevalence of weak identification. For this reason, we also report in Table 2 the 95 percent robust confidence intervals obtained from the Anderson and Rubin (1949) test. These intervals remain valid regardless of whether identification is weak or not. In general, point estimates fall within the boundaries of the confidence intervals. However, there is a lot of uncertainty as the intervals are very wide and always include zero (except for the survey inflation expectations' estimate). This corroborates findings in the literature that confidence sets for the NKPC model's parameters tend to be wide and contain zero, see for example Dufour et al. (2006) or Nason and Smith (2008b) and the references therein.

A quick glance at the results reveals that in six out of the eight estimated models, the parameter pre-multiplying the survey inflation expectations variable ($\hat{\beta}_s$) has the largest weight (ranging between 0.58 and 0.7) and is statistically significantly different from zero, using the robust confidence intervals. The two exceptions are the NKPC models estimated using final vintage data and the rolling-window VAR-based inflation forecasts. In this instance, the estimated coefficient for survey inflation expectations is aound 0.45, while the coefficient for VAR-based inflation expectations ($\hat{\beta}_{var}$) ranges between 0.54 and 0.6.

All in all, it can be seen that estimations of the NKPC using final vintage data yield different conclusions depending on the methods used to derive VAR-based inflation expectations. It is also worth noting that in the case of real-time vintage data, the estimated parameter for survey inflation expectations has the largest weight regardless of which type of VAR-based inflation forecasts variable used.

Except for the case corresponding to the NKPC model estimated with real-time data and recursive VAR-based inflation expectations, the coefficient pre-multiplying the myopic inflation expectations variable ($\hat{\beta}_m$) is not statistically different from zero. While the weight of the myopic inflation expectations parameter is very close to zero when the NKPC equation is estimated from final vintage data, it turns out to be roughly 0.2 in the models estimated with real-time data. Finally, the coefficient for the output gap ($\hat{\gamma}$) is never significantly different from zero: This variable does not contribute significantly to the US inflation dynamics.

Table 3 reports Wald tests statistics (and their p-values) of hypotheses of interest on NKPC parameters estimates. Practically, there appears to be no statistically significant difference between the weights of survey and VAR-based inflation expectations, as confirmed by the third and sixth lines of this table. Except for one case (hybrid NKPC model estimated with real-time data and recursive VAR-based inflation forecasts), the hypothesis of equality between the VAR-based and survey inflation expectations cannot be rejected at the 5%-level.

Table 3: Wald tests for parameters restrictions in the NKPC model

	Final vintage		Real-time vintage	
	Recursive $E_t\pi_{t+1}$	Rolling $E_t\pi_{t+1}$	Recursive $E_t\pi_{t+1}$	Rolling $E_t\pi_{t+1}$
Hybrid model				
H_0: $\beta_{var}=1$, $\beta_s=0$, $\beta_m=0$	30.35 (<0.01)	12.13 (<0.01)	33.17 (<0.01)	11.29 (<0.01)
H_0: $\beta_{var}=0$, $\beta_s=1$, $\beta_m=0$	16.12 (<0.01)	20.14 (<0.01)	14.55 (<0.01)	15.37 (<0.01)
H_0: $\beta_{var}=\beta_s$, $\beta_m=0$	0.77 (0.68)	0.43 (0.81)	7.49 (0.02)	2.75 (0.25)
Purely forward-looking model				
H_0: $\beta_{var}=1$, $\beta_s=0$	29.76 (<0.01)	14.16 (<0.01)	29.28 (<0.01)	13.39 (<0.01)
H_0: $\beta_{var}=0$, $\beta_s=1$	15.53 (<0.01)	20.05 (<0.01)	6.76 (0.01)	6.08 (0.01)
H_0: $\beta_{var}=\beta_s$	0.57 (0.45)	0.13 (0.72)	1.97 (0.16)	0.36 (0.55)

Notes: $p-$values into ( ).

As such, these tests suggest that VAR-based and survey inflation expectations are equally relevant and important in explaining US inflation dynamics in the NKPC framework. Then, the hypothesis that only VAR-based inflation expectations matter is strongly rejected at the 5%-level across all models (first and fourth lines of Table 3). The same applies for survey inflation expectations (second and fifth lines).

As a robustness check of these findings, all variants of the NKPC model are estimated using four-quarter-ahead VAR-based inflation forecasts instead of one-quarter-ahead ones. In this fashion, VAR-based inflation expectations match the horizon of survey counterparts used in the study. Tables 4 and 5 generally confirm our conclusions.

As shown in Table 4, survey inflation expectations generally tend to have larger weights than VAR-based expectations. Nonetheless, both expectation measures are statistically equivalent in most cases (see Table 5, third and sixth lines). The only difference with the main results is the case corresponding to the use of real-time data in the estimation: There, the hypothesis that only survey inflation expectations matter in explaining US inflation dynamics cannot be rejected.

Similar to the main findings, Table 4 shows that the overidentifying restrictions are valid based on the J test. Also, Anderson and Rubin (1949) 95% weak identification-robust confidence intervals are wide and they contain the point estimates in most cases. Again,

Table 4: Estimates of the NKPC model with four-quarter VAR-based expectations

	Final vintage				Real-time vintage			
	Recursive $E_t\pi_{t+1}$		Rolling $E_t\pi_{t+1}$		Recursive $E_t\pi_{t+1}$		Rolling $E_t\pi_{t+1}$	
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\hat{\beta}_{var}$	0.54	0.40	0.66	0.58	-0.02	0.25	0.04	0.30
	(0.18)	(0.11)	(0.17)	(0.12)	(0.19)	(0.13)	(0.27)	(0.18)
	[0.00, 0.54]	[0.00, 0.54]	[0.00, 0.80]	[0.00, 0.80]	[0.00,0.45]	[0.00,0.45]	[0.00,0.79]	[0.00,0.79]
$\hat{\beta}_s$	0.55	0.60	0.38	0.42	0.74	0.75	0.71	0.70
	(0.12)	(0.11)	(0.13)	(0.12)	(0.14)	(0.13)	(0.20)	(0.18)
	[0.09, 1.00]	[0.09, 1.00]	[0.03, 1.00]	[0.03, 1.00]	[0.06,0.80]	[0.06,0.80]	[0.00,0.76]	[0.00,0.76]
$\hat{\beta}_m$	-0.10	—	-0.04	—	0.28	—	0.25	—
	(0.10)		(0.09)		(0.09)		(0.11)	
	[0.00, 0.49]		[0.00, 0.44]		[0.00,0.39]		[0.00,0.32]	
$\hat{\gamma}$	0.12	0.12	0.02	0.03	0.03	-0.17	0.01	-0.11
	(0.08)	(0.08)	(0.08)	(0.08)	(0.16)	(0.15)	(0.14)	(0.14)
	[-0.16,0.25]	[-0.16,0.25]	[-0.17,0.25]	[-0.17,0.25]	[-0.25,0.25]	[-0.25,0.25]	[-0.25,0.25]	[-0.25,0.25]
J	71%	78%	76%	83%	76%	64%	77%	63%

Notes: Standard errors are in ( ); Anderson and Rubin (1949)-based robust 95% confidence intervals are in [ ]; J gives the p-value for the GMM overidentifying restrictions test.

they do not contain zero for the survey inflation expectations estimate in six out of eight models. On the other hand, they consistently contain zero for other expectational variables across all models.

5 Concluding remarks

Using both final and real-time vintage data, we assess the relative contributions of VAR-based, survey-based and myopic inflation expectations in the NKPC. The computation of VAR-based inflation expectations data accommodates major changes in the conduct and propagation mechanisms of the U.S. monetary policy which occurred since World War II using recursive and rolling-widow forecasting methods. We find that VAR- and survey-based inflation expectations contribute significantly to inflation dynamics and statistically speaking, point estimates of these inflation expectations coefficients are not significantly different from each other: The null hypothesis H_0: $\beta_{var} = \beta_s$ is almost never rejected at the 5%-level. Contrarily to the conflicting outcomes in the literature (Nunes, 2010; Fuhrer, 2012), we conclude that none of the two types of forward-looking inflation expectations is able, on its own, to capture inflation dynamics in the NKPC. Moreover, myopic inflation expectations play very little role, if at all, in explaining inflation dynamics.

Table 5: Wald tests for parameter restrictions in the NKPC model with four-quarter VAR-based expectations

	Final vintage		Real-time vintage	
	Recursive $E_t\pi_{t+1}$	Rolling $E_t\pi_{t+1}$	Recursive $E_t\pi_{t+1}$	Rolling $E_t\pi_{t+1}$
Hybrid model				
H_0: $\beta_{var} = 1$, $\beta_s = 0$, $\beta_m = 0$	25.65 (<0.01)	9.75 (0.01)	31.38 (<0.01)	13.15 (<0.01)
H_0: $\beta_{var} = 0$, $\beta_s = 1$, $\beta_m = 0$	13.81 (<0.01)	22.92 (<0.01)	16.00 (<0.01)	14.12 (<0.01)
H_0: $\beta_{var} = \beta_s$, $\beta_m = 0$	1.37 (0.50)	0.92 (0.63)	10.28 (0.01)	5.11 (0.08)
Purely forward-looking model				
H_0: $\beta_{var} = 1$, $\beta_s = 0$	29.95 (<0.01)	12.31 (<0.01)	32.11 (<0.01)	15.46 (<0.01)
H_0: $\beta_{var} = 0$, $\beta_s = 1$	13.71 (<0.01)	22.99 (<0.01)	3.74 (0.06)	2.96 (0.09)
H_0: $\beta_{var} = \beta_s$	0.78 (0.38)	0.41 (0.52)	3.48 (0.06)	1.22 (0.27)

Notes: p-values into ( ).

Even though our inflation data seems to be stationary for the samples under scrutiny in this paper, this variable is known for its strong persistence. For this reason, Cogley and Sbordone (2008) have suggested to introduce trend inflation among the explanatory variables in the NKPC equation (see also Stock and Watson (2007); Nason and Smith (2016); Cecchetti et al. (2017); Eusepi and Preston (2018); Forbes et al. (2019)). Although very appealing, this extension has the drawback that this extra right hand side variable is not observable, and as such, it is not so convenient to implement. Nonetheless, the inclusion of such a trend inflation variable in the NKPC is on our research agenda.

References

Anderson, T. and H. Rubin (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics 20*(1), 46–63.

Andrade, P. and H. Le Bihan (2013). Inattentive professional forecasters. *Journal of Monetary Economics 60*(8), 967–982.

Branch, W. (2004). The theory of rationally heterogeneous expectations: evidence from survey data on inflation expectations. *The Economic Journal 114*(497), 592–621.

Brayton, F., E. Mauskopf, D. Reifschneider, and P. Tinsley (1997). The role of expectations in the FRB/US macroeconomic model. *Fed. Res. Bull. 83*, 227.

Cecchetti, S. G., M. Feroli, P. Hooper, A. K. Kashyap, and K. Schoenholtz (2017). Deflating Inflation Expectations: The Implications of Inflation's Simple Dynamics. CEPR Discussion Papers 11925.

Christiano, L., M. Eichenbaum, and C. Evans (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy 113*(1), 1–45.

Clements, M. and A. Galvão (2013). Real-time forecasting of inflation and output growth with autoregressive models in the presence of data revisions. *Journal of Applied Econometrics 28*(3), 458–477.

Cogley, T. and A. Sbordone (2008). Trend inflation, indexation, and inflation persistence in the New Keynesian Phillips Curve. *American Economic Review 98*(5), 2101–2126.

Coibion, O., Y. Gorodnichenko, and R. Kamdar (2017). The formation of expectations, inflation and the Phillips curve. Technical report, National Bureau of Economic Research.

Croushore, D. (1993). Introducing: the survey of professional forecasters. *Business Review-Federal Reserve Bank of Philadelphia 6*, 3.

Croushore, D. and T. Stark (2001). A real-time data set for macroeconomists. *Journal of Econometrics 105*(1), 111–130.

Dufour, J.-M., L. Khalaf, and M. Kichian (2006). Inflation dynamics and the New Keynesian Phillips Curve: an identification robust econometric analysis. *Journal of Economic Dynamics and Control 30*(9-10), 1707–1727.

Estrella, A. and J. Fuhrer (2002). Dynamic inconsistencies: counterfactual implications of a class of rational-expectations models. *The American Economic Review 92*(4), 1013–1028.

Eusepi, S. and B. Preston (2018). The science of monetary policy: An imperfect knowledge perspective. *Journal of Economic Literature 56*(1), 3–59.

Fanelli, L. (2008a). Evaluating the New Keynesian Phillips Curve under VAR-based learning. *Economics Discussion Paper* (2008-15).

Fanelli, L. (2008b). Testing the New Keynesian Phillips Curve through vector autoregressive models: Results from the Euro area. *Oxford Bulletin of Economics and Statistics 70*(1), 53–66.

Fanelli, L. and G. Palomba (2011). Simulation-based tests of forward-looking models under VAR learning dynamics. *Journal of Applied Econometrics 26*(5), 762–782.

Forbes, K., L. Kirkham, and K. Theodoridis (2019). A trendy approach to UK inflation dynamics. *The Manchester School*. doi:10.1111/manc.12293.

Fuhrer, J. (2012). The role of expectations in inflation dynamics. *International Journal of Central Banking 8*(Supplement 1), 137–166.

Fuhrer, J. (2017). Expectations as a source of macroeconomic persistence: evidence from survey expectations in a dynamic macro model. *Journal of Monetary Economics 86*, 22–35.

Fuhrer, J. and G. Moore (1995). Inflation persistence. *The Quarterly Journal of Economics 110*(1), 127–159.

Fuhrer, J. and G. Olivei (2010). The role of expectations and output in the inflation process: an empirical assessment. Technical report, Federal Reserve Bank of Boston.

Gali, J. and M. Gertler (1999). Inflation dynamics: a structural econometric analysis. *Journal of Monetary Economics 44*(2), 195–222.

Gali, J., M. Gertler, and J. Lopez-Salido (2005). Robustness of the estimates of the hybrid New Keynesian Phillips Curve. *Journal of Monetary Economics 52*(6), 1107–1118.

Guisinger, A., M. Owyang, and H. Shell (2018). Comparing measures of potential output. *Federal Reserve Bank of St. Louis Review 100*(4), 297–316.

Koenig, E., S. Dolmas, and J. Piger (2003). The use and abuse of real-time data in economic forecasting. *Review of Economics and Statistics 85*(3), 618–628.

Mankiw, G., R. Reis, and J. Wolfers (2003). Disagreement about inflation expectations. *NBER Macroeconomics Annual 18*, 209–248.

Mavroeidis, S., M. Plagborg-Møller, and J. Stock (2014). Empirical evidence on inflation expectations in the New Keynesian Phillips Curve. *Journal of Economic Literature 52*(1), 124–188.

Milani, F. (2005). Adaptive learning and inflation persistence. Working papers 050607, University of California, Irvine - Department of Economics.

Milani, F. (2007). Expectations, learning and macroeconomic persistence. *Journal of Monetary Economics 54*(7), 2065–2082.

Milani, F. (2012). The modeling of expectations in empirical DSGE models: a survey. In *DSGE Models in Macroeconomics: Estimation, Evaluation, and New Developments*, pp. 3–38. Emerald Group Publishing Limited.

Nason, J. and G. Smith (2008a). Identifying the New Keynesian Phillips Curve. *Journal of Applied Econometrics 23*(5), 525–551.

Nason, J. and G. Smith (2008b). The New Keynesian Phillips Curve: Lessons from single-equation econometric estimation. *FRB Richmond Economic Quarterly 94*(4), 361–395.

Nason, J. and G. Smith (2016). Sticky professional forecasts and the unobserved components model of US inflation. Manuscript, Department of Economics, Queen's University.

Nunes, R. (2010). Inflation dynamics: the role of expectations. *Journal of Money, Credit and Banking 42*(6), 1161–1172.

Roberts, J. (1995). New Keynesian economics and the Phillips curve. *Journal of Money, Credit and Banking 27*(4), 975–984.

Roberts, J. (1997). Is inflation sticky? *Journal of Monetary Economics 39*(2), 173–196.

Roberts, J. (1998). *Inflation expectations and the transmission of monetary policy*. Divisions of Research & Statistics and Monetary Affairs, Federal Reserve Board.

Sbordone, A. (2002). Prices and unit labor costs: a new test of price stickiness. *Journal of Monetary Economics 49*(2), 265–292.

Smets, F. and R. Wouters (2003). An estimated dynamic stochastic general equilibrium model of the EURO area. *Journal of the European Economic Association 1*(5), 1123–1175.

Stock, J. H. and M. W. Watson (2007). Why has US inflation become harder to forecast? *Journal of Money, Credit and banking 39*, 3–33.

Tulip, P. (2014). Fiscal Policy and the Inflation Target. *International Journal of Central Banking 10*(2), 63–96.

Appendix

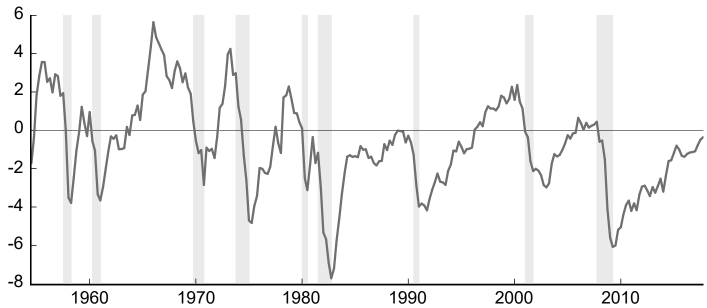
Table A1: Real-time database structure: Real GDP

Sample period	Vintages 1965Q4	1966Q1	1966Q2	...	2017Q3	2017Q4	2018Q1
1947Q1	306.4	306.4	306.4	...	1934.5	1934.5	1934.5
1947Q2	309.0	309.0	309.0	...	1932.3	1932.3	1932.3
1947Q3	309.6	309.6	309.6	...	1930.3	1930.3	1930.3
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
1965Q3	609.1	613.0	613.0	...	4006.2	4006.2	4006.2
1965Q4	NA	621.7	624.4	...	4100.6	4100.6	4100.6
1966Q1	NA	NA	633.8	...	4201.9	4201.9	4201.9
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
2017Q2	NA	NA	NA	...	17010.7	17031.1	17031.1
2017Q3	NA	NA	NA	...	NA	17156.9	17163.9
2017Q4	NA	NA	NA	...	NA	NA	17272.5

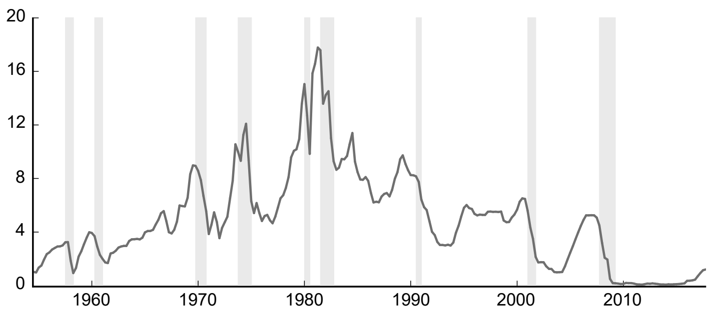
Source: Philadelphia Fed Real-time Database.

Figure A1: Plots of variables (1954Q3-2017Q4)

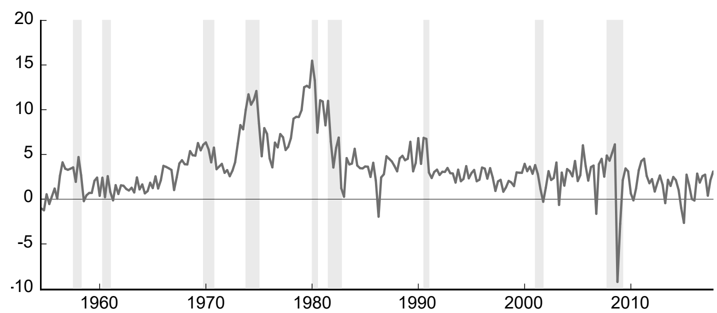
(a) Output gap ($\tilde{y}_t$)



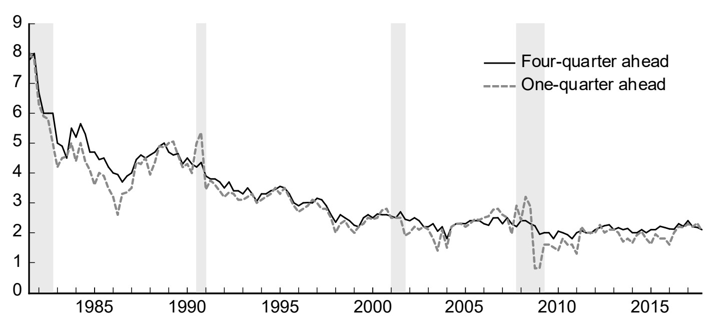
(b) Nominal interest rate (i_t)



(c) Inflation rate (π_t)



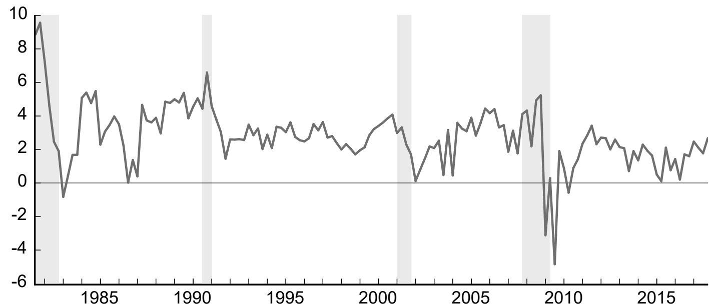
(d) Survey inflation forecasts ($S_t\pi_{t+4}$ & $S_t\pi_{t+1}$) (1981Q3-2017Q4)



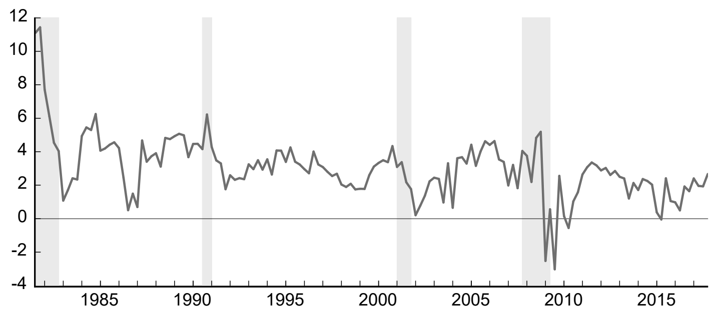
Note: Shaded regions represent the National Bureau for Economic Research (NBER) recession dates.

Figure A2: VAR-based expectations ($E_t \pi_{t+1}$) (1981Q3-2017Q4)

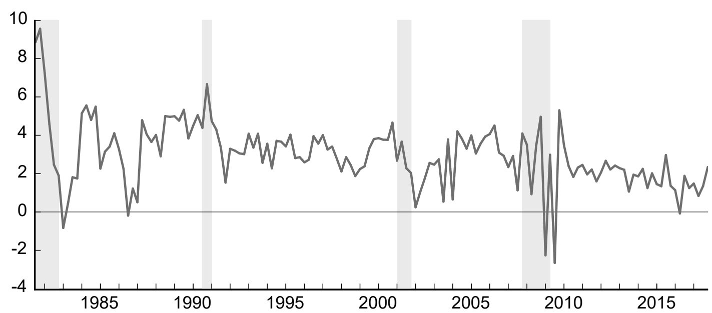
(a) Final vintage recursive



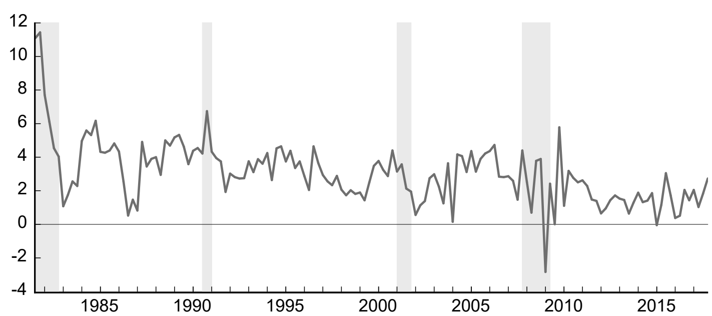
(b) Real-time vintage recursive



(c) Final vintage rolling

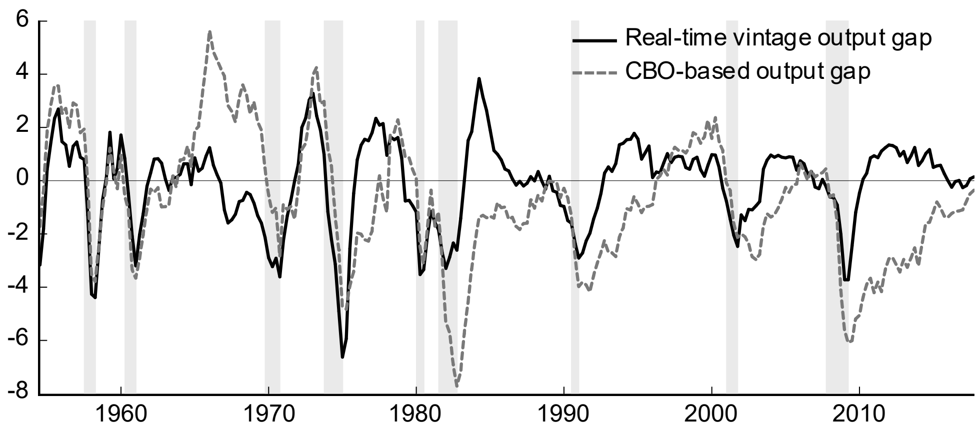


(d) Real-time vintage rolling



Note: Shaded regions represent the National Bureau for Economic Research (NBER) recession dates.

Figure A3: Output gap: CBO (final vintage) *vs.* real-time vintage (HP filter-based)



Note: Shaded regions represent the National Bureau for Economic Research (NBER) recession dates.