EFFECTIVE USE OF SURVEY INFORMATION IN ESTIMATING THE EVOLUTION OF EXPECTED INFLATION

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Abstract: The evolution of the term structure of expected US inflation is modeled using survey data to provide timely information on structural change not contained in lagged inflation data. To capture shifts in subjective perceptions, the model is adaptive to long-horizon survey expectations. However, even short-horizon survey expectations inform shifting-endpoint estimates that capture the lag between inflation and the perceived inflation target which anchors inflation expectations. Results show movements of the perceived target are an important source of inflation persistence and suggest historical US monetary policy was not fully credible for much of the post-war sample.

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1 Introduction

Information on expected inflation at short and long horizons is key to assessing the credibility of monetary policy, to examining how borrowing decisions of households and firms respond to shifts in real costs of debt, and to evaluating the expected inflation response to monetary policy actions. Interestingly, as important as expectations are in economic models, few studies explicitly model the behavior of expectations using data on expectations.[1] Most likely this is because direct observations on market expectations of inflation are limited. In particular, as a consequence of the incomplete sampling design of available surveys, only short time series are available for surveys that sample at quarterly frequencies or higher, and lengthy time series are available only for surveys of short-horizon forecasts, generally two- or four-quarter outlooks, and are often collected only at semiannual intervals.

Survey limitations have generally led researchers to search for proxies of expected inflation. One approach to construct expected inflation proxies follows Breedon and Chadha (1997) and Söderlind and Svensson (1997) and extracts estimates of average expected inflation from data for nominal and indexed bond yields under restrictive assumptions on term premiums and relative liquidity of the assets. However such measures may be distorted, as discussed by Shen and Corning (2001) and Shen (2006) with reference to U.S. data, and Côté, Jacob, Nelmes, and Whittingham (1996) with reference to Canadian data. In particular, using Canadian data, Christensen, Dion, and Reid (2004) find that the break-even inflation rate (BEIR), defined as the difference between nominal and real return bond yields, is on average higher and more variable than survey measures of expected inflation due to movements of risk

[1] A few studies have used survey data directly. Examples include Roberts (1995 and 1997) and Kozicki and Tinsley (2003).

premiums and other factors not directly linked to inflation expectations.

Another approach to proxy for expected inflation is to use forecasts from reduced-form time-series models. Reduced-form time series models are popular specifications that are easy to use in multi-period forecasting exercises owing to their linearity. They don't require practitioners to take a stand on the underlying structural model, yet forecast relatively well over short horizons.[2] For example, Harvey (1988) forecasts inflation using an IMA(1,1) model to construct an expected inflation series, and Laubach and Williams (2003) proxy inflation expectations with the forecast of the four-quarter-ahead percentage change in the price index for personal consumption expenditures excluding food and energy generated from an AR(3) of inflation estimated over the prior 40 quarters. However, the ability of such econometric specifications to effectively accommodate structural change is limited.[3]

By contrast, perceived structural change can immediately be incorporated into judgement and will tend to immediately influence expectations captured in survey measures. Each survey participant is implicitly providing information on his/her beliefs about how the economy operates. While some participants may be reporting forecasts generated by unadjusted econometric models of the U.S. economy, most will incorporate judgement into their views about what they expect the future to bring.[4]

[2] McNees (1986) provides evidence that forecasts from Bayesian VARs are among the most accurate for forecasting several key US macroeconomic variables. That said, Wallis et al (1986, 1987) finds that for UK data, VAR forecasts do not dominate model-based forecasts.

[3] For instance, one approach to introducing the prospect for structural change is to allow all model coefficients to change. A simple approach taken by some researchers is to estimate VARs over moving windows of data. As time progresses, earlier observations are discarded in favor of more recent data, and model coefficients are reestimated. However, allowing all coefficients in VARs to be time-varying and use of rolling windows tend to lead to in-sample overfitting problems and result in poor out-of-sample forecasting performance.

[4] Wallis (1989) reviews developments in macroeconomic forecasting, including a discussion of judgemental forecasts as well as structural and time-series models. Sims (2002) discusses forecasting exercises at several central banks, and offers commentary on the role of " 'subjective' forecasting based on data analysis by sectoral 'experts'." See also Reifschneider, Stockton, and Wilcox (1997)

Such forecasts tend to reflect information that is not well summarized by historical data or econometric equations. Examples include structural changes, such as changes in tax laws, perceived shifts in the long-run inflation goals of policy, or changes in perceptions of policy credibility.[5]

Overall, the direct information on expectations as provided by survey data is likely superior to the econometric and yield-based proxies. Moreover, the superior forecasting performance of surveys documented by Ang, Bekaert, and Wei (2007) and Chernov and Mueller (2008) lends support to the view that survey measures are informative measures of expected inflation.[6] Given this evidence on the forecast performance of survey measures of expectations, it is interesting to note that the validity of proxies is generally based on theoretical arguments or on the ability of the proxies to forecast the underlying data. Comparisons of proxies to direct measures of expectations and empirical models of the expectations data themselves are rare.

An important contribution of this paper is that it explicitly models the evolution of expected inflation. This modeling exercise confirms that subjective perceptions that enter into surveys and influence bond pricing differ significantly from forecasts implied by standard econometric models, a result also evident in Kozicki and Tinsley (1998, 2001a,b) and Kim and Orphanides (2005). The results also support the view that direct measures of expectations provide additional information beyond that contained in historical data on the economic variables themselves. An additional conclusion of

for the use of judgement with econometric models in the Federal Reserve's monetary policy process.

[5]The possibility that survey participants may have more information about the economy than econometricians is also discussed by Kim (2008) and Ang, Bekaert, and Wei (2007). As noted in Kim (2008), the value-added of expected inflation surveys appears to be, in the context of forecasting inflation and bond yields, that surveys capture variations in perceived trend inflation that is not revealed by simple time series models that reference the recent history of inflation.

[6]Superior forecast performance of surveys of expected inflation provides strong evidence against the view expressed by some analysts that surveys may not be good measures because participants have no incentives to provide their true expectations.

the current paper is that it is not enough to just use survey data, they need to be used in a model that is adaptive to their subjective information on long-horizon expectations.

The empirical specification in this paper jointly models the evolution of inflation and expected inflation under an assumption that expectations are model-consistent. This model is then used to construct a 50-year history of monthly measures of expected inflation and a *term structure of expected CPI inflation* for the United States to be consistent with the Livingston Survey data on expected inflation.[7] The constructed measures of expected inflation (time t forecasts of inflation in $t + h$) provide more frequent observations and a longer history of expected inflation by providing consistent proxies for missing monthly observations (t) as well as over all horizons (h). In addition, they provide good fits of survey observations when they are available. The constructed measures can be used directly in empirical exercises without the impediments, such as infrequent observations or short histories, that have limited the use of direct measures of expectations.[8]

One use of the constructions of long-horizon expected inflation is to examine the historical credibility of monetary policy. Inflation expectations are generally anchored by private sector perceptions of the central bank's inflation target. By comparing private sector long-horizon expectations of inflation to estimates of the "effective" inflation target of U.S. monetary policy, the article provides information on the historical credibility of monetary policy.

[7]The objective of the current study is clarified by use of a single survey: a term structure of expected CPI inflation consistent with economist expectations of inflation is produced.

[8]A simple approach to expand histories of expected inflation might splice measures from different sources. Unfortunately, as noted by Chernov and Mueller (2008), there are systematic differences across surveys—in concepts of inflation and agents being surveyed—implying that splicing measures from various sources could lead to an inconsistent history of expected inflation with possible subsample biases. However, even in the absence of such possibilities, spliced series provide only small improvements in the availability of expected inflation observations.

The next section describes the Livingston Survey data on expected CPI inflation and the empirical model of the evolution of expected CPI inflation. The estimation uses a time-varying forecast methodology that assumes the unobserved cross-section of expectations formulated in a given period is consistent with recent inflation and available survey observations of expected inflation.[9] The third section presents the empirical results. A state-space model is estimated and used to construct the monthly term structure of expected inflation, and robustness checks are provided. In the fourth section, the perceived inflation target implicit in the term structure of expected inflation is compared with estimates of the central bank's effective inflation target and provides strong evidence of asymmetry in expectations. While large differences in the 1980s suggest less than full credibility of low-inflation policy objectives at the time, more recent convergence signals an improvement in credibility. The article concludes with final comments in section five.

2 A model of expected inflation

Livingston Survey data on expected CPI inflation was chosen as the measure of expected inflation. One advantage of the Livingston Survey is that it has good forecast properties compared with other survey measures of expected inflation (Chernov and Mueller 2008). In addition, the Livingston Survey has been in existence for a much longer period of time, with surveys conducted in June and December starting in

[9] The analysis in this paper is related to Chernov and Mueller (2008), which was developed independently. The data and methodology of the current paper differ from that in Chernov and Mueller, but most importantly, the two studies take different approaches to resolving systematic differences and biases across survey measures. In addition, the constructions in this paper start 15 years earlier than those in Chernov and Mueller and are monthly rather than quarterly.

1946.[10] While the original survey provided information on short-horizon expected inflation, the survey was expanded to also include 10-year inflation expectations in 1990.

The choice of modeling techniques was influenced by data constraints and the desire that expectations be model consistent—i.e., that the same data generating mechanism be able to explain the dynamics of inflation and inflation expectations. A shifting-endpoint AR model (cast in the format of an unobserved components model) is used as the underlying data generating process (DGP) for monthly inflation. Under the assumption that expected inflation is consistent with this DGP, the multi-month (and year) horizon of the survey expectations implies that they are nonlinear functions of the AR parameters of the shifting-endpoint model. Expressions for inflation and expectations are set in a state space framework so that the unobserved perceived inflation target that anchors long-horizon expectations can be estimated. The state-space framework is well-suited to accommodate data limitations, including different observation frequencies of inflation (monthly) and survey data (semi-annually) as well as missing observations of long-horizon expectations for most of the survey sample.

2.1 A shifting-endpoint AR model for inflation

The remainder of this section discusses the empirical model used to jointly model inflation and expected inflation. For the application in this paper, the main difficulty encountered with most univariate and multivariate time series specifications for inflation is that they tend to generate multiperiod forecasts that do not resemble

[10] Documentation describing the Livingston Survey data is available on the Federal Reserve Bank of Philadelphia website at www.phil.frb.org. Croushore (1997) provides a description of the survey and its history. Additional details on the Livingston Survey that are relevant for the current analysis are reviewed in section 3.

available survey expectations (Kozicki and Tinsley 1998, 2001a, 2001b). In particular, long-horizon forecasts of inflation from mean-reverting AR specifications are too insensitive to recent inflation, while those from models that impose unit root restrictions on inflation tend to be excessively sensitive to recent inflation. The latter suggests, for instance, that the Atkeson and Ohanian (2001) model, which incorporates a unit root assumption and forecasts quite well at short horizons, would not be as effective at matching long-horizon inflation expectations. Consequently, this paper follows Kozicki and Tinsley (2001a, 2001b) by using a shifting-endpoint variant to approximate the implicit forecasting model for inflation that underlies survey expectations. As will be shown, the shifting endpoint specification can be cast in the format of the unobserved components model of Watson (1986).

An advantage of the shifting-endpoint AR specification is that it can capture the implications of structural change that lead to shifting long-horizon expectations. In addition, the AR structure is better suited to capturing the seasonality in the Livingston Survey data than IMA structures recommended by Stock and Watson (2007). Furthermore, as the model has relatively few parameters, it is less likely to overfit the data than more complicated time series specifications.

The general inflation forecasting model with *shifting inflation endpoints* can be represented as

$$\pi_{t+1} = \iota_1' z_{t+1} = \iota_1' C z_t + \iota_1'(I - C)\iota \mu_\infty^{(t)} + \iota_1' \iota_1 \epsilon_{t+1}, \tag{1}$$

where π_t is inflation, $z_t \equiv [\pi_t \quad \ldots \quad \pi_{t-p+1}]'$, ϵ_t is an innovation assumed to be independent Normal with mean zero, I is a $p \times p$ identity matrix, ι is a $p \times 1$ vector of ones, ι_1 is a $p \times 1$ vector with a one in the first element and remaining elements zero, and

$$C \equiv \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_{p-1} & \alpha_p \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}.$$

Define $\alpha(L) \equiv \alpha_1 + \alpha_2 L + \cdots + \alpha_p L^{p-1}$, a polynomial in the lag operator L, where $L\pi_t \equiv \pi_{t-1}$. If all roots of $(1 - \alpha(L))$ lie outside the unit circle, then the conditional expectation of π_{t+k} will revert to the endpoint in the long run, i.e., $\lim_{k\to\infty} E_t y_{t+k} = \mu_\infty^{(t)}$.[11]

The endpoint is the level to which inflation expectations eventually converge as the forecast horizon is increased, conditional on a given information set. Intuitively, because the inflation endpoint is the conditional long-horizon forecast of inflation generated by the model, in a model of private sector expectations it can be thought of as the private sector perception of the inflation target. Endpoints may shift according to information and beliefs at the time the forecast is made.[12] The potential for endpoint shifts is an essential feature of the model of expectations as endpoint shifts can accommodate the possibility of rapid reaction to structural change in survey expectations independent of recent movements in actual inflation.

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[11] Cases where roots of $(1 - \alpha(L))$ lie inside the unit circle, or where there are more than one unit root are not considered in the current analysis. Note that if $(1 - \alpha(L))$ contains a unit root, then the endpoint is not independently identified. However, the limiting forecast continues to exist and the endpoint can be calculated as $\mu_\infty^{(t)} = \lim_{k\to\infty} \iota_1' C^k z_t$, which is a moving average of order p of inflation since in this case $\alpha(1) = 1$ and $\iota_1'(I - C) = 0$.

[12] Evidence of shifts in the mean of inflation are provided by Garcia and Perron (1996). They model inflation using a Markov switching specification with three states. As in their specification, parameters governing the speed of adjustment to long-run equilibrium (C) are assumed to be constant in the current implementation, even with shifts in the description of long-run equilibrium. The implications and relevance of other generalizations to the forecasting system are left for future research.

In thinking about the dynamics of such long-horizon perceptions, note that if survey participants could forecast future changes to their perceptions of the level at which inflation would stabilize, then such changes would be immediately incorporated in their long-run perceptions. Consequently, changes in the endpoint should not be forecastable. This property is captured by assuming that the endpoint evolves according to a random walk:[13]

$$\mu_{\infty}^{(t+1)} = \mu_{\infty}^{(t)} + v_{t+1}. \tag{2}$$

More details on the properties of ϵ_t and v_t will be provided with the state-space description of the model in section 2.3.

As described above, the shifting endpoint specification is a generalization of the local level model of Harvey (1989) and a version of the unobserved components model discussed by Watson (1986).[14] In particular, for $\theta^c(L) \equiv (1 - \alpha(L)L)^{-1}$ and $\tau_{t+1} \equiv$

[13] A potential shortcoming with this approach is that expected inflation data is only available semi-annually. Since this data is expected to be the most informative about the unobserved shifting endpoint, it is possible that the interpolation algorithm may overly smooth higher frequency fluctuations in the endpoint. However, lack of variation in more frequent (quarterly) 10-year expected inflation data as reported by the Survey of Professional Forecasters (SPF), suggests that over-smoothing of endpoint variation is unlikely to be a major problem. The best anecdote relates to the May 6, 2003 FOMC statement that referred to the "probability of an unwelcome substantial fall in inflation." This statement may have led to an instantaneous upward adjustment in the perceived inflation target of monetary policy. However, quarterly-sampled median 10-year inflation expectations as reported by the SPF did not vary from 2.5 percent throughout 2003 and mean expectations only dropped by 0.5 basis points from the Q2 survey to the Q3 survey (and by 1 basis point from the Q1 survey to the Q2 survey). While it is still possible that the endpoint exhibited more fluctuations at a frequency higher than a quarter, the available evidence suggests that such fluctuations may be reversed within one quarter. But within-quarter reversals are inconsistent with the random-walk structure of long-run expectations and are less likely to be relevant for macroeconomic analysis.

[14] Unobserved components models are frequently used to model trend-cycle decompositions of real GDP (or GNP), as in Harvey (1985), Watson (1986), and Stock and Watson (1988).

$\mu_\infty^{(t)}$, the shifting endpoint specification can be rewritten as:

$$\pi_{t+1} = \tau_{t+1} + c_{t+1} \tag{3}$$

$$\tau_{t+1} = \tau_t + v_{t+1} \tag{4}$$

$$c_{t+1} = \theta^c(L)\epsilon_{t+1}. \tag{5}$$

In a recent study comparing several simple models, Stock and Watson (2007) found that a version of this specification with $\theta^c(L) = 1$ and time-varying estimates of the variances of ϵ_t and v_t performed remarkably well at forecasting quarterly GDP price inflation. However, in their experience the IMA(1,1) specification was not effective with quarterly CPI inflation and they did not evaluate the ability of their model to fit expectations data. Moreover, the IMA(1,1) specification is too restrictive here owing to seasonality in the data, which a more general AR lag structure is able to effectively capture.[15]

The shifting endpoint specification shares features with other specifications proposed in the literature. For instance, the specification resembles the regressive expectations model of Figlewski and Wachtel (1981). They expressed expected inflation as a weighted average of lagged inflation and long-run "normal" inflation, where the latter is defined as the rate toward which inflation is expected to regress. However, whereas Figlewski and Wachtel assumed that the normal inflation rate

[15] A more general specification of inflation might admit time-varying slopes in addition to a time-varying mean. While such a specification is relatively straightforward to introduce for inflation, the same is not true for multi-period survey expectations restricted to be consistent with the inflation DGP. In particular, time-varying slopes introduce several complications into the current set-up. First, time-variation in the seasonal components may differ from time-variation that captures non-seasonal persistence, and distinguishing these two aspects may be important. Second, as will be shown in the next section, multi-period model-consistent expectations will be non-linear functions of the time-varying slopes. Thus, the model of the multivariate system including expressions for inflation and multi-period expectations would be nonlinear in unobserved state variables (the slopes). While an interesting extension, such a generalization is beyond the scope of the state-space modeling environment of the current paper.

was equal to a five-year moving average of inflation, here the shifting endpoint is treated as an unobserved component to be estimated. Caskey (1985) estimated a time-varying constant in a more general learning model of Livingston 8-month inflation expectations. Caskey's learning model was a time-varying parameter model that included a constant and several macroeconomic variables. He interpreted a loose prior on the variance of the constant as evidence that the Livingston panel were willing to quickly revise their beliefs about the constant, and concluded that Livingston inflation forecasts could be explained as the product of a learning process.

In other related work, Ang, Bekaert, and Wei (2007) found that a non-linear regime switching model with 2 regimes (allowing both the mean and lag coefficients to switch) was a good forecasting specification for CPI inflation in the post-1995 period. They attribute this advantage to a reduction in the persistence of inflation at the end of the sample that can be captured through a regime switch. By allowing the endpoint to follow a random walk, the shifting-endpoint model can implicitly capture more than two regimes. Shifts of the endpoint capture structural change and absorb some of the persistence of inflation. Although AR parameters in C are constant, lower persistence is captured with a decrease in the relative importance of endpoint movements relative to inflation deviations for explaining inflation dynamics at the end of the sample.

2.2 Approximating Survey Expectations with AR Expectations

As outlined earlier, survey data provides timely information on perceived economic structural change. Because survey data on expectations includes judgemental views as well as the output of econometric forecasting models, such data is likely to immediately reflect perceptions that there have been structural shifts in the economy. The consequences for inflation expectations of these perceptions of structural shifts can be extracted by linking the AR-based forecasting model to survey data on multiple horizon expectations.

Survey data report average inflation expectations over multiple periods. Let $s_{t+k,t}$ denote the survey data for average expected inflation over the k periods ending in $t+k$, conditional on information available at t:

$$s_{t+k,t} = \frac{1}{k} \sum_{j=1}^{k} E_t^S \pi_{t+j}, \tag{6}$$

where E_t^S signifies that expectations are made by survey participants and conditional on information available at t.

Multi-step forecasts of inflation based on the shifting-endpoint AR model are:

$$\begin{aligned} E_t \pi_{t+j} &= \iota_1' E_t z_{t+j} \\ &= \iota_1' C^j z_t + \iota_1'(I - C^j)\iota \mu_\infty^{(t)}. \end{aligned} \tag{7}$$

and conditional forecasts of average inflation over the next k periods are:

$$(1/k) \sum_{j=1}^{k} E_t \pi_{t+j} = \iota_1'((1/k) \sum_{j=1}^{k} C^j) z_t + \iota_1'(I - ((1/k) \sum_{j=1}^{k} C^j)) \iota \mu_\infty^{(t)}. \tag{8}$$

Assuming the average inflation forecasts from the shifting-endpoint AR model of inflation provides an approximation of the survey expectation,

$$\begin{aligned} s_{t+k,t} &= (1/k)\sum_{j=1}^{k} E_t\pi_{t+j} + \eta_{k,t} \\ &= \iota_1'((1/k)\sum_{j=1}^{k} C^j)z_t + \iota_1'(I - ((1/k)\sum_{j=1}^{k} C^j))\iota\mu_\infty^{(t)} + \eta_{k,t} \end{aligned} \tag{9}$$

where $\eta_{k,t} = (1/k)\sum_{j=1}^{k}(E_t^S\pi_{t+k} - E_t\pi_{t+k})$ is approximation error. The approximation error reflects differences between the implicit forecasting model of the survey participants and the shifting-endpoint AR model, and measurement error in survey data, among other contributors. However, as both the survey data and the AR-based average-inflation forecast are conditioned on information in t, the approximation error does not reflect differences between actual inflation and predictions. Similarly, there is no reason to expect that approximation errors will be serially correlated. The latter is in contrast to the difference between actual average inflation over k periods and k-period predictions, which will in general follow an MA(k-1).[16]

2.3 A state-space model of the inflation endpoint

Estimates of parameters of the model and a time-series for the unobserved endpoint can be obtained by representing the model in state space format and using the Kalman filter to provide linear least squares predictions of the unobserved endpoint.[17] In state space format, the endpoint is the unobserved state variable. As noted earlier, it is assumed to evolve according to a random walk:

$$\mu_\infty^{(t+1)} = \mu_\infty^{(t)} + v_{t+1}. \tag{10}$$

[16] Hansen and Hodrick (1980) propose a methodology for examining restrictions on a k-step ahead forecasting equation.

[17] State space representations, the Kalman filter, and approaches to estimating unobserved parameters are described in Harvey (1989) and Hamilton (1994).

Innovations, v_t, are distributed Normal$(0, Q)$ with mean square error matrix $Var_t(\mu_\infty^{(t+1)}) = P_{t+1|t}$.

Expressions for inflation and survey data constitute the measurement equations. Letting $k_1,\ k_2,\ \ldots k_n$ denote the various horizons for which the survey data are available, and defining $y_{t+1} = [\pi_{t+1}\quad s_{t+k_1,t}\quad s_{t+k_2,t}\quad \ldots\quad s_{t+k_n,t}]'$, the measurement equations are:

$$y_t = A' z_{t-1} + H' \mu_\infty^{(t)} + w_t, \tag{11}$$

where

$$A' = \begin{bmatrix} \iota_1' C \\ \iota_1'((1/k_1)\sum_{j=1}^{k_1} C^j) \\ \iota_1'((1/k_2)\sum_{j=1}^{k_2} C^j) \\ \vdots \\ \iota_1'((1/k_n)\sum_{j=1}^{k_n} C^j) \end{bmatrix}$$

$$H' = \begin{bmatrix} \iota_1'(I - C)\iota \\ \iota_1'(I - (1/k_1)\sum_{j=1}^{k_1} C^j)\iota \\ \iota_1'(I - (1/k_2)\sum_{j=1}^{k_2} C^j)\iota \\ \vdots \\ \iota_1'(I - (1/k_n)\sum_{j=1}^{k_n} C^j)\iota \end{bmatrix} \tag{12}$$

and $w_t = [\epsilon_{t+1}\quad \eta_{k_1,t}\quad \eta_{k_2,t}\quad \ldots\quad \eta_{k_n,t}]'$ is distributed as Normal$(0, R)$, and v_t and w_t are independent of each other. The system described in (11) and (12) imposes the cross equations restrictions necessary to ensure that the survey forecasts incorporate model-consistent expectations.

The structure of the covariance matrix, R, depends on the assumed relationships between inflation equation residuals (ϵ_{t+1}) and survey measurement errors ($\eta_{k,t}$), the assumed relationships between measurement errors of surveys of different horizons, and variances. Results are presented for the case of R diagonal with the variances of the measurement errors assumed to be the same for any choice of k_i, but with the variance of ϵ_{t+1} allowed to be different from the variance of measurement errors.

Maximum likelihood estimation is described in Harvey (1989) and Hamilton (1994). Under normality of v_t and w_t, the log-likelihood function can be constructed using the Kalman filter. With starting values for the unobserved state and it's mean square error, maximum likelihood techniques can be used to estimate parameters in A, H, Q, and R.

To develop basic intuition for the model, it is useful to consider a simple shifting endpoint AR(1) model of inflation, for $0 < \alpha < 1$, and a single k-period survey expectation. The measurement equations are:

$$\begin{bmatrix} \pi_t \\ s_{t+k,t} \end{bmatrix} = \begin{bmatrix} \alpha \\ \delta_k \end{bmatrix} \pi_{t-1} + \begin{bmatrix} (1-\alpha) \\ (1-\delta_k) \end{bmatrix} \mu_\infty^{(t)} + \begin{bmatrix} \epsilon_t \\ \eta_{k,t} \end{bmatrix}, \tag{13}$$

where $\delta_k = \alpha(1-\alpha^k)/(k(1-\alpha))$. Notice that inflation and expectations are weighted averages of lagged inflation and the endpoint and that the weight on the endpoint is smallest for inflation and increasing monotonically with forecast horizon k. This suggests an ordering to the data for each t with expectations bounded by inflation on one side and the unobserved endpoint on the other, with shorter-horizon (i.e., smaller k) expectations closer to inflation and longer-horizon expectations closer to the endpoint. Figure 1 shows that, in fact, the data is generally ordered with inflation closest to the 8-month expectations, followed by the 14-month expectations, and then the 10-year expectations.[18]

[18] Since annualized monthly inflation is very volatile, in the figure monthly observations are shown for inflation over the prior twelve months and survey expectations are annualized and shown as

This simple example also helps illustrate why survey expectations provide an important empirical advantage when trying to estimate the endpoint. The model structure is designed to be responsive to information in survey expectations such that survey expectations with large k will generally receive more weight when updating estimates of $\mu_\infty^{(t)}$ than survey expectations with small k, or than inflation. This is evident from the expression describing Kalman updates of predictions of the state variable:

$$E_t\mu_\infty^{(t+1)} = E_{t-1}\mu_\infty^{(t)} + K_t(y_t - A'z_{t-1} - H'E_{t-1}\mu_\infty^{(t)}) \tag{14}$$

where K_t is the Kalman gain and is defined according to:

$$K_t = P_{t|t-1}H(H'P_{t|t-1}H + R)^{-1}. \tag{15}$$

For the simplified AR(1) specification, with only one survey expectation, (14) can be rewritten as:

$$\begin{aligned} E_t\mu_\infty^{(t+1)} &= E_{t-1}\mu_\infty^{(t)} + D_t^{-1}\begin{bmatrix} (1-\alpha)R_{\eta_k} & (1-\delta_k)R_\epsilon \end{bmatrix}\begin{bmatrix} \pi_t - \alpha\pi_{t-1} - (1-\alpha)E_{t-1}\mu_\infty^{(t)} \\ s_{t+k,t} - \delta_k\pi_{t-1} - (1-\delta_k)E_{t-1}\mu_\infty^{(t)} \end{bmatrix} \\ D_t &= P_{t|t-1}\left[((1-\alpha)^2 + P_{t|t-1}^{-1}R_\epsilon)((1-\delta_k)^2 + P_{t|t-1}R_{\eta_k}) + (1-\alpha)^2(1-\delta_k)^2\right], \end{aligned} \tag{16}$$

where R_ϵ and R_{η_k} are the variances of ϵ and η_k, respectively. As the forecast horizon (k) increases, δ_k decreases towards zero and $(1-\delta_k)$ approaches unity. From the expression above, this implies that updates to estimates of the endpoint will put a relatively large weight on information in long-horizon expectations ($s_{t+k,t}$) and a relatively small weight on inflation (π_t), all else equal. The relative sizes of R_ϵ and R_{η_k} are also important—the larger the variance of noise in the inflation equation and

available—twice per year.

the smaller the variance of the expectations measurement error, the more weight will be put on survey expectations and the less weight will be put on inflation. Since the model is expressed in a format where expectations converge to μ_∞ with horizon, this is exactly what one would want. Long-horizon expectations should provide more information about the limit of expectations (the endpoint) and, consequently, should receive more weight in estimating the endpoint, unless they are measured with sizable errors.

2.4 Dealing with missing observations

One drawback of the Livingston survey data is that it is available less frequently and for a shorter horizon than inflation data.[19] One option would be to only use observations for t when data is available for every component of y_t. However, this would result in an extremely limited dataset as long-horizon expectations of inflation are only available since 1990. An alternative would be to drop observations for the long-horizon expectation, and include observations with shorter-horizon expectations and inflation. While this would expand the set of available observations considerably, analysis would still be limited to only two observations per year.

The approach taken in the next section was to use all available data starting in 1955. Using this approach, monthly observations are available for every year for the inflation measurement equation, two observations are available every year for the measurement equations of two relatively short-horizon expectation series, and for the 10-year expected inflation series, two observations are available each year starting in 1991, with one observation for 1990.[20]

[19]The Livingston survey data is described in more detail in the next section.

[20]Results from estimations that exclude long-horizon expectations entirely, or that only use semi-annual observations of inflation and shorter-horizon expectations were used to check the

The methodology outlined in Harvey (1989, p144) was used to deal with missing observations. In particular, the model just described is transformed into a system with measurement equations for $y_t^* = W_t y_t$, where W_t is a matrix that selects those elements of y_t for which observations are available. In the description of the measurement equations, $A_t^{*\prime} = W_t A'$, $H_t^{*\prime} = W_t H'$, and $R_t^* = W_t R W_t'$, respectively, replace A', H', and R.

Once the model is estimated, the estimated specifications can be used to construct term structures of expected inflation—i.e., profiles of expected inflation over different forecast horizons. Model estimation provides monthly observations of the shifting endpoint. This series, combined with the estimated model parameters and monthly inflation data, can be used to construct monthly forecasts of inflation at any horizon using expression (7) and predictions of average inflation over any horizon using expression (8). Thus, although available survey data is limited to *semiannual* observations on only *three* horizons, the model can be used to construct *monthly* predictions at *any* horizon.

3 Empirical Results

The model was estimated using monthly observations, with the techniques described in section 2.4 used to deal with missing observations of inflation expectations. As discussed earlier, Livingston Survey measures of expected inflation were used. Expected inflation was expressed at an annual rate. To be consistent with the survey data, monthly inflation was measured using non-seasonally adjusted CPI inflation, also expressed at an annual rate. The next subsection discusses some additional details related to the data. The subsequent subsection discusses empirical results.

robustness of the results.

3.1 Data

Twice a year, participants in the Livingston Survey are asked to give 6-month and 12-month forecasts of the CPI level. However, because CPI data is released with a lag, the recommendation of Carlson (1977) is followed and it is assumed that when making their forecasts economists had access to CPI data through April and October respectively. Thus, the survey data is treated as 8-month and 14-month forecasts of the CPI level. While informational assumptions may differ across survey participants, Carlson (1977) reports that this assumption is likely consistent with the practice of the majority of those surveyed.

While use of the longest possible sample (1946 is the first year for which 8- and 14-month surveys are available) was desired, three factors motivated consideration of a somewhat shorter sample. First, as noted by Carlson (1977), Livingston tended to adjust survey data with the release of inflation data for months prior to the survey date. Such adjustments in the first part of the survey history may distort the data relative to more recent observations. Second, distortions owing to rounding and rebasing of CPI data are larger for earlier observations. Finally, inflation itself appeared to be generated by a different process in the years immediately following WWII—inflation was more variable and the duration of lower frequency fluctuations was shorter. Choice of 1955 as a starting observation reflected a compromise, and a robustness check suggested that similar results were obtained for shorter samples.

A complication that arises when when trying to use the survey data is that in a few instances since the start of the Survey, the CPI has been rebased to 100 and rounded, but the Survey levels have not been rebased. To minimize distortions that rounding and rebasing introduce, the alternative base year CPI published by the Bureau of Labor Statistics (rebased with 1967=100) was chosen for the empirical analysis and both survey data and price level data were converted to inflation rates. As reported by Kozicki and Hoffman (2004), distortions associated with rounding are considerably smaller in the alternative base year CPI, and inflation rates will be comparable even if the index levels of the actual and survey series are not scaled to the same base year.[21]

Another feature of the Livingston survey data is that the CPI index being forecast is not a seasonally adjusted series. For this reason, an AR(13) specification was chosen. Specifications with fewer lags were also considered, but tended to generate excessively volatile near-term forecasts.[22]

3.2 Results

Results for two alternative specifications are included for comparison. The alternatives include a constant endpoint and unit root model of inflation. As noted earlier, the choice of the shifting endpoint specification was partially motivated by the failure of constant endpoint and unit root models of inflation to match survey data in a different setup (Kozicki and Tinsley 1998, 2001a, 2001b). However, since those studies did not use survey data during estimation and conclusions were based on a different survey, the performance of these alternatives might be better in the current application.

The constant endpoint AR specification for inflation is (1) with $\mu_\infty^{(t)} \equiv \mu$, a constant. The unit root specification is a restricted version of (1) where $\alpha(1) = 1$

[21] CPI data is generally not revised, so the only differences between inflation calculated using the alternative base-year CPI and real-time data are due to rounding that may occur during rebasing. In preliminary work on semi-annual data, real-time CPI data was used and similar results to those reported in the paper were obtained.

[22] In preliminary work, autoregressive specifications with seasonal dummies were less successful at capturing the seasonality. Moreover, coefficients on seasonal dummies tended to be insignificantly different from zero.

has been imposed. A transition equation describing the evolution of the endpoint is not required for either of these variants. Thus, parameters in A, H, and R (and μ in the constant endpoint case) are estimated by applying maximum likelihood to the measurement equations summarized in (11).

To proceed with maximum likelihood estimation of the shifting endpoint specification, starting values for the endpoint and its mean square error are required. Given the random walk transition equation for the shifting endpoint, a diffuse prior was assumed. In particular, the mean square error was set to 1000 and the mean was set to 2.5 percent (the value of μ estimated in the constant endpoint variant).

Results using data from 1955 through April 2005 are summarized in Table 1. In many respects, the models are similar. Point estimates of individual autoregressive parameters (α_i) are similar: estimated coefficients on the first lag are all slightly larger than 0.3; and, all models capture seasonality in the data with statistically significant estimates of the coefficient on the twelfth lag close to 0.2. In addition, standard errors of the measurement equation for inflation differ by less than .01 percentage point, suggesting that the three specifications explain the behavior of inflation equally well at one-month horizons.

The major difference between the three specifications is that persistence as measured by the sum of autoregressive coefficients ($\sum_i \alpha_i$) is lower in the shifting endpoint specification than in the constant- or moving-average-endpoint specifications. This result is consistent with Kozicki and Tinsley (2003), who reported a notable decline in the sum of AR coefficients after allowing for a shifting endpoint, and with Kozicki and Tinsley (2001b), who found that unit root tests on the deviation of inflation from an estimated inflation endpoint were rejected whereas those on inflation were not. In an extension to multiple countries, Levin and Piger (2004) confirmed that inflation persistence decreases after accounting for mean shifts. Benati

(2009) also argues that inflation persistence may result from shifts in trend inflation. The intuition behind these results comes from recognizing that inflation can be rewritten as $\pi_t = \mu_\infty^{(t)} + (\pi_t - \mu_\infty^{(t)})$ and that some of the persistence in inflation (π_t) is absorbed into low frequency movements of the shifting endpoint that anchor long-horizon inflation expectations $(\mu_\infty^{(t)})$, leaving less persistence in the deviations $(\pi_t - \mu_\infty^{(t)})$.

The shifting endpoint specification combines relatively fast reversion of inflation expectations to the endpoint as the forecast horizon increases with moderate time-variation in the endpoint. This moderate time-variation is reflected in the specification's predictions of long-horizon inflation expectations. The constant endpoint specification has higher estimated persistence implying more gradual mean reversion and sluggish adjustments of near-term inflation expectations, but forecasts revert to a constant and long-horizon inflation expectations exhibit relatively little variation. Finally, the unit root restriction in the third specification implies that forecasts at all horizons remain close to recent inflation.

A second important difference between the specifications is in their ability to capture the dynamic behavior of survey expectations. The standard error of the measurement equations for the survey data is considerably smaller for the shifting endpoint specification than for the other two specifications. This result provides an early indication that it is not sufficient to use survey expectations during estimation. Such information should be used in a model that is adaptive to the subjective information embedded in long-horizon expectations.

The importance of explicitly allowing the long-horizon anchor to adapt is revealed in Figures 2 and 3, as well as in Table 2. Survey expectations and predictions based on the three specifications are shown in Figure 2 for the 8-month forecast horizon and in Figure 3 for the 10-year horizon.[23] In both cases, the shifting endpoint model effectively captures the evolution of expected inflation. By contrast, in Figure 2, both the constant-endpoint and unit root specifications generate predictions of 8-month inflation expectations that are more volatile than survey expectations.

In Figure 3, the shifting-endpoint specification generates 10-year expected inflation predictions that appear to provide a compromise between predictions based on the other two specifications. In particular, the prediction from the constant endpoint specification exhibits relatively little variation and appears strongly anchored to 2.5 percent over most of the sample. At the other extreme, the unit root specification predicts considerable volatility and, owing to the unit root restriction, follows actual inflation closely.

Table 2 provides formal evidence on the shifting behavior of long-horizon expectations. The model that incorporates shifts explicitly through a shifting endpoint is clearly superior in its ability to capture the evolution of long-horizon expected inflation. Entries are root mean squared deviations (RMSD) between survey expectations and model-based predictions of multi-period inflation forecasts. What is interesting about this comparison is that the shifting-endpoint specification clearly dominates the other specifications even though all three specifications were fit to survey data and inflation and the ability of each to fit inflation was similar. These results illustrate that using survey data during estimation and having a good model of inflation are *not* necessarily sufficient to empirically explain movements of long-run expectations of inflation.

Evidence on the ability of the models to capture the dynamics of long-horizon expectations is confirmed by comparison of 10-year constructions to a spliced survey

[23] A figure showing results for the 14-month horizon has been excluded because they were visually similar to those for the 8-month horizon.

measure of long-horizon expectations from other survey sources. The spliced measure uses survey data on long-horizon inflation expectations taken from the *Blue Chip Economic Indicators* (available twice per year) through March 1991 and from the *Survey of Professional Forecasters* from November 1991 through the end of the sample (available quarterly). The spliced survey data was not used during estimation out of concern for biases originating from differences across surveys in underlying concepts of inflation or agents being surveyed. Nevertheless, the spliced survey data provides an external check on the validity of the predictions from the shifting endpoint specification.[24] Overall, 10-year inflation predictions of the shifting-endpoint specification clearly dominate the predictions of the constant and unit root specifications in their ability to capture the historical evolution of expected inflation (Table 2). RMSDs between available spliced survey expectations and the predictions are 75 percent larger for the constant endpoint specification and over twice as large for the unit root specification. Thus, this comparison provides additional evidence in favor of the shifting endpoint model, including in the period prior to 1990.

While the analysis discussed so far was conditioned on choices regarding sample

[24] A visual comparison confirms that the shifting-endpoint predictions track the path of the spliced survey observations quite closely and fluctuations in the two are synchronized. That said, there is weak evidence that long-horizon predictions are a little too sensitive to recent movements in inflation. Relative to the spliced survey data, predictions are somewhat high prior to the Volcker disinflation and somewhat low afterwards.This might be due to distortions in the 8-month and 14-month survey data that resulted from adjustments made to the raw survey data made by Livingston. As noted by Carlson (1977), when new data was released between when the survey was conducted and when the survey results were published, Livingston sometimes adjusted raw survey data in the direction of surprises in the data. Alternatively, the assumption made in the model that the AR parameters were constant over the entire sample may be overly restrictive. Cogley and Sargent (2005) find evidence of time-variation in the persistence of inflation even when allowing for a shifting mean. Finally, in contrast to Stock and Watson (2007), the analysis in this paper assumes homoskedasticity of shocks to the endpoint, v_t, and inflation innovations, ϵ_t. However, the excessive movement of the endpoint in the 1980s compared to the survey data suggests that stochastic volatility would not resolve these deviations as higher volatility of v_t in this period would increase the size of endpoint shifts rather than suppress them.

period, autoregressive lag length, and inclusion of very limited 10-year survey data, further investigation provides evidence that the results are remarkably robust. Table 3 compares estimation results for three different sample periods. Overall, results appear to be robust to the sample period chosen. Estimates of persistence (i.e., the sum of AR coefficients, $\sum_i \alpha_i$) are in the range of 0.45, with the largest AR coefficient applying to the first lag on inflation, and standard errors on the innovation to the state variable are close to 0.23. Although the estimated first autoregressive coefficient is somewhat larger for the shortest sample than for the other two, the implications are largely unwound by more negative second and third autoregressive coefficients.

Table 4 compares results from the baseline shifting endpoint specification already discussed to a variant that excludes the survey data on 10-year inflation expectations. Parameter estimates, including the sum of AR coefficients, are very close, providing evidence of robustness and model-consistency of expectations at multiple horizons. One interpretation of the results is that even short-horizon expectations may provide considerable information on the endpoint. Indeed, point estimates in Table 4 suggest that estimates of the endpoint are much more responsive to the information in the 8-month and 14-month survey expectations than to inflation. Appealing to equation (16) to provide intuition, if $\alpha = 0.45$, $R_\epsilon = 2.7^2$, and $R_{\eta_k} = 0.25^2$, then in updating the endpoint, the weight on survey expectations would be larger than the weight on inflation by a factor of $(1-\delta_k)R_\epsilon/((1-\alpha)R_{\eta_k})$, or 190 and 200, respectively, for 8-month and 14-month expectations. This factor can be separated into a component related to the forward-looking nature of expectations ($(1-\delta_k)/((1-\alpha))$), and a component related to the relative volatilities of the measurement equation errors (R_ϵ/R_{η_k}). In the current example, the forward-looking factors are 1.6 (8-month) and 1.7 (14-month), while the volatility factor is 116, reflecting the high volatility of the inflation data relative to the survey expectations.

4 Asymmetric Perceptions of Inflation Targets

Although monetary policy in the United States was conducted without announced numerical targets for inflation, policy decisions were designed with inflation objectives in mind. Likewise, nominal debt contracts, wage and price setting behavior and other economic decisions by households and firms are influenced by inflation expectations, which are anchored by private perceptions of the central bank's inflation target. In the absence of an announced numerical inflation goal and full information, private and central bank perceptions of the effective inflation target may diverge.

The shifting endpoint estimated in the previous section provides a measure of private sector perceptions of the implicit inflation goal of monetary policy. In Figure 4, these private sector perceptions (labeled *shifting endpoint*) can be compared to estimates of central bank perceptions to assess policy credibility. Two views of central bank perceptions are represented in the figure by estimates of the effective inflation target of monetary policy. The *Effective Greenbook inflation target* is the effective target of monetary policy estimated by Kozicki and Tinsley (2009) using real-time Federal Reserve Board staff forecast data. The *Effective inflation target (VAR)* is an alternative construction of the effective inflation target obtained from an unobserved components VAR estimated using retrospective data (Kozicki and Tinsley 2005). By both measures of the effective target, policy actions through the 1970s were *as if* the central bank was willing to accept inflation of roughly 6 to 7 percent. By contrast, the private sector was slow to adjust their views, and their perceptions of the inflation goal only gradually increased from about 3 percent in 1970 to about 7 percent by the end of the decade.

The opposite outcome was observed in the 1980s. Both measures of the effective target exhibited a rapid decline near the end of 1979. However private sector perceptions adjusted much more slowly. Gaps between private sector perceptions and the central bank effective target provide evidence that the Volcker disinflation was not initially viewed as fully credible, offering further support to discussions of Goodfriend and King (2005) and Kozicki and Tinsley (2005), among others, on imperfect policy credibility during that period. Indeed, private sector perceptions of long-run inflation began consistently tracking the effective inflation target only in the early 1990s, well into the Greenspan tenure as Chairman of the FOMC, indicating a lengthy lag before private sector perceptions aligned with the effective inflation goal of monetary policy.[25]

An important feature evident in Figure 4 is the lag in low frequency movements of private sector perceptions compared to the effective inflation target series. A similar lag is evident between actual inflation and private sector perceptions. This phase shift is essential for explaining the behavior of expected inflation and also the behavior of long-term bond rates.[26] Time-variation of coefficients, by itself, is not enough to capture the lags involved in real-time learning. For instance, Cogley and Sargent (2005) estimated a VAR with random walks in intercepts and slopes (although the latter were constrained to yield a stable VAR), yet their core inflation measure (labeled *Cogley and Sargent (2005)* in Figure 4) did not capture the phase shift in endpoints displayed in expected inflation and financial forecasts. Use of survey expectations (or financial forecasts implicit in bond yields) to inform estimates of the shifting endpoint effectively captures the phase shift.

[25] While the perceived and effective goals were similar by the 1990s, FOMC documents indicate that inflation continued to be higher than would be consistent with the price stability portion of the Federal Reserve's mandate for some time. For instance, minutes for the FOMC meeting on January 30-31, 1996 noted: "The members anticipated that inflation would remain contained in 1996, but they did not expect significant progress toward more stable prices.

[26] See the discussion in Kozicki and Tinsley (1998, 2001a, and 2001b).

5 Concluding Comments

The paper estimated a joint model of inflation and survey expectations and used the empirical model to construct a 50-year monthly term structure of expected inflation that is consistent with infrequent observations of expected inflation from the Livingston Survey. A shifting-endpoint AR model of inflation fits inflation comparably to more commonly implemented AR models with constant endpoints or unit root constraints imposed. However, even when expected inflation data is used during estimation, the latter two models are incapable of matching the profiles of expected inflation. Forecasts from constant endpoint models are too volatile at short forecast horizons and too flat at long horizons. By contrast, forecasts from unit root specifications are excessively volatile at all horizons.

An important lesson from this analysis is that survey expectations include independent information on expected inflation relative to that summarized in recent inflation. In order to describe the evolution of expected inflation, it is important to use a model structure that can adapt in response to this information. Otherwise, it is quite possible that models may fit inflation well and yet not be able to explain the behavior of expected inflation, even if survey expectations are used during estimation.

A monthly term structure of expected inflation is easily constructed using the estimated model. Estimates of long-horizon expectations are consistent with constructions based on other datasets and different methodologies, as well as with available survey data (including both survey data used during estimation and survey data from other sources not used during estimation). In one robustness check on the validity of the model specification for inflation expectations at different horizons, it was found that term structures constructed only on the basis of inflation and short-horizon survey expectations are close to those that also use longer-horizon survey expectations. The observation that long-horizon constructions are close to long-horizon survey data, even when the latter are not used during estimation, provides evidence on the consistency of inflation expectations across horizons and, importantly, with the chosen model specification. In addition, it suggests that movements in relatively short-horizon expectations may indicate that there have also been shifts in long-horizon views.

The model provides an estimate of the private sector perceptions of the effective inflation goal of monetary policy. Divergences between private sector perceptions and estimates of the effective inflation target from other studies provides evidence on historical levels of monetary policy credibility. Indeed, the paper finds strong historical evidence of asymmetric perceptions of inflation targets for US monetary policy, particularly from the mid-1960s through the 1980s. Private sector inflation expectations in line with estimates of the effective central bank inflation objective were not obtained until the early 1990s.

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Table 1: Estimation Results

Parameter	Shifting endpoint Estimate	Shifting endpoint SE	Constant endpoint Estimate	Constant endpoint SE	MA endpoint Estimate	MA endpoint SE
α_1	.325	.036	.344	.038	.351	.039
α_2	.020	.040	.040	.042	.078	.042
α_3	-.073	.039	-.025	.040	-.026	.041
α_4	.001	.037	.050	.040	.082	.040
α_5	.049	.041	.046	.042	.052	.042
α_6	.012	.041	.003	.041	.012	.041
α_7	.056	.038	.078	.041	.087	.041
α_8	-.041	.041	-.003	.042	.026	.042
α_9	.013	.038	.029	.040	.012	.040
α_{10}	-.055	.038	.019	.041	.047	.040
α_{11}	.049	.039	.067	.042	.080	.042
α_{12}	.172	.038	.198	.041	.204	.041
α_{13}	-.085	.031	-.025	.035	-.008	.000
$\sum_i \alpha_i$	.445		.819		1.000	
μ			2.575	.153	-2.615	.736
$R_\epsilon^{1/2}$	2.732	.112	2.726	.079	2.716	.079
$R_\eta^{1/2}$	.243	.016	.909	.044	1.047	.051
$Q^{1/2}$	.232	.021				

All models were estimated using maxiumum likelihood with data starting in 1955. The shifting endpoint specification employed Kalman filtering techniques to estimate the unobserved state variables (the perceived inflation target). The variance covariance matrix of the measurement equation shocks was restricted to be diagonal during estimation and variances of measurement equations for survey data were assumed to be the same. R_ϵ denotes the variance of the shocks to the inflation equation and R_η denotes the variance of the measurement errors on survey data. Results are presented for three AR (13) model specifications. The *shifting endpoint* model has a shifting mean, estimated using a Kalman filter procedure, the *constant endpoint* model is a standard unrestricted AR(13) process with a constant mean, and the *MA endpoint* model is an AR(13) with a unit root restriction imposed. In the latter specification, to ensure the sum of AR coefficients equals one, α_{13} is set to be equal to $1 - \sum_{i=1}^{12} \alpha_i$ and consequently α_{13} has a standard error of zero; also, the entry for μ is the estimate of a constant included in the regression, not an estimate of the endpoint.

Table 2: Comparison of Fits to Survey Data

Forecast Horizon (Survey)	Shifting endpoint	Constant endpoint	MA endpoint
8 month (Livingston)	0.22	0.94	1.35
14 month (Livingston)	0.14	0.93	1.39
10 year (Livingston)	0.25	0.65	0.68
10 year (Blue Chip)	0.40	1.29	1.39

This table contains root mean squared errors (RMSEs) constructed as the square root of the average squared deviation of inflation predictions from survey data over those observations for which survey data are available. The row labeled *10 year (Livingston)* uses 10-year inflation expectations data from the Livingston survey. This is the data that was used during estimation. The row labeled *10 year (Blue Chip)* uses 10-year inflation expectations data from the *Blue Chip Economic Indicators* through March 1991 and from the *Survey of Professional Forecasters* from November 1991 through the end of the sample (available quarterly). This data was not used during estimation. Inflation predictions are constructed over the reported horizon for three different times series models of inflation. All three models are AR(13) specifications. The *shifting endpoint* model has a shifting mean, estimated using a Kalman filter procedure, the *constant endpoint* model is a standard unrestricted AR(13) process with a constant mean, and the *MA endpoint* model is an AR(13) with a unit root restriction imposed (i.e., the sum of AR coefficients is constrained to equal one). Estimates of model parameters are provided in Table 1.

Table 3: Robustness of results to sample

	1955:1 - 2005:4		1965:1 - 2005:4		1975:1 - 2005:4	
Parameter	Estimate	SE	Estimate	SE	Estimate	SE
α_1	.325	.036	.367	.040	.461	.046
α_2	.020	.040	-.029	.047	-.160	.057
α_3	-.073	.039	-.043	.042	-.011	.057
α_4	.001	.037	-.026	.042	-.047	.053
α_5	.049	.041	.087	.047	.127	.056
α_6	.012	.041	-.011	.047	-.118	.055
α_7	.056	.038	.101	.044	.184	.053
α_8	-.041	.041	-.068	.046	-.075	.054
α_9	.013	.038	.003	.042	.001	.051
α_{10}	-.055	.038	-.063	.043	-.075	.051
α_{11}	.049	.039	.080	.045	.117	.053
α_{12}	.172	.038	.156	.044	.123	.052
α_{13}	-.085	.031	-.071	.035	-.073	.038
$\sum_i \alpha_i$	.445		.482		.455	
$R_\epsilon^{1/2}$	2.732	.112	2.767	.090	2.587	.098
$R_\eta^{1/2}$	.243	.016	.237	.017	.239	.019
$Q^{1/2}$	.233	.021	.257	.021	.235	.026

Results are for maximum likelihood estimation of the shifting endpoint model specification over the sample periods indicated. Kalman filtering techniques were used to estimate the unobserved state variables (the perceived inflation target). The variance covariance matrix of the measurement equation shocks was restricted to be diagonal during estimation and variances of measurement equations for survey data were assumed to be the same. R_ϵ denotes the variance of the shocks to the inflation equation and R_η denotes the variance of the measurement errors on survey data.

Table 4: Robustness of results to use of 10-year survey data

	10-year survey used		10-year survey not used	
Parameter	Estimate	Standard Error	Estimate	Standard Error
α_1	.325	.036	.320	.037
α_2	.020	.040	.043	.040
α_3	-.073	.039	-.053	.039
α_4	.001	.037	.024	.038
α_5	.049	.041	.032	.041
α_6	.012	.041	-.017	.041
α_7	.056	.038	.027	.039
α_8	-.041	.041	-.028	.041
α_9	.013	.038	.038	.037
α_{10}	-.055	.038	-.022	.038
α_{11}	.049	.039	.037	.039
α_{12}	.172	.038	.139	.038
α_{13}	-.085	.031	-.088	.031
$\sum_i \alpha_i$	.445		.452	
$R_\epsilon^{1/2}$	2.732	.112	2.727	.079
$R_\eta^{1/2}$	.243	.016	.203	.015
$Q^{1/2}$	.232	.021	.240	.021

Results are for maximum likelihood estimation of the shifting endpoint model specification with data starting in 1955. Results in the columns labeled *10-year survey used* included measurement equations for 8-month, 14-month, and 10-year survey data on inflation expectations. Results in the columns labeled *10-year survey not used* only included measurement equations for 8-month and 14-month survey data on inflation expectations. Kalman filtering techniques were used to estimate the unobserved state variables (the perceived inflation target). The variance covariance matrix of the measurement equation shocks was restricted to be diagonal during estimation and variances of measurement equations for survey data were assumed to be the same. R_ϵ denotes the variance of the shocks to the inflation equation and R_η denotes the variance of the measurement errors on survey data.

Figure 1: Inflation and Survey Expectations

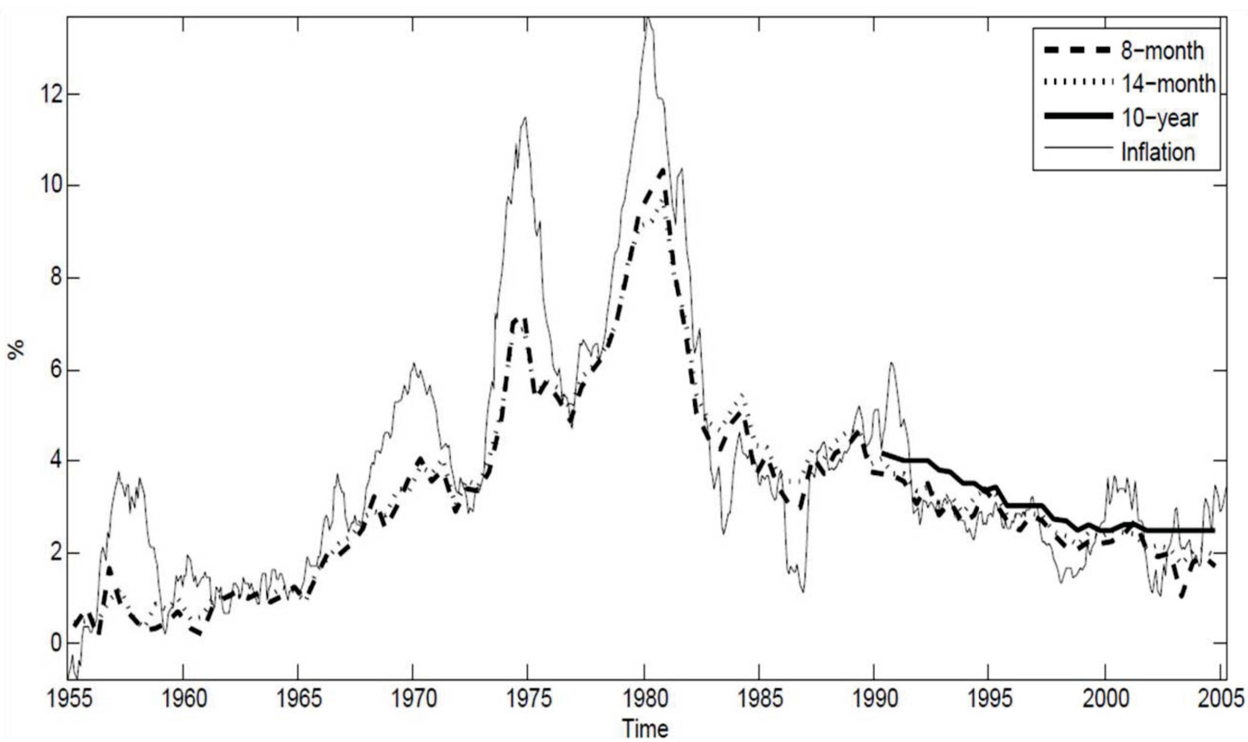

Figure 2: 8-month expected inflation: Livingston survey and model predictions

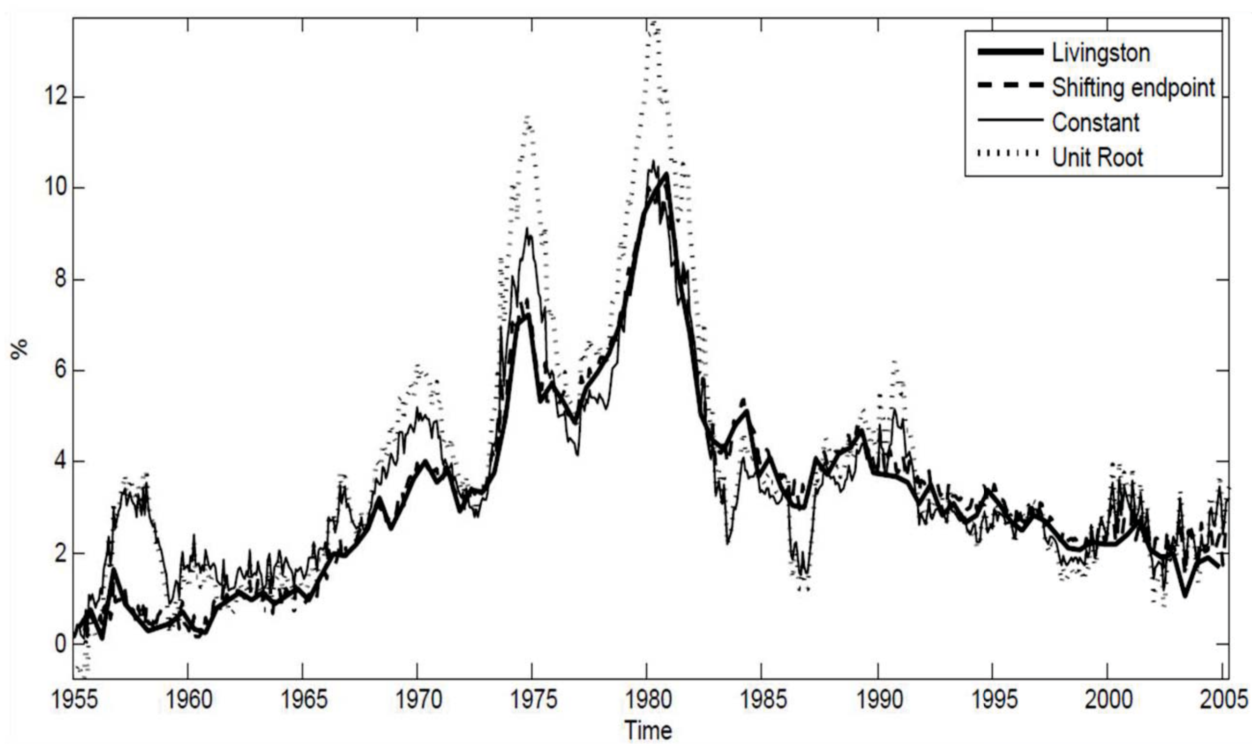

Figure 3: 10-year expected inflation: Livingston survey and model predictions

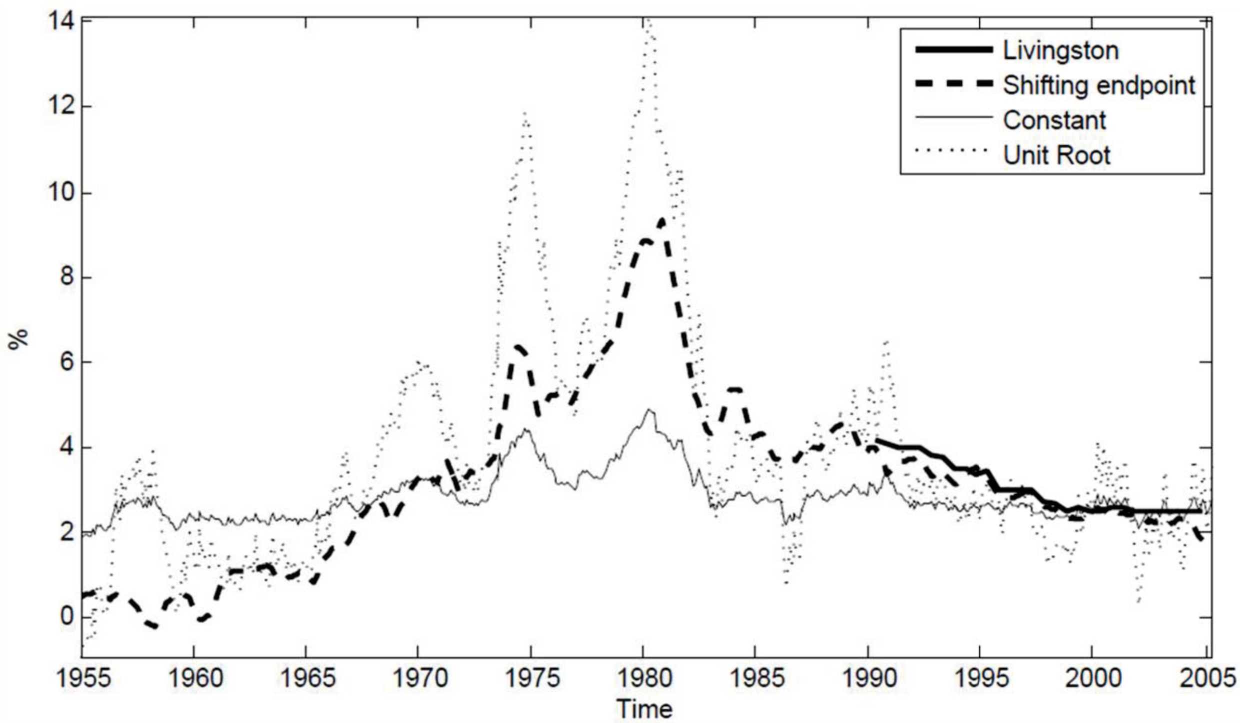

Figure 4: Alternative estimates of long-horizon inflation