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Richard K. Crump | Stefano Eusepi | Emanuel Moench

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Abstract

Most macroeconomic models impose a tight link between expected future short rates and the term structure of interest rates via the expectations hypothesis (EH). While the EH has been systematically rejected in the data, existing work evaluating the EH generally assumes either full-information rational expectations or stationarity of beliefs, or both. As such, these analyses are ill-equipped to refute the EH when these assumptions fail to hold, fueling hopes for a “resurrection” of the EH. We introduce a model of expectations formation which features time-varying means and accommodates deviations from rationality. This model tightly matches the entire joint term structure of expectations for output growth, inflation, and the short-term interest rate from *all* surveys of professional forecasters in the U.S. We show that deviations from rationality and drifting long-run beliefs consistent with observed measures of expectations, while sizable, do not come close to bridging the gap between the term structure of expectations and the term structure of interest rates. Not only is the EH decisively rejected in the data, but model-implied short-rate expectations generally display, at best, only a weak co-movement with the forward rates of corresponding maturities.

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Crump: Federal Reserve Bank of New York (email: richard.crump@ny.frb.org). Eusepi: University of Texas at Austin (email: stefano.eusepi@austin.utexas.edu). Moench: Frankfurt School of Finance & Management (email: e.moench@fs.de). This paper substantially builds on and complements previous work circulated as “The Term Structure of Expectations and Bond Yields” (Crump, Eusepi, and Moench 2018). The authors thank Tobias Adrian, John Cochrane, Keshav Dogra, Marco Del Negro, Domenico Giannone, Sam Hanson, Albert Marcet, Emi Nakamura, Bruce Preston, Giorgio Primiceri, Harald Uhlig, Jonathan Wright, and participants at various seminars, workshops, and conferences for helpful comments and discussions. They also thank Kenneth Froot for sharing the Goldsmith-Nagan survey data.

This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author(s) and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the author(s).

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1 Introduction

The expectations hypothesis of the term structure of interest rates states that yields on government bonds reflect the average short rate expected to prevail over the life of the bond. Since the 1930s, the expectations hypothesis (EH) has been the natural starting point for linking longer-term yields to short-term yields (e.g., [Lutz 1940](#)). To this day, it remains a maintained assumption in most macroeconomic models, where the monetary transmission mechanism relies on a tight relationship between expectations of future short rates and longer-term interest rates (e.g., [Woodford 2003](#)). The preeminent role of the EH stands in tension with the overwhelming empirical evidence stacked against it.

However, analyses of the EH are only as good as the expectations-formation process they are based on. [Friedman \(1979\)](#) and [Froot \(1989\)](#) first emphasized that standard tests of the EH are, in fact, *joint* tests of the EH and full information rational expectations (FIRE). [Campbell and Shiller \(1991\)](#) find that when the term spread is high, long-term rates are expected to fall, rather than rise, as the theory would suggest. However, these patterns are also consistent with the EH, under bounded rationality and learning ([Sinha 2016](#); [Farmer, Nakamura, and Steinsson 2023](#)). Furthermore, economic agents are commonly assumed to operate in a stationary environment, where they quickly come to understand the long-run behavior of the economy. Their corresponding long-run expectations, therefore, are stable and, under the EH, would fail to match the substantial variability in longer-maturity interest rates ([Fuhrer 1996](#); [Kozicki and Tinsley 2001](#); [Gürkaynak, Sack, and Swanson 2005](#)).¹

In this paper, we reevaluate the empirical evidence regarding the EH by proposing a model of expectations formation that allows for deviations from FIRE and accounts for time-varying beliefs about the long-run. Agents form forecasts about the path of the short-term interest rate based on noisy signals about the true state of the economy. Based on this information, they estimate a non-stationary trend and a stationary cyclical component and form forecasts based on their joint dynamics. Importantly, we do not impose that subjective expectations coincide with those of the true data-generating process.

We estimate the model using the *universe* of consensus forecasts from all U.S. surveys of professional forecasters covering more than 600 survey-horizon pairs at a monthly frequency. This simple expectations formation model provides a tight fit to forecasts of real GDP growth, CPI inflation, and the 3-month Treasury bill for all horizons from the very-short (current quarter) term to the long-run (11 years and beyond). We show that signals about inflation and output are an important factor shaping their interest-rate expectations which is

¹Observed long-rates display “excess volatility” relative to those predicted by the EH ([Shiller 1979](#); [Campbell and Shiller 1991](#)).

consistent with conventional views about central bank reaction functions (Andrade, Crump, Eusepi, and Moench 2016). This implication would be notably absent in univariate models; moreover, we demonstrate that a univariate version of our model fails to match the behavior of observed short-term interest rate forecasts.

In favor of our model, we show that revisions of long-horizon expectations strongly co-move with realized short-term forecast errors, which are not used in the model’s estimation, indicating that forecasts are revised in response to new information. Furthermore, these forecast revisions result in substantial variability of long-horizon forecasts even as compared to those of statistical models such as Laubach and Williams (2003) and Del Negro, Giannone, Giannoni, and Tambalotti (2017). The estimated model also exhibits meaningful deviations from full rationality. In fact, as in Sinha (2016) and Farmer, Nakamura, and Steinsson (2023), treating data generated from the model as observed yields (i.e., imposing the EH), would nonetheless lead an empirical researcher to frequently reject the EH using standard statistical tests.

While deviations from rationality and drifting long-run beliefs are sizable, they do not come close to bridging the gap between the model-implied term structure of expectations and the term structure of interest rates. Far from resurrecting the EH, the tight connection between short-term interest rate expectations and the term structure of interest rates, assumed to hold in theory, demonstrably fails to hold in practice. Expected interest rates beyond two years have, at best, only a weak co-movement with forward rates of the corresponding maturities. In fact, the correlation between changes in longer-term forward rates out to ten years and corresponding longer-horizon short rate forecasts converges towards zero as the maturity increases. In light of this evidence, it is unsurprising that formal tests in the spirit of Froot (1989) using our model-implied expectations result in decisive rejections of the EH. Importantly, these tests do not require any assumption about the expectations formation mechanism.

The flip side of our results is that the wedge between observed yields and expected future short-term interest rates captures the vast majority of yield variability at medium and long maturities. In models where agents are risk averse, this wedge represents time-varying compensation for bearing risk. However, using linear regressions we show that this wedge is only partially explained by the underlying factors shaping beliefs about the state of the economy. This implies that any model designed to explain both the term structure of short rate expectations and the term structure of interest rates would need to involve additional drivers.

Our results have crucial implications for the study of the two-way interaction between asset markets and the macroeconomy. Deviations from the EH from sources such as finan-

cial frictions, behavioral asset pricing or heterogeneity of beliefs induce a complex mapping between key state variables driving macroeconomic fluctuations and the government bond market that needs to be better understood. In turn, these deviations represent a channel of first-order importance to better understand the effect of the term structure of interest rates on the aggregate economy that is absent in most macroeconomic models.

Related Literature This paper is related to an exploding literature using survey data to inform about economic agents' expectations formation process.² While the literature has not settled on a unified framework, a few lessons have emerged: survey forecasts deviate systematically from FIRE predictions, resulting in predictable forecast errors and over- and under-reaction to new information.³ Moreover, professional forecasters' interest rate expectations, which are formed in real time, behave quite differently compared to forecasts available to an econometrician observing the full sample.⁴ This indicates that agents are learning about the economic environment they operate in.

Models where agents operate in a non-stationary environment, and have to constantly adapt to structural change, can generate sizable fluctuations in long-horizon expectations. For example, [Fuhrer \(1996\)](#) and [Kozicki and Tinsley \(2001\)](#) show that interest rate expectations consistent with monetary policy regime shifts during the US post-war period can generate movements in yields under the EH that well approximate the variation in observed yields. Similarly, [Cogley \(2005\)](#) proposes a model of the term structure of interest rates based on a VAR with drifting coefficients and shows that the EH cannot be rejected in this environment.⁵ More recently, using models of bounded rationality and learning, [Sinha \(2016\)](#) and [Farmer, Nakamura, and Steinsson \(2023\)](#) provide examples where the EH would be rejected in the data even when it holds in the true data generating process. [Sinha \(2016\)](#) explores a New Keynesian model with long-term government bonds and bounded rationality, where agents learn about the long-run evolution of the economy. [Farmer, Nakamura, and Steinsson \(2023\)](#) propose a univariate trend-cycle model for the short-term interest rate. They show that their calibrated model matches existing stylized facts capturing departures from FIRE using survey forecasts out to four quarters ahead.

Our results stand in stark contrast to the conclusions from this literature. Although

²See [Angeletos, Huo, and Sastry \(2020\)](#) and [Eusepi and Preston \(2023\)](#) for recent surveys.

³See, for example, [Eusepi and Preston \(2011\)](#), [Coibion and Gorodnichenko \(2012\)](#), [Bordalo, Gennaioli, Ma, and Shleifer \(2020\)](#), and [Angeletos, Huo, and Sastry \(2020\)](#).

⁴See [Friedman \(1979\)](#), [Piazzesi, Salomao, and Schneider \(2015\)](#), [Cieslak \(2018\)](#), [Singleton \(2021\)](#), and [Eusepi, Giannoni, and Preston \(2020\)](#).

⁵Similarly, [Dewachter, Iania, and Lyrio \(2011\)](#) propose a structural model where agents learn about the inflation target and show that this model, based solely on macro-factors provides a better fit of observed yields than rational expectations models.

imperfect information and learning has the potential to deliver EH-implied yields with similar features as observed yields, we show that such models cannot simultaneously fit the term structure of interest rates and the term structure of short-rate expectations as measured from professional surveys. Said differently, the true unobservable “market expectation” of the short-term interest rate would require substantial deviations from observed expectations to reconcile the EH with the realized data.

Survey expectations of interest rates have also been used in conjunction with no-arbitrage term structure models to analyze the behavior of yields. [Kim and Wright \(2005\)](#) and [Kim and Orphanides \(2012\)](#) employ survey forecasts of the nominal short rate at a few select horizons to discipline the dynamics of the state variables under the historical measure in small samples. [Wright \(2011\)](#) uses expectations from an affine term structure model and survey-based expectations to study the global decline in yields beginning in the 1980s. [Piazzesi, Salomao, and Schneider \(2015\)](#) use survey forecasts of the short rate, inflation, and of longer-term Treasuries to disentangle subjective (i.e. survey forecasters’) beliefs and objective (i.e. those of a statistician endowed with full-sample information) beliefs. In contrast to these papers, we generate the entire term structure of short-rate expectations without relying on information from yields.

In summary, we make three distinct contributions relative to the existing literature. First, the convention in the study of expectations is to evaluate expectations formation for a single variable (e.g., [Coibion and Gorodnichenko 2012](#), [Bordalo, Gennaioli, Ma, and Shleifer 2020](#) and [Farmer, Nakamura, and Steinsson 2023](#)). In contrast, we present a multivariate model of expectations formation and show that modeling short-rate forecasts along with those of output growth and inflation is essential to match the observed term structure of survey forecasts. Second, the vast majority of the aforementioned literature focuses on stationary models and the study of short-term expectations (see [Crump, Eusepi, Moench, and Preston 2023](#) for a survey). However, observed subjective long-horizon expectations from survey data exhibit substantial time variation consistent with economic agents facing considerable uncertainty about the long-run behavior of the economy (e.g., [Crump, Eusepi, Moench, and Preston 2023, 2024](#)). Here, we propose a model in which agents learn about both the short-run *and* the long-run and show that it fits the survey data at all available forecast horizons. Third, and most importantly, we show that once we discipline the expectations formation process using survey expectations, we find no evidence that imperfect information and learning can vindicate the EH.

The argument that deviations from full-information rational expectations could invalidate tests of the EH goes back to [Friedman \(1979\)](#) and [Froot \(1989\)](#). While these earlier seminal papers use survey data to explore the validity of the EH without imposing any assumptions

about the expectations formation process, limited data hindered their ability to reach clear-cut conclusions. Our analysis expands on these early approaches by using multiple surveys over a much longer sample. More importantly, while these papers only focus on the short-term, we cover the entire term structure of survey forecasts, including forecast horizons many years out.

The remainder of this paper is structured as follows. In Section 2, we introduce our model of expectations formation. In Section 3, we discuss our data and estimation approach, document the tight fit to the observed term structure of nominal short rate forecasts, and demonstrate other appealing properties of the model. In Section 4 we compare the term structure of short-rate expectations to the term structure of interest rates, formally test for the EH, and provide our main results. We end this section with a conceptual discussion comparing the average investor and the marginal investor in the bond market. Section 5 concludes. In the Appendix we present some additional details of the model and a Supplementary Appendix (hereafter, “SA1”) collects additional results and robustness checks.

2 A Model of Expectations Formation

Consider an agent who observes the nominal short-term interest rate directly along with noisy signals of other key macroeconomic variables. The aggregate state of the economy is defined by $z_t = (g_t, \pi_t, i_t)'$ where g_t is real output growth, π_t is price inflation, and i_t is the short-term nominal interest rate. The perceived law of motion for z_t is

$$z_t = \omega_t + x_t \tag{2.1}$$

where

$$\omega_t = \omega_{t-1} + \eta_t \tag{2.2}$$

is the *trend* component and

$$x_t = \Phi x_{t-1} + \nu_t \tag{2.3}$$

is a stationary *cycle* component. The innovations, η_t and ν_t , are *i.i.d.* Gaussian innovations with joint variance-covariance matrix Σ_z . We assume that the agent perceives the trend component to be slow-moving as compared to the stationary component, implying that innovations to the former have a much smaller variance than innovations to the latter.

To form expectations, the agent requires an estimate of the unobserved components x_t and ω_t . However, the forecaster faces two important informational constraints. First, they can only imperfectly observe real output growth and inflation as only the short-term interest rate is fully known at any point in time. This constraint is consistent with the fact that economic variables such as real GDP and inflation are released with a delay and feature sizable and significant subsequent revisions. In addition, observed measures of price inflation are contaminated with volatile sub-components that mask underlying inflation, π_t , which is the relevant state variable for forecasting.

Second, agents face an additional signal extraction problem. They have to infer to what extent changes in observed data are due to transitory shocks related to the business cycle, x_t , or reflect shifts in the slow-moving permanent components, as captured by the innovation to ω_t . The latter component may reflect regime changes such as long-term shifts in productivity, the savings rate or fiscal policy, which directly impact the evolution of the long term real rate of interest, or shifts in the perceived long-run mean of inflation, reflecting perceived credibility of monetary policy.

We assume that the agent receives two sets of signals, collected in the $m \times 1$ vector \mathcal{S}_t . The first set of signals represents the noisy signals of real output growth and inflation coming from economic releases and the short-term interest rate which is perfectly observed. The agent also observes additional noisy signals on the sub-components, x_t and ω_t . This second set of signals captures information from alternative channels such as other data releases or central bank communications. For example, forward guidance about the short-term path of the policy rate (x_t) or central-bank announcements that alter perceptions about the inflation target (ω_t). The mapping between an agent's model and observed signals is then summarized by the following observation equation

$$\mathcal{S}_t = H' \begin{pmatrix} x_t \\ \omega_t \end{pmatrix} + s_t. \quad (2.4)$$

where H is an $6 \times m$ matrix with m the number of signals and s_t is a vector of *i.i.d.* Gaussian measurement errors with variance-covariance matrix Σ_s . The agent uses the Kalman filter to estimate the latent trend and cycle components,

$$\begin{pmatrix} x_{t|t} \\ \omega_{t|t} \end{pmatrix} = F \begin{pmatrix} x_{t-1|t-1} \\ \omega_{t-1|t-1} \end{pmatrix} + f_t, \quad F = \begin{bmatrix} \Phi & 0 \\ 0 & I_3 \end{bmatrix}, \quad (2.5)$$

where

$$f_t \equiv \mathcal{K} (\mathcal{S}_t - \mathcal{S}_{t|t-1}). \quad (2.6)$$

In words, the current estimates of x_t and ω_t depend on their previous estimates, along with f_t , which is the “surprise” relative to the agent’s prediction, $(\mathcal{S}_t - \mathcal{S}_{t|t-1})$, scaled by the $6 \times m$ steady-state Kalman matrix \mathcal{K} .⁶

Given current estimates, the model then produces the *full* term structure of expectations for all forecast horizons, h , via

$$\mathbb{E}_t [z_{t+h}] \equiv z_{t+h|t} = \omega_{t|t} + \Phi^h x_{t|t}. \quad (2.7)$$

Forecasts at all horizons depend on $x_{t|t}$ and $\omega_{t|t}$ and are interlinked by the autoregressive matrix, Φ . To obtain $x_{t|t}$ and $\omega_{t|t}$ we need to designate the joint dynamic evolution of these two objects. Using equation (2.5), this requires assumptions on the behavior of f_t .

Under rational expectations the agent’s perceived law of motion, as governed by equations (2.1)–(2.3), coincides with the true data generating process of z_t . In this case, f_t is an *i.i.d.* Gaussian process with variance-covariance matrix tied directly to the model’s parameters (see Appendix A). However, we would like to place minimal restrictions on f_t . We do so for two reasons. First, the agent may not have the correct law of motion of their signals, \mathcal{S}_t and, therefore, f_t will not satisfy the restrictions implied by rational expectations. Second, as econometricians, we want to avoid taking a stand on exactly which signals, \mathcal{S}_t , the agent observes and their associated true data generating process.

To accommodate (possible) deviations from full rationality we allow the forecast errors, f_t , to be autocorrelated across time reflecting a potentially serially correlated gap between subjective expectations and the true data generating process. Further, the variance-covariance matrix of the innovation to the forecast errors is left completely unrestricted allowing for general forms of model misspecification by the agent. In particular we assume

$$f_t = Gf_{t-1} + \varepsilon_t, \quad (2.8)$$

where ε_t is *i.i.d.* Gaussian white noise with full variance-covariance matrix Σ_ε and $G = (I_2 \otimes \phi_f)$ with $\phi_f = \text{diag}(\rho_{fg}, \rho_{f\pi}, \rho_{fi})$ where \otimes denotes the Kronecker product.⁷ By equation (2.8), we then have that the forecast errors for the true state of the economy, $z_{t|t} - z_{t|t-1}$, will be serially correlated. Agents fail to take into account the persistence of their forecast errors when forming expectations, i.e., that $\mathbb{E}_t [f_{t+1}] = 0$ (see equation (2.7)). This aligns with

⁶The steady-state Kalman matrix decomposes prediction errors into estimates of trend, cycle, and noise components. As shown in Appendix A, it depends on the persistence of the cycle component (Φ), the volatility of the innovations (Σ_z), and the volatility of the measurement error (Σ_s). Broadly speaking, the Kalman matrix is a function of the “signal-to-noise” ratio in the model.

⁷We assume the number of signals m is sufficiently large such that, given the parameters of the model, Σ_ε is nonsingular.

the empirical evidence documenting predictability of forecast errors of interest rate, GDP and inflation forecasts.⁸ That said, it is important to emphasize that we do not impose a deviation from rationality, rather, it is nested under specific restrictions on G and Σ_ε .

In sum, we make no assumption that equations (2.1)–(2.3) constitute the true data generating process for the economy. Instead, equations (2.5) and (2.8) describe the evolution of the agent’s beliefs about the current state of the economy and its sub-components. Given those beliefs, equation (2.7) produces the full term structure of expectations in every time period. While our model captures a large class of learning models in macroeconomics and finance, the evolution of expectations is regulated by only a small set parameters: $\Theta \equiv (\Phi, \phi_f, \Sigma_\varepsilon)$.

3 Bringing the Model to the Data

In this section, we show how to use our model of expectations formation to explain survey forecasts of professional forecasters in the U.S. We first introduce our unique data set in Section 3.1. We discuss estimation of the model in Section 3.2, and document the fit of the term structure of short-rate expectations in Section 3.3.

3.1 Data

We estimate the model’s parameters using *all* available surveys of professional forecasters in the U.S. There are several advantages of using surveys of professional forecasts instead of surveys of households or firms. First, multiple surveys covering a wide range of forecast horizons spanning “nowcasts” to the very long run are available going back at least to the early 1980s. Second, professional forecasters closely watch the evolution of the economy and the conduct of monetary policy. As they often represent firms active in financial markets, their predictions are likely a good proxy to those of actual traders in the bond market. We obtain nominal and real short-rate expectations by combining all available surveys of professional forecasts of the 3-month Treasury bill rate, consumer price index (CPI) inflation, and real GDP growth covering more than 600 survey-horizon pairs at a monthly frequency.

To the best of our knowledge, our data span the universe of professional forecasts for the United States. Our forecast data are obtained from nine different survey sources: (1) Blue Chip Financial Forecasts (BCFF); (2) Blue Chip Economic Indicators (BCEI); (3) Consensus Economics (CE); (4) Decision Makers’ Poll (DMP); (5) Economic Forecasts: A Worldwide Survey (EF)⁹; (6) Goldsmith-Nagan (GN)¹⁰; (7) Livingston Survey (Liv.); (8) Survey of

⁸See [Eusepi and Preston \(2023\)](#) for a recent survey.

⁹To our knowledge, the only other paper to use these survey data is [Ehrbeck and Waldmann \(1996\)](#).

¹⁰We thank Kenneth Froot for sharing the Goldsmith-Nagan survey data.

Primary Dealers (SPD); (9) Survey of Professional Forecasters (SPF). For each survey and each forecast horizon we use the consensus forecast, or the mean across forecasters. We focus on three sets of forecasts. For output growth we rely on forecasts of real GNP growth prior to 1992 and forecasts of real GDP growth thereafter. For inflation we use forecasts of growth in the CPI. Finally, we employ the 3-month Treasury bill (secondary market) rate as our measure of a short-term interest rate as it is by far the most frequently surveyed short-term interest rate available.¹¹ Combined, these surveys provide a rich portrait of professional forecasters’ macroeconomic expectations. Our results are based on 627 variable-horizon pairs spanning the period 1983 to 2019. The survey data differ in frequency, forecast timing, target series, sample availability and forecast horizons.¹² Near-term survey forecasts (target period is up to two years ahead) are available for the longest sample with CPI forecasts from the Livingston Survey beginning in the mid-1940s. Medium- and long-term forecasts (target period includes three-years ahead and longer) are available for real output growth and inflation starting in the late 1970s. However, a more comprehensive set of long-term forecasts (a target period of five or more years ahead) for all three variables is available only starting in the mid-1980s which is where we start our sample. At all horizons there are fewer forecasts for the 3-month Treasury bill than for output growth and inflation.

3.2 Estimation

To estimate the model we use only the professional survey data listed above and do not include any realized economic data. Our goal is to model the expectations formation process and reserve the realized data for our analysis of forecast errors in later sections.¹³ We estimate the parameters of the model, Θ , over the sample period from January 1983 to December 2019. The linearity of the model allows us to use a standard state-space framework. The main challenge is to construct the nonlinear mapping between observed survey forecasts and model-implied expectations.

We assume that observed survey forecasts are noisy signals of the true underlying expectations. To cement ideas, suppose our dataset only included monthly forecasts of z_t for different monthly horizons. Let $\text{SVYEXP}_{t+h|t}$ be a 3×1 vector collecting the survey forecasts of real output growth, inflation, and the nominal short rate for the forecast horizon h . Then the

¹¹For example, forecasts of the Federal Funds rate, the target rate of U.S. monetary policy are only available in two of the eight surveys we consider (BCFF and SPD).

¹²See [Crump, Eusepi, Moench, and Preston \(2023\)](#) for a full discussion of the data sources.

¹³In theory, we could include the monthly realized 3-month T-bill in the estimation as the agent is assumed to observe it perfectly. In practice, forecasters are surveyed at different times in the month and may not fully observe the average short rate for that month. We verify that their model-implied monthly nowcast of the short-term interest rate is nearly identical to the realized series.

observation equation for each survey-horizon pair could be straightforwardly characterized as

$$\text{SVYEXP}_{t+h|t} = \mathbb{E}_t [z_{t+h}] + o_t^{(h)} = \omega_{t|t} + \Phi^h x_{t|t} + o_t^{(h)}, \quad (3.1)$$

where $o_t^{(h)}$ is a horizon-specific measurement error which is assumed to be Gaussian white noise with a diagonal variance-covariance matrix. Even if we were able to observe $\text{SVYEXP}_{t+h|t}$ for every forecast horizon h , equation (3.1) shows that it would still be only a noisy signal of the true expectations. In reality, we have multiple surveys for forecasts of the same variable at the same horizon but also face substantial gaps where no forecasts are available. The model allows us to combine these noisy signals in a principled way and fill gaps to obtain model-implied forecasts at all horizons.

In practice, our observation equation is more involved than that of equation (3.1). For example, many of the observed survey forecasts are expressed at quarterly or yearly horizons. In addition, recorded forecasts often involve quarterly averages or annualized growth rates. We exploit the fact that all of these more general forecast targets can be tightly approximated by specific (weighted) linear combinations of $\text{SVYEXP}_{t+h|t}$ for appropriate choices of h which maintains linearity of the observation equation. For example, a forecast formed in the last month of a quarter, for the next quarter’s average of the short-term interest rate, may be well approximated by the third element of $\sum_{j=1}^3 \zeta_j \mathbb{E}_t [z_{t+j}] + o_t$ where $\zeta_j = \frac{1}{3}$ for each j . Appendix B provides full details and additional examples.

Overall, the empirical exercise involves a sizable observation equation including 627 time series of survey forecasts for different horizons. To limit the number of parameters to be estimated, we group the variances of the measurement errors o_t by the target variable of interest and the horizon of the forecast (but not by the specific survey). In particular we group forecast horizons by: *very short term*, up to two quarters ahead, *short term*, up to two years ahead, *medium term*, from three to four years ahead, and *long term*, five or more years ahead. This allows for a parsimonious yet flexible fitting of observed forecasts.

While the state of the economy is re-estimated in every period, the model’s parameters remain constant, reflecting agents’ invariant priors. This simplifying assumption retains linearity. It is plausible that, over such a long sample, agents would re-evaluate their estimates of the model’s parameters to adapt to structural change. We accommodate this process by allowing a structural break in the innovation process of the estimated trends ε_t^ω . We date the structural break in the first month of 1999. While the choice of the month may appear arbitrary, it reflects two considerations. First, as shown by [Carvalho, Eusepi, Moench, and Preston \(2023\)](#), long-term inflation expectations begin to stabilize around that period. Separately, [Hanson, Lucca, and Wright \(2021\)](#) show that the sensitivity of long-term interest rates to changes in short term interest rates declined substantially after 1998. This evidence

suggests important revisions to agents’ priors about the variability of long-term trends. This structural break allows our model to capture this revision in beliefs using the observed term structure of expectations.

Priors and Posteriors. We use a Bayesian estimation approach which requires prior distributions for the parameters of the model. In general, we use loose priors throughout. The one exception is we assume the perceived trend component, ω_t , measuring structural shifts in the economy, is slow-moving relative to the cycle component, x_t . Consequently, we impose this restriction in our priors. To do so, we express the variance-covariance matrix of ε_t in equation (2.8) as

$$\Sigma_\varepsilon = \begin{bmatrix} \sigma_x & 0 \\ 0 & \sigma_\omega \end{bmatrix} \times C_\varepsilon \times \begin{bmatrix} \sigma_x & 0 \\ 0 & \sigma_\omega \end{bmatrix} \quad (3.2)$$

where $\sigma_x, \sigma_\omega > 0$ are vectors collecting the standard deviations of the innovations to f_t which are linked to the evolution of $x_{t|t}$ and $\omega_{t|t}$ by equation (2.5), and C_ε is a correlation matrix. Define the three-dimensional vector measuring the element-by-element ratio $\lambda \equiv \sigma_\omega \odot \sigma_x^{-1}$ where \odot denotes the Hadamard product. We let each element of this vector be distributed according to a beta distribution. As shown in Table 1, the prior mean for all elements in λ is 10% with 90% of the density between 6% and 14%, reflecting the assumption that the trend component is perceived to be slow moving. Priors on the elements of σ_x are fairly diffuse – set as an independent inverse Gamma distribution with a prior mean of 0.1 and a standard deviation of 2.

The prior on the correlation matrix, C_ε , is defined by the Lewandowski-Kurowicka-Joe (LKJ) distribution (Lewandowski, Kurowicka, and Joe 2009). In terms of moments, the prior mean is the identity matrix I_n with $n = 6$ and the scalar ψ regulates the variance of each off-diagonal entry.¹⁴ We choose a fairly loose prior value on this parameter, setting $\psi = 2$.¹⁵ For reference, $\psi = 1$ implies a uniform distribution across all entries, while $\psi > 1$ favors covariance matrices with stronger diagonal elements (weaker correlations). We set priors on the diagonal matrix ϕ_f so that each autocorrelation coefficient has a beta distribution with mean 0.2, reflecting a prior corresponding to a modest degree of autocorrelation in forecast errors.

Although we observe a large amount of survey data we do not observe any survey forecasts

¹⁴Let $B(\cdot, \cdot)$ denote the Beta function. The density function is

$$p(C_\varepsilon) = 2^{\sum_{j=1}^{n-1} (2(\psi-1)+n-j)(n-j)} \times \prod_{h=1}^{n-1} (B(\psi + (n-h-1)/2, \psi + (n-h-1)/2))^{n-j} \times \det(C_\varepsilon)^{\psi-1}.$$

¹⁵We also considered a few different choices, but $\psi = 2$ delivered the highest marginal likelihood

which satisfy equation (3.1) for $h = 1$. The reason is that forecast horizons in surveys of professional forecasters typically follow quarterly or annual increments while our model is estimated at the monthly frequency. This means that every element of our observation equation corresponds to Φ raised to different powers of h which makes full identification of Φ challenging. To circumvent this problem, we impose positivity on the diagonal elements by the choice of a prior which follows the gamma distribution with mean of 0.5 and standard deviation of 0.1.

Table 1: **Prior and Posterior Distributions for Selected Parameters** This table collects information about the prior and posterior distributions for the key parameters of the model. We compute the posterior parameter distribution using the Random Walk Metropolis-Hastings (RWMH) algorithm. See Section SA1-2 in SA1 for all details.

	Prior			Posterior		
	Dist.	Mean	[5% - 95%]	Mode	Mean	[5% - 95%]
$\lambda_{1983-1998}$						
g_t	Beta	0.10	[0.06, 0.14]	0.19	0.19	[0.17, 0.22]
π_t	Beta	0.10	[0.06, 0.14]	0.44	0.44	[0.39, 0.49]
i_t	Beta	0.10	[0.06, 0.14]	0.38	0.39	[0.34, 0.44]
$\lambda_{1999-2019}$						
g_t	Beta	0.10	[0.06, 0.14]	0.08	0.08	[0.07, 0.10]
π_t	Beta	0.10	[0.06, 0.14]	0.14	0.14	[0.12, 0.17]
i_t	Beta	0.10	[0.06, 0.14]	0.16	0.16	[0.13, 0.20]
Forecast Errors						
ρ_{fg}	Beta	0.20	[0.02, 0.49]	0.54	0.55	[0.49, 0.61]
$\rho_{f\pi}$	Beta	0.20	[0.02, 0.49]	0.51	0.52	[0.46, 0.58]
ρ_{fi}	Beta	0.20	[0.02, 0.49]	0.72	0.72	[0.66, 0.77]

Table 1 collects summary information on the prior and posterior distribution for the key parameters of our model. Given the wealth of survey information we employ, it is not surprising that the parameters are precisely estimated. The central tendency of the posterior distribution of λ , which is driven by the agent’s belief about the relative variability of the trend component as compared to the cycle, ranges from 20 to 40 percent before 1999. In contrast, in the second part of the sample the posterior distribution of λ shifts to the left and is centered at values between 10 to 20 percent. Finally, through the lens of our model, the posterior distribution confirms the empirical regularity that survey forecasts exhibit predictable forecast errors, with the central tendency of the autocorrelation coefficients all above 0.5.

3.3 The Term Structure of Short Rate Expectations

Figure 1 shows the predicted term structure of short-rate expectations from our model, together with selected survey forecasts.¹⁶ The model captures the evolution of consensus forecasts of nominal short rates extremely well.¹⁷ Given the rich survey data we employ, posterior uncertainty about the model-implied short rate expectations is negligible. In fact, it is visible only for long-horizon expectations for which we have fewer observations.

The model captures the fact that professional forecasters frequently revise their forecasts at all horizons. Furthermore, interest rate expectations behave as we expect over the monetary policy cycle. Comparing expectations across horizons, the term structure of policy rate expectations typically flattens (and often inverts) at the end of economic expansions and steepens in the aftermath of recessions. For example, the term structure of short rate expectations inverts in early 1989 when expectations at short-term horizons reached their local peak, leading into the 1990-91 recession. After the short rate reached the zero lower bound in 2008, the term structure of expectations flattened at first, and then steepened again as forecasters persistently expected an imminent lift-off.¹⁸

Role of output growth and inflation forecasts Given that our main focus is on nominal short-rate expectations, one might ask why we employ a multivariate model of expectations formation? The short-term nominal interest rate, which is primarily governed by the choices of the central bank, is informed by assessments of current and future real activity and inflation.¹⁹ This necessitates a multivariate model of expectations formation. The top panel of Figure 2 compares the fit of our model with that of a univariate version of our model. The univariate model cannot simultaneously match short-horizon interest rate forecasts and medium or longer-horizon forecasts. The chart shows that the univariate model produces longer-horizon forecasts which are too volatile relative to the survey data.²⁰ This implies that conditioning on inflation and output growth expectations is a key requirement for explaining the behavior of policy rate expectations. Put differently, we find strong evidence that survey forecasts are formed jointly as predicted by our modeling framework. More importantly, it

¹⁶In the second Supplemental Appendix (SA2) available at https://www.dropbox.com/scl/fi/8x4yx91q0iclc9i50i1f2/CEM_Appendix_Fitted_2024-04-04.pdf?rlkey=trylgof2rlmw3wa2nuergboa8&dl=0 we show the fit for each of the 627 series. To construct the forecast for each horizon we sample the unobserved states $(x_{t|t}, \omega_{t|t})$ using a simulation smoother.

¹⁷The tight fit of our model-implied expectations to the survey data implies that the array of existing stylized facts about survey expectations (e.g., as summarized in Farmer, Nakamura, and Steinsson 2023) are inherited by our measure of expectations.

¹⁸Note that these estimated measures of short rate expectations based on survey forecasts are consistent with a perceived zero lower bound (ZLB) on nominal interest rates.

¹⁹See https://www.federalreserve.gov/monetarypolicy/files/fomc_longerrungoals.pdf.

²⁰Appendix SA1-2 provides an array of formal statistical evidence in favor of our multivariate model.

confirms the term structure of short-term interest rate expectations is broadly consistent with the type of monetary policy rules that are usually assumed in conventional monetary models (Andrade, Crump, Eusepi, and Moench 2016). This also suggests that testing theories of expectation formation using forecasts for a single variable may provide misleading results (see Crump, Eusepi, Moench, and Preston (2024) for evidence at the individual forecaster level).

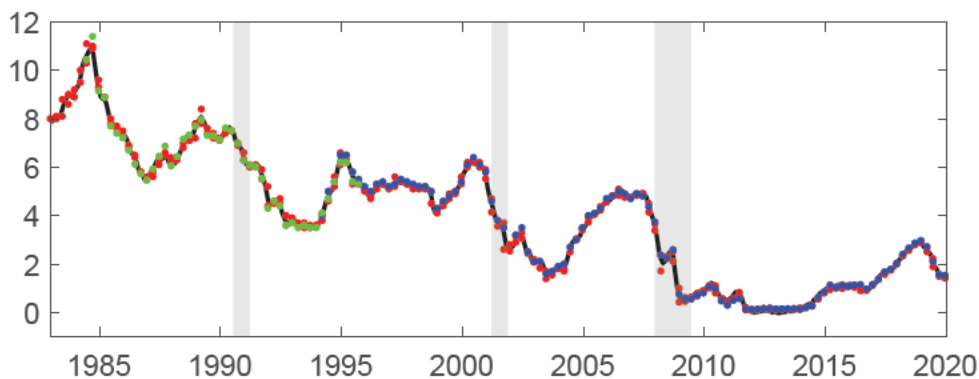
Forecast updating Inspecting Figure 1 it is immediate that expectations at different forecasting horizons appear to *co-move* over time throughout the whole sample, with long-term forecasts displaying stronger co-movement before the 2000s. Through the lens of our model (equation (2.5), revisions to forecasts at any horizon h are closely linked to current short-term forecast errors since

$$\mathbb{E}_t [z_{t+h}] - \mathbb{E}_{t-1} [z_{t+h}] = F^h f_t. \quad (3.3)$$

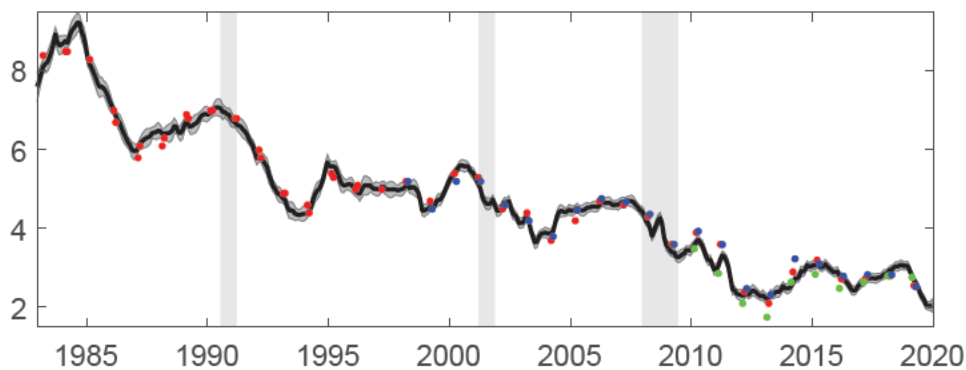
Under our assumptions, only the short-term interest rate is perfectly observed, and so it is natural to explore the link between model-implied forecast revisions and realized forecast errors for the short rate. The bottom panel of Figure 2 shows that there is a close co-movement between interest rate forecast errors and long-term interest rate forecast revisions. The figure plots the realized forecast error for $h = 12$ (i.e., $z_t - \mathbb{E}_{t-12} [z_t]$) against the twelve-month revision of the model-implied long-term forecast (i.e., $\omega_{t|t} - \omega_{t-12|t-12}$). A positive forecast error, when realized interest rates are above expectations, leads to an upward revision to the long-term forecast. The figure also highlights the cyclicity of the revisions, with sizable forecast errors at turning points leading to changes in long-run expectations. Perhaps not surprisingly, the co-movement is stronger before the Great Recession when the interest rate reached the zero lower bound. In the prolonged aftermath to the financial crisis, other information beyond short-term interest rates such as forward guidance announcements or balance-sheet interventions likely influenced long-horizon expectations.

Figure 1: **Term Structure of Interest Rate Expectations.** This figure compares model-implied survey forecasts to selected individual survey-horizon pairs. The top panel displays four-quarter ahead forecasts taken in the last month of the quarter (“Short-Term”); the middle panel displays forecasts for the one-year average interest rate three years ahead taken in the first half of the year (“Medium-Term”); the bottom panel features the forecast for the one-year average interest rate five years ahead taken in the first half of the year (“Long-Term”). The dots indicate forecasts from different surveys: BCEI and BCFF shown in red, CE shown in blue; EF and SPF are shown in green in the top and middle panel, respectively. The black line denotes the median prediction from the model, and the dark grey area the 99% posterior coverage interval. Light grey shaded areas denote NBER recessions. The sample period is 1983m1–2019m12.

(a) *Short-Term Forecasts*



(b) *Medium-Term Forecasts*



(c) *Long-Term Forecasts*

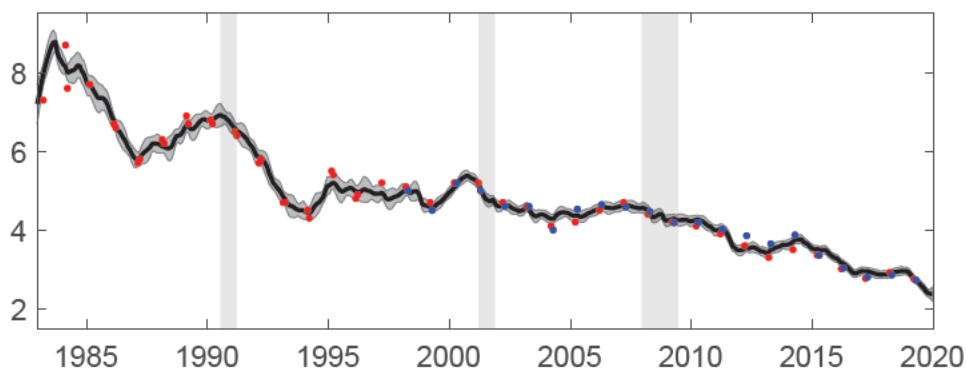
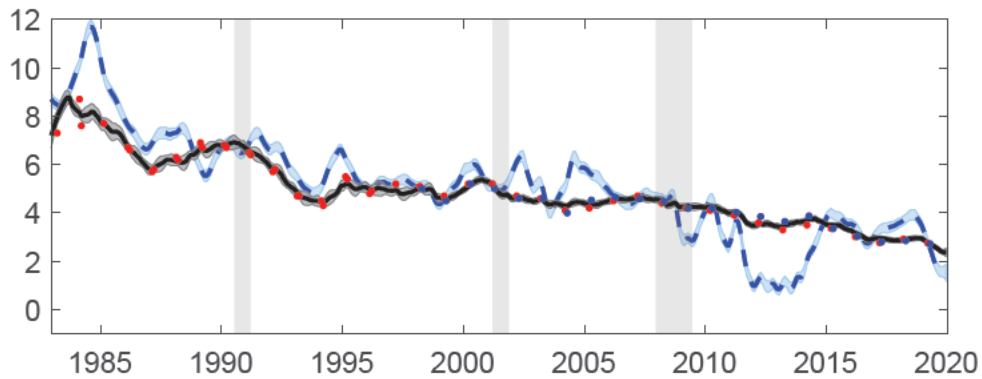
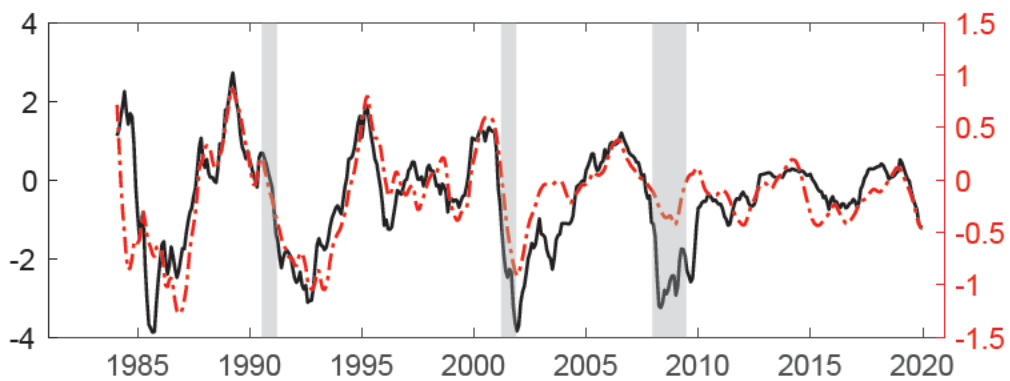


Figure 2: **Properties of the Model.** This figure demonstrates the properties of our multivariate model of expectations formation. The top chart compares the model-implied long-term forecasts from the baseline model introduced in Section 2 (black line, grey shading) with the corresponding model-implied long-term forecasts from a univariate version of the same model (blue line, blue shading). Solid lines denotes the median prediction from the model, and the shaded area denotes the 99% posterior coverage interval. The bottom chart illustrates the co-movement between revisions to long-run nominal short-rate forecasts (red line) and short-run forecast errors (black line). The sample period is 1983m1–2019m12.

(a) *Model Fit: Multivariate vs. Univariate*



(b) *Forecast Revisions and Forecast Errors*



3.4 Expectations and the EH

As we stressed in the Introduction, our re-evaluation of the EH is founded upon nontrivial deviations from FIRE and significant time-variation in long-term forecasts. In this section we proceed to evaluate our model in light of these two key ingredients.

Deviations from FIRE We first consider a simulation exercise in the spirit of [Sinha \(2016\)](#) and [Farmer, Nakamura, and Steinsson \(2023\)](#) to show that our model deviates sufficiently from the FIRE benchmark. As in [Sinha \(2016\)](#) and [Farmer, Nakamura, and Steinsson \(2023\)](#), we rely on the regression tests of [Campbell and Shiller \(1991\)](#). We simulate EH-consistent yields using our fitted model parameters and show that rejections of the EH are frequent even though it holds in our simulated data by construction.

The strong form of the EH states that the yield of maturity n is equal to the average expected short rate over the life of the bond. Under the EH, longer-term interest rates are then

$$y_t^{EH}(n) = \frac{1}{n} \sum_{h=0}^{n-1} \mathbb{E}_t [i_{t+h}]. \quad (3.4)$$

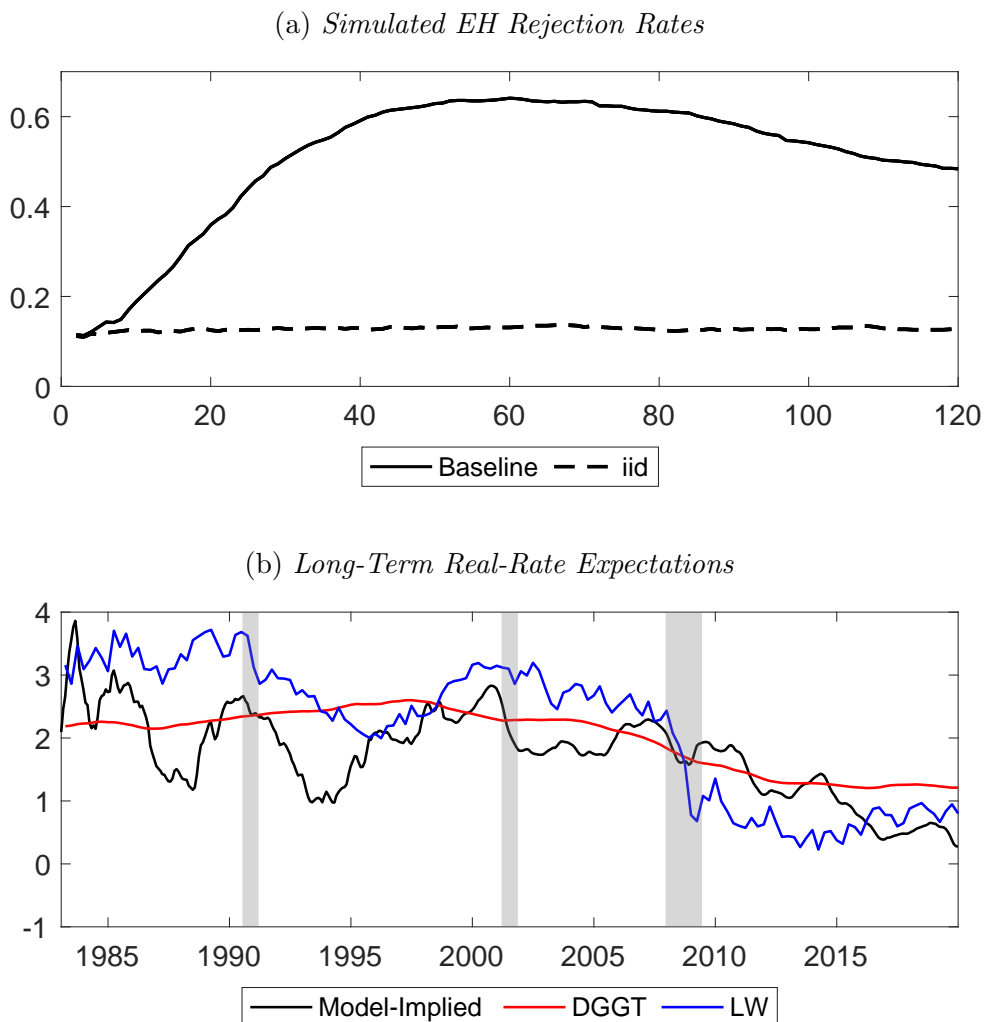
We simulate interest-rate forecasts using equations (2.5), (2.8), and (3.1) setting the measurement error, o_t , to zero for all forecast horizons. For each simulation, we obtain i_t^* along with the associated expectations, $\mathbb{E}_t [i_{t+h}^*]$, for all t and $h \in 1, \dots, 120$. We impose the EH by constructing the simulated term structure of interest rates using equation (3.4). This gives $\{(i_t^*, y_t^*(2), \dots, y_t^*(N)) : t = 1, \dots, T\}$ where T is the same length as our data sample. We can test the null hypothesis that the EH holds ($\beta = 1$) in the [Campbell and Shiller \(1991\)](#) regression:

$$y_{t+1}^*(n-1) - y_t^*(n) = \alpha + \beta \left(\frac{1}{n-1} \right) (y_t^*(n) - i_t^*) + u_t^*, \quad (3.5)$$

for $n = 2, \dots, N$.

The top panel of [Figure 3](#) shows the share of rejections across 1,000 independent simulations of the model for all maturities out to ten years. The nominal size of the test is 10%. For maturities beyond two years, the rejection rates are never below 40%, suggesting that an empirical researcher would frequently conclude that the EH was rejected in the data. As a robustness check, we also include the corresponding results when the data are generated with no serial correlation in forecast errors (i.e., under the assumption that $\phi_f = 0$). In this case the share of rejections across simulations is essentially equivalent to the nominal size of the test.

Figure 3: **Properties of Model-Implied Expectations.** The top chart of this figure reports empirical rejection rates across 1,000 independent simulations using our baseline model (labelled “baseline”) and under the assumption that forecast errors are not serially correlated (labelled “i.i.d.”). Hypothesis tests are formed using a t-statistic with the equal-weighted cosine variance estimator of Lazarus, Lewis, Stock, and Watson (2018). The bottom chart displays the model-implied long-run forecast of the real interest rate using the results from Section 2 (labelled “Model-Implied”) as compared to those from Laubach and Williams (2003) (labelled “LW”) and Del Negro, Giannone, Giannoni, and Tambalotti (2017) (labelled “DGGT”). The sample period is 1983Q1–2019Q4.



Time-Varying Longer-Run Expectations Given the variability of long-maturity yields, a necessary condition for the EH to hold is that longer-horizon expectations exhibit significant time variation. We have documented in Figure 2 that professional forecasters revise their long-run expectations as a function of their short-term forecast errors. Here, we further illustrate the degree of variability of the model-implied forecasts by comparing directly long-

horizon forecasts of the real interest rate to those from two well-known statistical models. For this exercise, we use real interest rates as long-run inflation expectations are roughly constant in the second part of the sample. To compute the model-implied expected real rate we exploit the multivariate nature of our model and use forecasts of the nominal short rate and inflation.²¹

As shown in the bottom panel of Figure 3, the long-run estimate of the real interest rate from our model displays a significant degree of variation when compared to popular alternative model-based measures that explicitly allow for trending interest rates. The red line shows the evolution of the 30-year forecast from the VAR model with time-varying means of Del Negro, Giannone, Giannoni, and Tambalotti (2017) which uses information from both macroeconomic and financial variables. The blue line is the long-run estimate of the short-term real rate from the unobserved components model of Laubach and Williams (2003). We use the one-sided estimate for a better comparison with our survey-based expectations model (black line). The chart shows that our measure of long-run expectations is more volatile than its counterpart in these statistical models. In particular, the standard deviation of twelve-month changes in our model, at 43 percent, is higher than Laubach and Williams (2003) (35 percent) and Del Negro, Giannone, Giannoni, and Tambalotti (2017) (7 percent).

4 Is There Hope for the Expectations Hypothesis?

Our model-implied term structure of short-rate expectations can now be compared directly to the term structure of interest rates at all maturities. To separate longer-term from short-term expectations, we conduct our analyses in terms of *forward rates*, defined as the current yield of an n -year bond maturing in $n + m$ years:

$$f_t(n, m) = \frac{1}{n} [(n + m)y_t(n + m) - my_t(m)]. \quad (4.1)$$

Because our empirical model of expectations is estimated at a monthly frequency, we construct annual forward rates as the annual average of monthly forward rates. For example, a 4Y1Y forward (i.e., the one-year rate, four-years ahead) would set $n = 12$ and $m = 48$. Expressing the EH in equation (3.4) in terms of forward rates gives

$$f_t^{EH}(n, m) = \frac{1}{n} \sum_{h=m+1}^{n+m} \mathbb{E}_t [i_{t+h}] = \frac{1}{n} \sum_{h=m+1}^{n+m} \mathbb{E}_t [r_{t+h} + \pi_{t+h+1}] \quad (4.2)$$

²¹Specifically, the ex-ante expected real rate for horizon h is defined as the expected nominal short rate for $h - 1$, minus the expected inflation rate for horizon h .

In words, the expectations hypothesis implies that the forward rate $f_t^{EH}(n, m)$ equals the average expected nominal short-term interest rate over the n months starting m months hence. This can be further decomposed into the average expected path of real short rates plus expected inflation. Note that this is an identity: there are no implicit assumptions about the rationality or bias of expectations or the data generating process for yields, expectations, or the difference between the two.

We can contrast the term structure of interest rates with the corresponding rates implied by the EH. We define the wedge $w_t(n, m)$ between the two as

$$w_t(n, m) = f_t(n, m) - f_t^{EH}(n, m), \quad (4.3)$$

so that observed forwards can be decomposed into three components: the expected average real short rate, expected inflation, and the EH wedge as

$$f_t(n, m) = f_t^{EH}(n, m) + w_t(n, m) \quad (4.4)$$

$$= \frac{1}{n} \sum_{h=m+1}^{n+m} \mathbb{E}_t [r_{t+h}] + \frac{1}{n} \sum_{h=m+1}^{n+m} \mathbb{E}_t [\pi_{t+h+1}] + w_t(n, m). \quad (4.5)$$

Under the strong-form of the EH, we have that $w_t(n, m) = 0$ for every t and pair (m, n) . The weak form of the EH, implies that $w_t(n, m) = \bar{w}(n, m)$ is constant for every t . This is the form of the EH that plays a key role in standard structural models in macroeconomics. Beyond the exact form of the EH, we also aim to assess the relative importance of the wedge in the evolution of forward rates.

We now turn to our formal test of the EH. The first regresses EH-consistent forward spreads on actual forward spreads (“Specification 1”):

$$f_t^{EH}(n, m) - i_t = \alpha_s^{(n, m)} + \beta_s^{(n, m)} (f_t(n, m) - i_t) + \xi_{s, t}. \quad (4.6)$$

Under the weak form of the EH we should have that $\beta_s^{(n, m)} = 1$ for all (n, m) pairs. Under the null hypothesis, we can subtract i_t from either side which ameliorates the trending behavior in yields and improves the sampling properties of the OLS estimator.

Equation (4.6) is identical to the implementation of [Froot \(1989\)](#) except that we can investigate a much wider range of forward maturities, including medium and long horizons, and over a much longer sample. We also consider a specification in 12-month differences (“Specification 2”)

$$\Delta_{12m} f_t^{EH}(n, m) = \alpha_d^{(n, m)} + \beta_d^{(n, m)} \Delta_{12m} f_t(n, m) + \xi_{d, t}. \quad (4.7)$$

Similarly, under the weak form of the EH $\beta_d^{(n,m)} = 1$ for all (n, m) pairs.

It is important to stress that neither test requires an assumption about the expectations formation mechanism and, in particular, we do not require rational expectations. Furthermore, since our measure of expectations is model-implied, we use it as the dependent variable. That said, the sampling uncertainty around the point estimates $\hat{\beta}_s^{(n,m)}$ and $\hat{\beta}_d^{(n,m)}$ could be affected by measurement error in the model-implied expectations. In an effort to accommodate the uncertainty arising from the model-generated expectations, we perform all regressions using 1,000 posterior draws and report the minimum and maximum p -values across these draws.

The regression-based tests of the EH based on [Froot \(1989\)](#) rely on the assumption that short-rate expectations at all future horizons are not constant. If they were constant, one would be bound to find coefficients $\hat{\beta}_s^{(n,m)}$ and $\hat{\beta}_d^{(n,m)}$ close to zero, since the actual forward rates on the RHS of equations (4.6) and (4.7) feature considerable time variation. In other words, a necessary condition for the EH to hold in the data is that short-rate expectations must vary over time at all forecast horizons. As shown in the previous section, this condition is easily satisfied by our model.

The upper panel of [Table 2](#) shows the test results for the first specification. The EH is overwhelmingly rejected across every maturity. The estimated $\hat{\beta}_s^{(n,m)}$ are comfortably below the theoretical coefficient equal to one implied by the expectations hypothesis across horizons. The associated maximal p -values are below four percent (and mostly below one percent) across horizons showing strong statistical support for rejections of the EH along the term structure.

The bottom panel of [Table 2](#) reports the corresponding range of estimates $\hat{\beta}_d^{(n,m)}$ and their associated p -values for the second specification, relying on twelve-month differences of model-implied and actual spreads. The coefficients are well below 0.3 across horizons with p -values that are very close to zero, providing further support for rejections of the EH across all forecast horizons including the very long-run. Note that this latter difference specification allows to eliminate trends in both the dependent and explanatory variables of the [Froot \(1989\)](#) regressions, and as such, some of the co-movement between expectations and yields that may be induced by common trends. This is an issue we return to in the next section.

4.1 Why do the Tests Reject the EH?

The previous section shows that the EH is rejected decisively; however, a statistical test is a dichotomous outcome. Instead we can ask by how much does the EH fail? To dissect this finding, we provide a simple variance decomposition of forward rates into expected inflation,

Table 2: **Regression Tests of the EH.** This table presents linear regression estimates and the associated p-values (in percent) for the null hypothesis $\hat{\beta}_s^{(n,m)} = 1$ and $\hat{\beta}_d^{(n,m)} = 1$. Hypothesis tests are formed using a t-statistic with the equal-weighted cosine variance estimator of [Lazarus, Lewis, Stock, and Watson \(2018\)](#). Minimum and maximum statistics are taken across 1,000 posterior draws. The sample period is 1983m1–2019m12.

<i>Specification 1</i>										
	1Y	1Y1Y	2Y1Y	3Y1Y	4Y1Y	5Y1Y	6Y1Y	7Y1Y	8Y1Y	9Y1Y
Min. $\hat{\beta}_s^{(n,m)}$	0.37	0.44	0.55	0.64	0.69	0.71	0.72	0.71	0.71	0.71
Max. $\hat{\beta}_s^{(n,m)}$	0.38	0.46	0.58	0.67	0.72	0.74	0.74	0.74	0.74	0.74
Min. p -val (%)	0.00	0.04	0.66	1.92	2.39	1.81	1.10	0.67	0.46	0.40
Max p -val (%)	0.00	0.07	1.06	3.06	3.98	3.30	2.28	1.55	1.17	1.06
<i>Specification 2</i>										
	1Y	1Y1Y	2Y1Y	3Y1Y	4Y1Y	5Y1Y	6Y1Y	7Y1Y	8Y1Y	9Y1Y
Min. $\hat{\beta}_d^{(n,m)}$	0.73	0.51	0.33	0.20	0.12	0.08	0.05	0.04	0.04	0.03
Max. $\hat{\beta}_d^{(n,m)}$	0.75	0.55	0.38	0.28	0.21	0.18	0.16	0.15	0.14	0.14
Min. p -val (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max p -val (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

expected real rates and the wedge using 12-month changes in each variable. In general, we have that

$$\hat{\mathbf{s}} \left(n^{-1} \sum_{h=m+1}^{n+m} \Delta_\tau \mathbb{E}_t [r_{t+h}] \right) + \hat{\mathbf{s}} \left(n^{-1} \sum_{h=m+1}^{n+m} \Delta_\tau \mathbb{E}_t [\pi_{t+h+1}] \right) + \hat{\mathbf{s}} (\Delta_\tau w_t(n, m)) = 1. \quad (4.8)$$

Here,

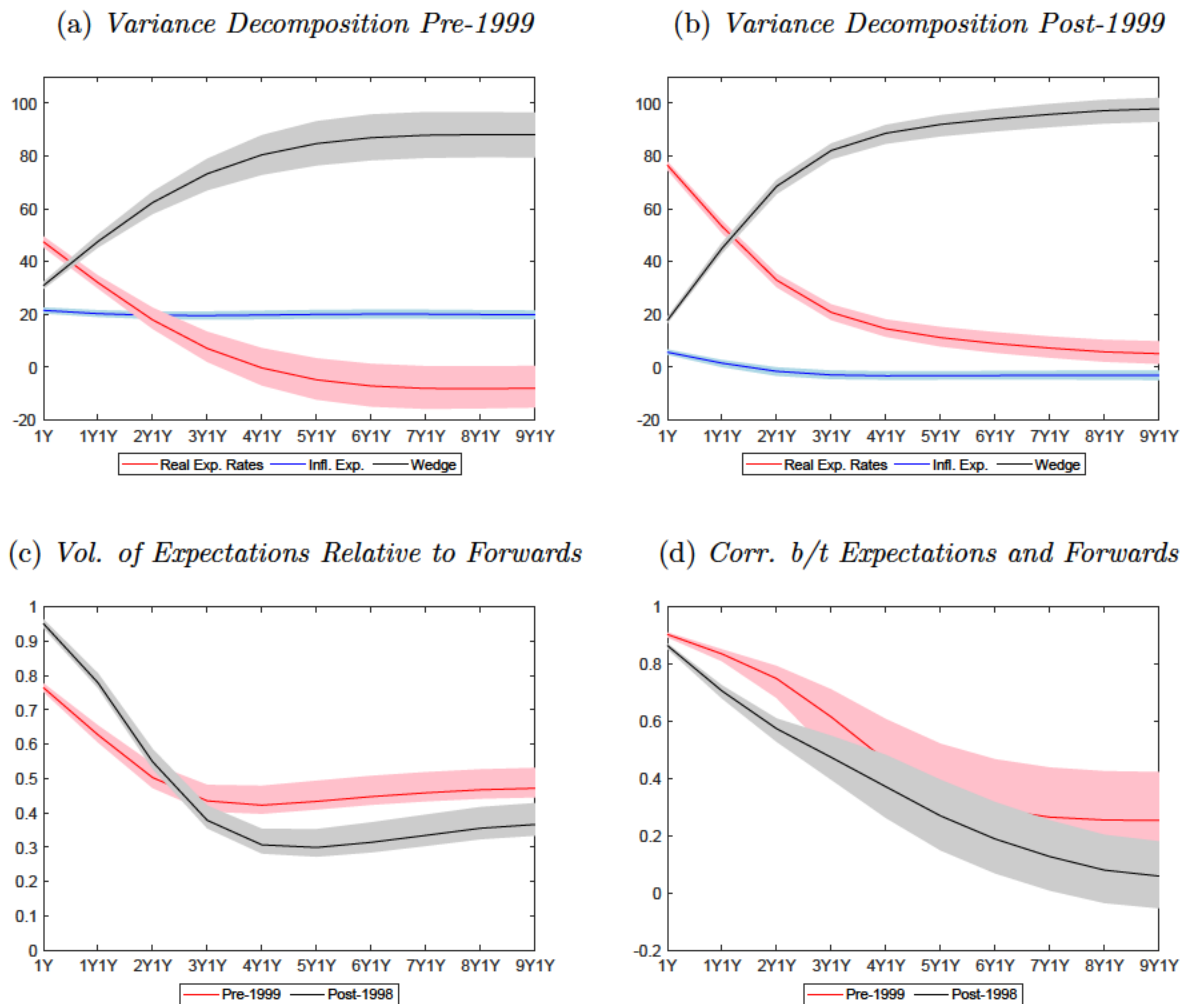
$$\hat{\mathbf{s}}(\cdot) = \frac{\widehat{\text{Cov}}(\Delta_\tau f_t(n, m), \cdot)}{\widehat{\text{Var}}(\Delta_\tau f_t(n, m))} \quad (4.9)$$

is the ratio between the corresponding sample covariance between forward rates and each constituent component and the sample variance of the forward rate, and $\Delta_\tau \varsigma_t = \varsigma_t - \varsigma_{t-\tau}$ for any time series ς_t .

The top panels in [Figure 4](#) show the contributions of the three components to the variance of forwards in the sample before and after 1998.²² The decomposition highlights the striking finding that beyond a maturity of three years (i.e., the 2Y1Y forward), over eighty percent of the variation in forward rates is driven by movements in the wedge rather than interest-rate expectations. Expected nominal short rates explain between 69% and 82% for the 1-year yield and between 52% and 55% for the 1Y1Y forward rate, and less than 50% for all other forward maturities. As the forward maturity increases, the contribution of expectations to the variability of forward rates declines sharply. This pattern is not affected by the specific

²²Note that individual contributions must sum to one but can be negative, depending on the sign of the covariance.

Figure 4: **Decomposing Forward Rates.** The top panels show the variance decomposition of the 12-month changes of forward rates at different maturities in real expected rates (red line), inflation expectations (blue line) and the wedge (black line) components. The bottom left panel displays the volatility of 12-month changes in interest rate expectations relative to forwards for the pre-1999 (red line) and post-1998 (black line) sample. Solid lines denote posterior medians while shaded regions denote the range of 1,000 posterior draws. The sample period is 1983m1–2019m12.



sample selected, suggesting that the volatility of forward rates has also declined in the post-1998 period. The only notable difference between sub-samples is the contribution of inflation expectations. In the pre-1999 period, inflation expectations contribute about twenty-percent to the variance of forward rates across all horizons. Conversely, their contribution is close to zero at all horizons in the post-1998 sample. This is mirrored by an increased role of expected real rates at shorter maturities. Finally, each plot also provides shaded regions reflecting sampling uncertainty about the model-generated expectations across 1,000 posterior draws. All the patterns and conclusions are unchanged when considering any of the individual

posterior draws.

The bottom panels in Figure 4 offer a further insight into the failure of the EH. The variance share of the components, $\mathfrak{s}(\cdot)$, can be re-expressed in terms of sample standard deviations and correlations

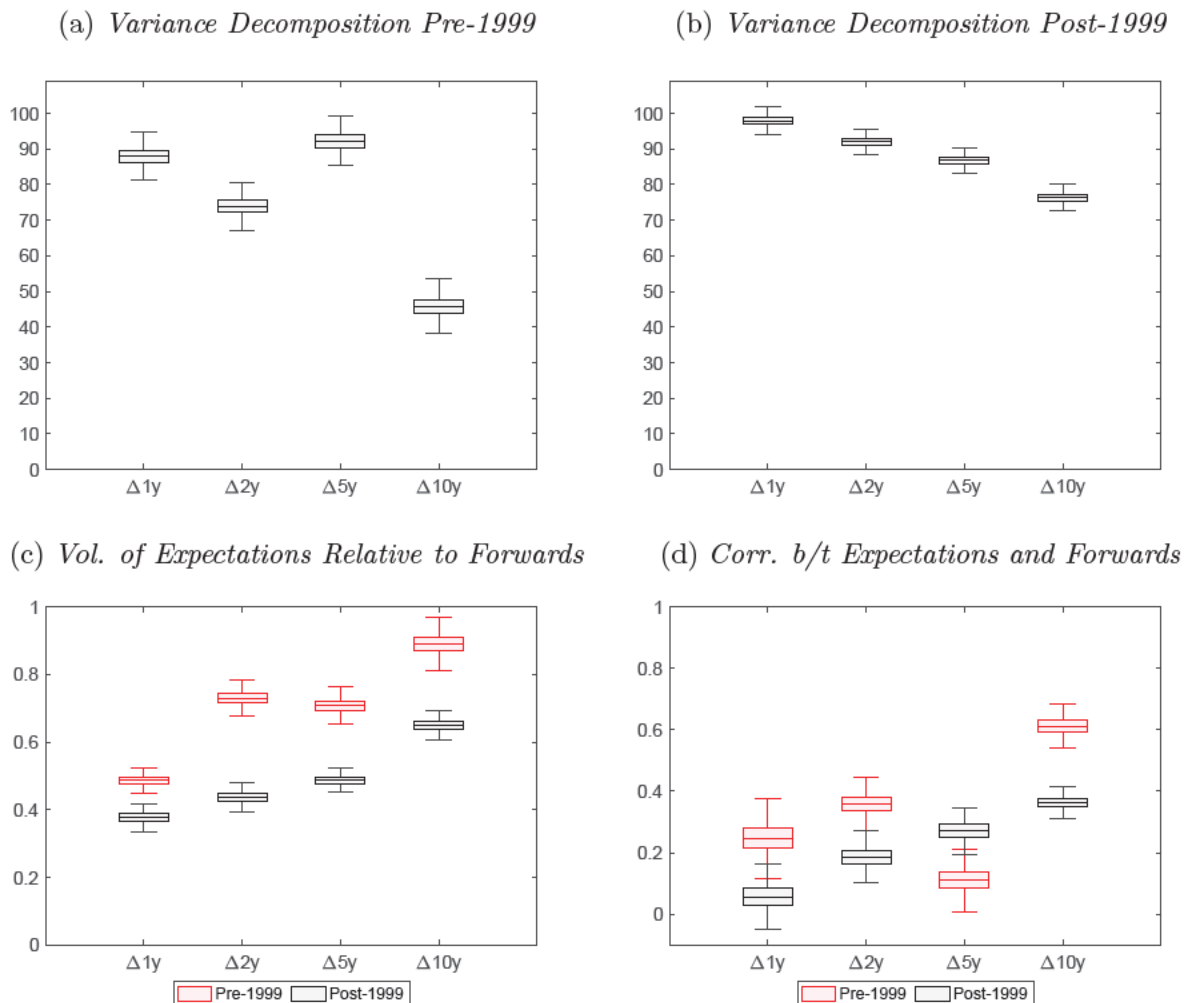
$$\hat{\mathfrak{s}}(\cdot) = \widehat{\text{Corr}}(\Delta_{\tau}f_t(n, m), \cdot) \left(\frac{\widehat{\text{Var}}(\cdot)}{\widehat{\text{Var}}(\Delta_{\tau}f_t(n, m))} \right)^{1/2}. \quad (4.10)$$

As we have already shown, the term structure of short-rate expectations implied by our estimated model exhibits substantial volatility. The bottom left panel supports this claim: the volatility of expectations remains above forty percent of the variability of forward rates across all maturities. This would suggest a more important role for expectations even at the longest horizons. However, as indicated by the right chart, the correlation between forward rates and expectations declines steadily towards zero as the maturity increases.

Importantly, these conclusions do not depend on the frequency of interest rate changes. We choose one year changes because it eliminates high frequency fluctuations in asset prices that may be short-lived. Figure 5 replicates the structure of Figure 4 for the 9Y1Y forward only but now for 1-year, 2-year, 5-year and 10-year changes.²³ When we expand the frequency up to five-year changes the conclusions from Figure 4 are essentially unchanged. The wedge explains over 85 percent of the variation in the forward rates for either the first or second half of the sample. At the same time, the relative volatility of expectations as compared to forwards is higher than for one-year changes. For 10-year changes, which are below business-cycle frequency, the presence of the downward trend in both yields and expectations in the first half of the sample plays a larger role. In the pre-1999 sample, the relative volatility of expectations as compared to the longer-horizon forward is close to one. Despite that, the 10-year change in expected short-rates only explains about 55% of the variation in the 9Y1Y forward. In the second half of our sample, when the downward trend is diminished, the variance decomposition is not significantly altered when calculated with 10-year changes as compared to the higher frequency changes. In fact, the wedge explains over 75% of the variation in longer-horizon forward rates. Taken in sum, not only is the EH decisively rejected in the data, but model-implied short-rate expectations generally display, at best, only a weak co-movement with the forward rates of corresponding maturities.

²³In Section SA1-3 of SA1, we present the full counterpart of Figure 4 for 2-year, 5-year and 10-year changes for all forward maturities.

Figure 5: **Decomposing Long-Horizon Forwards at Different Frequencies.** This figure replicates Figure 4 for the 9Y1Y forward rate for different choices of Δ_τ . We choose τ as 1-year, 2-year, 5-year and 10-year increments. The top row shows the variance share of forwards attributed to the wedge over the pre-1999 and post-1998 samples for different values of τ . The bottom left chart displays the relative volatility of changes in 9Y1Y short-rate expectations compared to the 9Y1Y forward rate for the pre-1999 (red) and post-1998 (black) sample. The bottom right chart shows the correlation between changes in expectations and forward rates for the pre-1999 (red) and post-1998 (black) sample. For all charts, the boxes indicate the interquartile range (with center line equal to the median) and the whiskers represent the maximum and minimum across 1,000 posterior draws. The sample period is 1983m1–2019m12.



4.2 Do the Driving Forces of Expectations Explain the Wedge?

Despite the results presented in the previous section, it is possible that the same underlying forces that drive expectations also drive the time variation in the wedge, $w_t(n, m)$. Recall from Equation (2.7) that expectations are linear in six underlying variables, $\omega_{t|t}$ and $x_{t|t}$, which we filter as $\hat{\omega}_{t|t}$ and $\hat{x}_{t|t}$. Thus, we can span forecasts at all horizons with only these

Table 3: **Spanning Tests.** The top panel (bottom panel) presents R^2 from regressions of changes in the forward rate (wedge) on a constant and the six state variables, $\hat{x}_{t|t}$ and $\hat{\omega}_{t|t}$. Minimum and maximum statistics are taken across 1,000 posterior draws. The sample period is 1983m1–2019m12.

Forward Rates: $f_t(n, m)$										
	1Y	1Y1Y	2Y1Y	3Y1Y	4Y1Y	5Y1Y	6Y1Y	7Y1Y	8Y1Y	9Y1Y
<i>12-month Changes</i>										
Min. R^2 (%)	79.6	65.6	55.1	47.2	41.9	38.5	36.5	35.1	33.6	32.8
Max. R^2 (%)	81.7	71.0	63.8	58.0	53.3	49.9	47.6	46.0	44.9	44.2
<i>60-month Changes</i>										
Min. R^2 (%)	92.6	84.2	72.7	60.8	51.6	45.8	42.2	39.9	38.3	37.5
Max. R^2 (%)	93.4	86.1	77.2	68.3	61.6	57.2	54.3	52.0	50.2	49.7
<i>120-month Changes</i>										
Min. R^2 (%)	89.2	80.4	73.5	68.4	64.5	61.5	59.1	57.0	55.4	54.5
Max. R^2 (%)	90.2	83.3	78.1	74.3	71.4	68.9	67.3	65.9	64.5	63.8
Wedges: $w_t(n, m)$										
	1Y	1Y1Y	2Y1Y	3Y1Y	4Y1Y	5Y1Y	6Y1Y	7Y1Y	8Y1Y	9Y1Y
<i>12-month Changes</i>										
Min. R^2 (%)	12.1	18.3	23.5	27.9	30.8	32.9	33.8	34.3	34.5	34.5
Max. R^2 (%)	19.3	27.2	33.5	38.2	41.1	43.1	44.1	44.5	44.5	44.5
<i>60-month Changes</i>										
Min. R^2 (%)	23.2	29.6	34.5	37.6	39.2	39.6	40.1	41.0	42.1	42.9
Max. R^2 (%)	29.5	37.4	43.4	46.9	48.1	48.4	49.1	49.7	50.3	50.8
<i>120-month Changes</i>										
Min. R^2 (%)	38.7	43.1	42.3	37.5	33.1	31.1	30.6	30.7	30.6	30.5
Max. R^2 (%)	44.2	50.0	50.9	47.4	43.6	41.1	40.8	40.8	40.7	40.5

six variables and consider regressions of the form,

$$\Delta_\tau w_t(n, m) = a^{(n, m)} + b_x^{(n, m)'} \Delta_\tau \hat{x}_{t|t} + b_\omega^{(n, m)'} \Delta_\tau \hat{\omega}_{t|t} + \xi_{w, t}^\tau. \quad (4.11)$$

and

$$\Delta_\tau f_t(n, m) = c^{(n, m)} + d_x^{(n, m)'} \Delta_\tau \hat{x}_{t|t} + d_\omega^{(n, m)'} \Delta_\tau \hat{\omega}_{t|t} + \xi_{f, t}^\tau, \quad (4.12)$$

where τ is 12, 60 or 120 months. For each of these regressions we assess the goodness of fit to examine how well forwards and the wedge are spanned by the state variables that drive beliefs.

The top panel of Table 3 reports the regression R^2 for Equation (4.12). Consistent with the evidence we have already presented, the co-movement between forwards and $\hat{x}_{t|t}$ and $\hat{\omega}_{t|t}$ is much stronger at shorter maturities. At medium and longer maturities, the R^2 decline monotonically. A useful benchmark for these results is the class of affine term structure

models (Duffee (2002), Ang and Piazzesi (2003), Joslin, Singleton, and Zhu (2011), Adrian, Crump, and Moench (2013)) which explicitly allow for time-variation in the price of risk. In this class of models, yields and forward rates are affine functions of the set of risk factors with coefficients obeying specific cross-maturity restrictions. As such, an affine term structure model using $\hat{\omega}_{t|t}$ and $\hat{x}_{t|t}$ as factors can have no higher R^2 than those reported in the top panel of Table 3. Furthermore, if the first three principal components of yields were instead chosen as the risk factors in an affine model – as is the case, e.g., in Joslin, Singleton, and Zhu (2011) – we would observe $R^2 \approx 1$ for all maturities and choice of τ .

We can now investigate directly whether the state variables that drive beliefs also explain the behavior of the wedge. The bottom panel of Table 3 reports the regression R^2 for Equation (4.11). When using the wedge as the left-hand side variable, the R^2 values drop precipitously at the short end of the curve and remain low elsewhere. Across all three choices of τ (and across all 1,000 posterior draws), the R^2 is no higher than 51%. This evidence is suggestive that other forces than those which drive expectations play a key role in explaining the wedge.

To conclude, these results suggest that allowing for time variation in risk premia in otherwise standard macroeconomic models would be insufficient to capture the behavior of the term structure of interest rates, as differences between observed yields and model-implied short rate forecasts seem to be driven by factors separate from those that explain the term structure of short rate expectations.

4.3 Consensus vs. the Marginal Investor

According to the EH, yields reflect “the market” expected path of the short-term interest rate, generally taken to be the average opinion (i.e., the consensus) among market participants. Following the existing literature, starting from Friedman (1979), we use consensus measures from professional survey forecasts as a noisy indicator of the average opinion of the market. The previous sections show that expectations consistent with this consensus measure deviate substantially from observed forward rates. This result is unlikely to stem from severe mis-measurement of the true unobserved market average opinion: professional forecasters are, after all, often drawn from market participants. An alternative criticism is that the “market expectation” does not correspond to that of the average investor but instead to the expectation of the *marginal* investor in the bond market. In this case, our wedge would be sourced to a large and time-varying gap between the beliefs of the average and the marginal investor.

Such a large gap is consistent with evidence from individual forecasts in professional survey

data. Surveys indicate a sizable and time-varying disagreement about the expected path of the short-term interest rate. Importantly, [Andrade, Crump, Eusepi, and Moench \(2016\)](#) show that the term structure of disagreement for the short-rate is upward sloping: belief dispersion increases at longer forecast horizons. This is consistent with the evidence we have presented where longer-maturity expectations and the corresponding forwards have little to no relation. Furthermore, [Cao, Crump, Eusepi, and Moench \(2021\)](#) show that professional forecasters’ disagreement about the short-term interest rate co-moves with our wedge for long forward maturities, providing empirical evidence for the “disagreement channel.”²⁴

These concepts are formalized in a theoretical literature that explores equilibrium bond prices with heterogenous beliefs. In these models, dispersed beliefs can lead to speculative behavior in the bond market, driving a wedge between bond prices and the EH-implied (consensus) expectations. For example, [Xiong and Yan \(2009\)](#), [Barillas and Nimark \(2017\)](#) and [Buraschi and Whelan \(2022\)](#) show that in standard economies with constant risk aversion and no market frictions, equilibrium bond prices violate the EH and depend on time-varying disagreement. In [Xiong and Yan \(2009\)](#) bond prices are driven by the weighted average of individual investors’ expectations, where the weights are time-varying and depend on the relative wealth of investors.

In these models, a gap between the average and marginal investor naturally arises. The presence of such a gap is entirely consistent with our finding that the EH does not hold: a key conclusion from this theoretical literature is that, in a market with dispersed beliefs, there does not exist a “market expectation” in the conventional sense. [Jouini and Napp \(2007\)](#) and [Xiong and Yan \(2009\)](#) show, in a standard complete markets economy, that equilibrium asset prices under heterogenous expectations can be replicated by a “representative investor” with a specific set of beliefs about the expected path of the interest rate. However, this representative investor’s beliefs do not satisfy standard probability laws, such as the law of iterated expectations. In other words, since the marginal investor changes over time, this representative investor’s expectations could not follow an expectations formation process like the one described in Section 2. Thus, heterogeneity of beliefs, which would drive a gap between the average and marginal investor’s views, in fact, takes us farther away (not closer) from the EH holding.

²⁴Additionally, [Giacoletti, Laursen, and Singleton \(2021\)](#) show that short-term disagreement in bond yield expectations helps predict bond returns.

5 Conclusion

In this paper, we reevaluate the empirical evidence regarding the EH by proposing a model of expectations formation that allows for deviations from FIRE and accounts for time-varying beliefs about the long-run. This class of models has shown promise to bridge the gap between EH-implied and observed yields, fueling hopes for a “resurrection” of EH. We estimate the model using the universe of consensus forecasts from all U.S. surveys of professional forecasters covering more than 600 survey-horizon pairs at a monthly frequency. While model-implied short-rate expectations move considerably at all horizons and suggest significant departures from rational expectations, they do not come close to matching the observed term structure of interest rates. Instead, the EH-implied short-rate expectations generally display, at best, only a weak co-movement with the forward rates of corresponding maturities. Not surprisingly, formal tests of the EH are soundly rejected.

These results suggest alternative explanations for the behavior of observed bond yields such as heterogenous beliefs, financial market frictions, nonstandard risk preferences and behavioral theories of asset pricing. Accommodating such features in models of equilibrium bond prices can have important implications for macroeconomic models, including in the transmission mechanism of monetary policy. In standard models, used by both academics and policymakers, the monetary transmission channel is based solely on the EH. The central bank can exert a tight control on longer-term interest rates by responding to changing economic conditions in a systematic manner, i.e. adhering to time-invariant policy rules, or by communicating directly about likely future policy moves through forward guidance. The sizable deviation of observed interest rates from the EH, which we document, calls in to question this conventional framework.

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Appendix

A Model

The perceived law of motion is as described in the main text. Revisions to the estimates of the state variables evolve as:

$$\begin{pmatrix} \omega_{t|t} \\ x_{t|t} \end{pmatrix} = \begin{pmatrix} \omega_{t|t-1} \\ x_{t|t-1} \end{pmatrix} + \mathcal{K} \times (\mathcal{S}_t - \mathcal{S}_{t|t-1})$$

where

$$\mathcal{K} \equiv \bar{P}H (H'\bar{P}H + \Sigma_s)^{-1}$$

and \bar{P} solves

$$\bar{P} = F \left[\bar{P} - \bar{P}H (H'\bar{P}H + \Sigma_s)^{-1} H'\bar{P} \right] F' + \Sigma_z.$$

Under the correct model (rational expectations) the estimates of the state variables evolve according to

$$\begin{pmatrix} \omega_{t|t} \\ x_{t|t} \end{pmatrix} = \begin{pmatrix} \omega_{t|t-1} \\ x_{t|t-1} \end{pmatrix} + \Sigma_\epsilon^{1/2} \epsilon_t$$

where the shock vector ϵ_t is normally distributed with zero mean and identity variance-covariance matrix and

$$\Sigma_\epsilon \equiv \mathcal{K} (H'\bar{P}H + \Sigma_s) \mathcal{K}' = \bar{P}H (H'\bar{P}H + \Sigma_s)^{-1} H'\bar{P}.$$

We do not make assumptions about rationality. The agent may have the “wrong” model and departures from rational beliefs can manifest itself in two ways: First, the agent might have the correct law of motion but the incorrect model parameters, so that their forecast error follows a different distribution. That is, the variance covariance of the innovations may differ from $\bar{P}H (H'\bar{P}H + \Sigma_s)^{-1} H'\bar{P}$. Second, forecast errors can display serial correlation, as discussed in the main text.

Now we can write the state space of our model as

$$\begin{pmatrix} z_t \\ z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ z_{t-4} \\ \xi_{t|t} \\ f_t \end{pmatrix} = \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 12} & [I_3 & I_3] F & [I_3 & I_3] G \\ I_3 & 0_{3 \times 12} & 0_{3 \times 6} & 0_{3 \times 6} \\ 0_{3 \times 3} & I_3 & 0_{3 \times 15} & 0_{3 \times 6} \\ 0_{3 \times 6} & I_3 & 0_{3 \times 12} & 0_{3 \times 6} \\ 0_{3 \times 9} & I_3 & 0_{3 \times 9} & 0_{3 \times 6} \\ 0_{6 \times 3} & 0_{3 \times 12} & F & G \\ 0_{6 \times 3} & 0_{6 \times 12} & 0_{6 \times 6} & G \end{bmatrix} \begin{pmatrix} z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ z_{t-4} \\ z_{t-5} \\ \xi_{t-1|t-1} \\ f_{t-1} \end{pmatrix} + \begin{bmatrix} [I_3 & I_3] \\ 0_{3 \times 6} \\ 0_{3 \times 6} \\ 0_{3 \times 6} \\ 0_{3 \times 6} \\ I_6 \\ I_6 \end{bmatrix} \Sigma_\epsilon^{1/2} \epsilon_t$$

where

$$F \equiv \begin{bmatrix} I_3 & 0 \\ 0 & \Phi \end{bmatrix}$$

$$G \equiv \begin{bmatrix} \Phi_f & 0 \\ 0 & \Phi_f \end{bmatrix},$$

and $\xi_{t|t} = (\omega_{t|t}, x_{t|t})'$. Importantly, the measurement equation of the model (from the econometrician's viewpoint) used to fit the survey forecasts is not a function of G . For example,

$$E_t z_{t+h} = e_3 \times \begin{bmatrix} 0_{3 \times 3} & 0_{3 \times 12} & [I_3 & I_3] F & 0_{3 \times 6} \\ I_3 & 0_{3 \times 12} & 0_{3 \times 6} & 0_{3 \times 6} \\ 0_{3 \times 3} & I_3 & 0_{3 \times 15} & 0_{3 \times 6} \\ 0_{3 \times 6} & I_3 & 0_{3 \times 12} & 0_{3 \times 6} \\ 0_{3 \times 9} & I_3 & 0_{3 \times 9} & 0_{3 \times 6} \\ 0_{6 \times 3} & 0_{3 \times 12} & F & 0_{6 \times 6} \\ 0_{6 \times 3} & 0_{6 \times 12} & 0_{6 \times 6} & 0_{6 \times 6} \end{bmatrix}^h \begin{pmatrix} z_t \\ z_{t-1} \\ z_{t-2} \\ z_{t-3} \\ z_{t-4} \\ \xi_{t|t} \\ f_t \end{pmatrix}$$

where e_3 selects the first three rows. Said differently, the agent is assumed to form expectations under the assumption $\mathbb{E}_t[f_{t+h}] = 0$ for all h .

B Measurement equation

In this section we provide greater detail on how we map survey forecasts to our modeling framework discussed in Section 3.2. Forecasts for the three-month Treasury bill rate are either a simple average over a period or end of period. For the latter we assign these forecasts to the last month in the period. For real output growth and inflation, survey forecasts come in three possible forms: quarter-over-quarter (QoQ) annualized growth, annual average growth and Q4/Q4 growth. The distinction between these growth rates are best illustrated through examples. In these examples we will ignore measurement error for simplicity. Let G_{2013Q1} and G_{2013Q2} be the level of real GDP in billions of chained dollars in the first and second quarter of 2013, respectively. Then, QoQ annualized growth rate is defined as $100 \cdot ((G_{2013Q2}/G_{2013Q1})^4 - 1)$. In our model we filter a month-over-month (annualized) real GDP growth rate series. To map the monthly series into this specific quarterly growth rate we follow [Crump et al. \(2014\)](#) and use

$$100 \cdot ((G_{2013Q2}/G_{2013Q1})^4 - 1) \approx \frac{1}{9} (g_{2013m2} + 2 \cdot g_{2013m3} + 3 \cdot g_{2013m4} + 2 \cdot g_{2013m5} + g_{2013m6}),$$

where, for example, g_{2013m2} represents month-over-month annualized real output growth in February 2013.

Annual average growth rates follow a similar pattern. For example, let G_{2012} and G_{2013} be the average level of real GDP in billions of chained dollars in the years 2012 and 2013, respectively. Then the annual average growth rate is $100 \cdot (G_{2013}/G_{2012} - 1)$ which we approximate via,

$$100 \cdot (G_{2013}/G_{2012} - 1) \approx \frac{1}{24} (g_{2012m2} + 2 \cdot g_{2012m3} + 3 \cdot g_{2012m4} + \dots + 12 \cdot g_{2013m1})$$

$$+11 \cdot g_{2013m2} + 10 \cdot g_{2013m3} + \cdots + 2 \cdot g_{2013m11} + g_{2013m12} \cdot$$

Finally, Q4/Q4 growth rates are calculated, for example, by $100 \cdot (G_{2013Q4}/G_{2012Q4} - 1)$ and approximated via

$$100 \cdot (G_{2013Q4}/G_{2012Q4} - 1) \approx \frac{1}{12} (g_{2013m1} + g_{2013m2} + g_{2013m3} + \cdots + g_{2013m12}).$$

The above shows that certain survey forecast horizons will implicitly include time periods which have already occurred. To avoid taking a stand on how forecasters treat past data (e.g., do forecasters use realized data, filtered versions or another measure?) we exclude all survey forecast horizons that include past months' values of y_t . The only exception we make is to include current quarter (Q0) and one-quarter ahead (Q1) forecasts for real output growth (which extend back, at most, four months and one month, respectively). This is why our measurement equation contains lags of z_t up to z_{t-4} . We do so to help pin down monthly real output growth since the actual series is only available at a quarterly frequency. Finally, for simplicity, forecasts which involve averages over multiple years are mapped as simple averages over the corresponding horizons.

Supplemental Appendix (SA1):
“Is There Hope for the Expectations Hypothesis?”

Richard K. Crump, Stefano Eusepi & Emanuel Moench
April 18, 2024

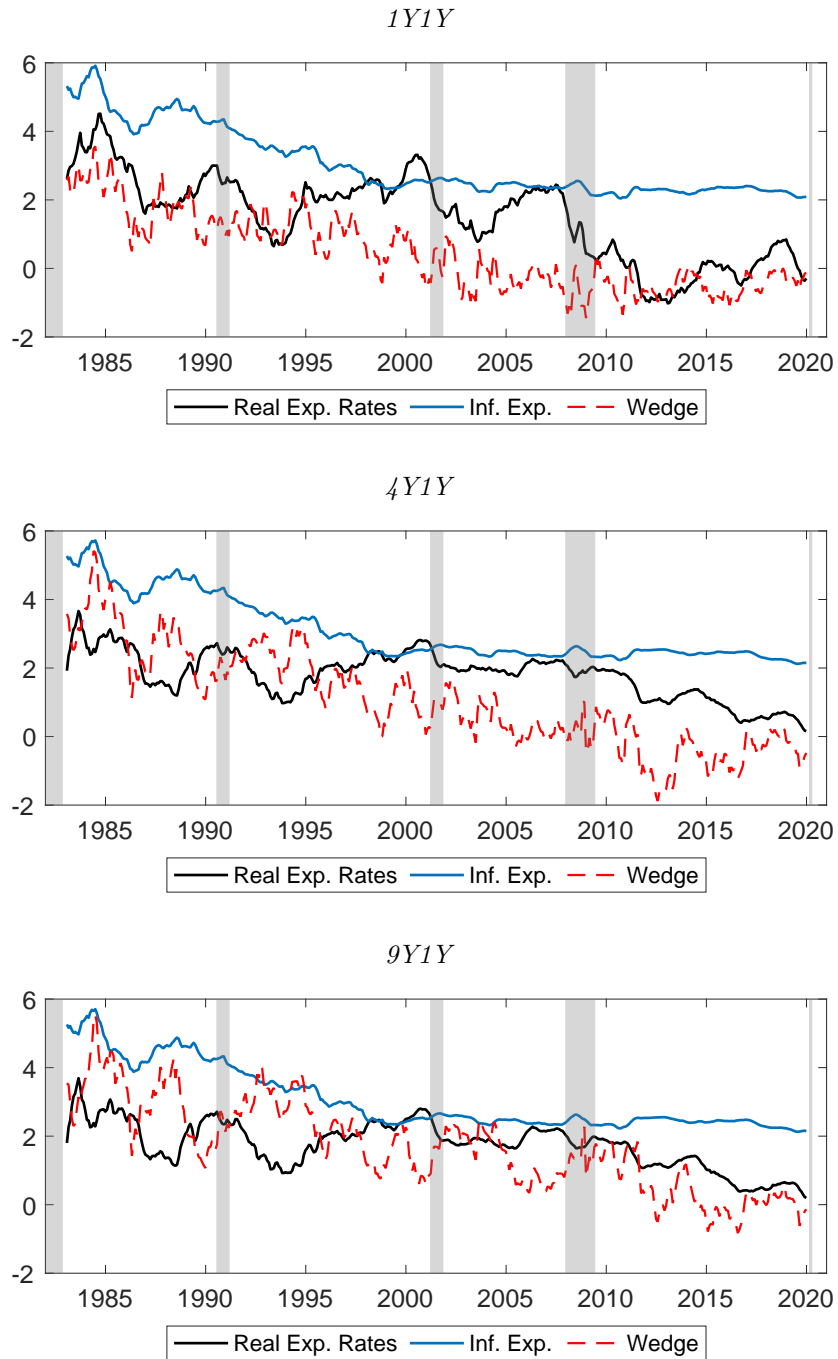
SA1-1 Decomposition of Forward Rates

Figure SA1-1 visualizes these three components of nominal Treasury forward rates for the 1Y1Y, 4Y1Y and 9Y1Y forward horizons (top, middle, and bottom panel, respectively).¹ Clearly, the wedges are sizable at all maturities and display substantial variation over time. Casual inspection of the figure suggests the expected real rate plays a dominant role at low maturities, but its relative importance decreases at longer horizons. In contrast, inflation expectations exhibit subdued cyclical fluctuations across all maturities. Both real rate and inflation expectations display lower variation after 1999, as captured by the structural shift in the second sample. All components display a downward trend in our sample. While inflation expectations stabilize, both expected real rates and wedges further decline in the aftermath of the financial crisis, with the wedges turning negative during this period.²

¹We obtain zero-coupon forward rates from the data set of Gurkaynak et al. (2007) available at <https://www.federalreserve.gov/data/nominal-yield-curve.htm>.

²Our finding of a secular decline in the wedges is consistent with the evidence in Wright (2011) who uses an affine term structure model to show that term premiums in the U.S. and in other developed countries have experienced sizable and persistent declines between 1990 and mid-2009.

Figure SA1-1. Decomposing Forward Rates. The figure shows the individual components of forward rates at different maturities. The blue line measures expected inflation, the black line the expected short-term real rate, and the red line the wedge. From top-to-bottom the figure visualizes the components of 1Y1Y, 4Y1Y and 9Y1Y forward rate respectively: at each maturity, the sum of the three components return the forward rate.



SA1-2 Estimation and Alternative Model Specifications

For all model specifications, we compute the posterior parameter distribution using the Random Walk Metropolis-Hastings (RWMH) algorithm. We estimate the mode of the posterior distribution by maximizing the log posterior function. In order to parametrize the proposal distribution (which is assumed to be multivariate normal), we use the Hessian matrix to produce 80,000 draws from the RWMH algorithm.³ In a second step, we employ the variance-covariance matrix obtained from these initial draws in order to refine the proposal distribution. We then generate 5 chains of 400,000 draws: a step size of 0.3 gave a rejection rate of around 65 percent in each sample (and each model specification). We evaluate convergence using the Gelman and Rubin potential scale reduction factor (the factor is well below 1.01 for all estimated parameters, in every model specification). The posterior distribution is obtained by combining the 5 chains. The model’s posterior coverage intervals are obtained using the Carter and Kohn simulation smoother. Model predictions and (independent) samples are obtained from 20,000 selected draws from the posterior distribution. The marginal data density (MDD) is obtained using Geweke’s harmonic estimator.

Table SA1.1 displays the MDD for different model specifications. We consider three additional specifications beyond our baseline model. Two of these specifications reduce both the model’s parameters and the information used in the estimation. The specification labelled “bivariate model” allows nominal interest rates and inflation to jointly evolve but leaves output growth as an independent process. As a result, the term structure of output forecasts, by assumption, does not convey any information about inflation and interest rate expectations. Similarly, in the “univariate” specification, inflation, the nominal interest and output growth are all treated as independent processes. Inspecting the first three columns in the table, it is clear that our baseline multivariate model provides, by far, the best fit of the survey-based term structure of expectations against the two alternatives. This implies the joint behavior of forecasts is best described by a multivariate model. The fourth column shows the fit of a restricted model with no autocorrelated forecast errors: this specification is substantially worse than our baseline, emphasizing, again, that observed forecasts display significant deviations from the FIRE benchmark.

Given the paper’s focus on the term structure of interest rate expectations, the bottom row in Table SA1.1 restricts attention to the model’s fit for these series. To achieve this we compute

$$\ln p \left(i_{1,T}^{(>1Y)} \mid \mathcal{Z}_{1,T}^M \right) = \ln p \left(i_{1,T}^{(>1Y)}, \mathcal{Z}_{1,T}^M \right) - \ln p \left(\mathcal{Z}_{1,T}^M \right)$$

where $i_{1,T}^{(>1Y)}$ denotes all survey forecasts of the short-term interest rate with a horizon longer than one year and $\mathcal{Z}_{1,T}^M$ denotes a set of observables that depends on the particular model specification. We have $\mathcal{Z}_{1,T}^{\text{Baseline}} = \{g_{1,T}^{\text{All}}, \pi_{1,T}^{\text{All}}, i_{1,T}^{(\leq 1Y)}\}$; $\mathcal{Z}_{1,T}^{\text{Bivariate}} = \{\pi_{1,T}^{\text{All}}, i_{1,T}^{(\leq 1Y)}\}$; $\mathcal{Z}_{1,T}^{\text{Univariate}} = \{i_{1,T}^{(\leq 1Y)}\}$. The predictive likelihood measures the fit of interest rate expectations at horizons longer than one year, conditional on the parameter distribution delivering the best fit of both short-horizon interest rate expectations and, depending on the model specification, the term structure of inflation and

³The Hessian proved difficult to evaluate for some parameters. We then use the Hessian only as a reasonable initial choice.

output growth expectations. For example, in the case of the univariate model only short-horizon forecasts ($i_{1,T}^{(\leq 1Y)}$) provide information in the estimation on the interest rate expectations formation mechanism. The bottom row in the table then confirms that observed expectations about output growth and inflation contain valuable information to explain the behavior of the term structure of interest rate expectations. Taken in sum, a multivariate model better describes how short-term interest rate expectations are formed.

MDD	Baseline	Bivariate	Univariate	$\phi_f = \mathbf{0}$
$\ln p(\mathcal{Y}_{1,T} M)$	994.23	-274.53	-1388.5	853.09
$\ln p(R_{1,T}^{>0Y} \mathcal{Z}_{1,T}^M)$	-1632.8	-2008.1	-2535.5	–

Table SA1.1. Model Comparison

Note: The top line in the table shows the the log-marginal data density (MDD) for the four alternative models. The second row shows the marginal density of the interest rate forecasts at horizons longer than four quarters, conditional on the data. Notice that the conditioning dataset changes with the model. We have $\mathcal{Z}_{1,T}^{\text{Baseline}} = \{g_{1,T}^{\text{All}}, \pi_{1,T}^{\text{All}}, i_{1,T}^{(\leq 1Y)}\}$; $\mathcal{Z}_{1,T}^{\text{Bivariate}} = \{\pi_{1,T}^{\text{All}}, i_{1,T}^{(\leq 1Y)}\}$; $\mathcal{Z}_{1,T}^{\text{Univariate}} = \{i_{1,T}^{(\leq 1Y)}\}$.

SA1-3 Variance Decompositions for 2-year, 5-year and 10-year Changes

Figure SA1-2. **Decomposing Forward Rates (2-Year Changes)**. The top panels show the variance decomposition of the 24-month changes of forward rates at different maturities in real expected rates (red line), inflation expectations (blue line) and the wedge (black line) components. The bottom left panel displays the volatility of 24-month changes in interest rate expectations relative to forwards for the pre-1999 (red line) and post-1998 (black line) sample. Solid lines denote posterior medians while shaded regions denote the range of 1,000 posterior draws. The sample period is 1983m1–2019m12.

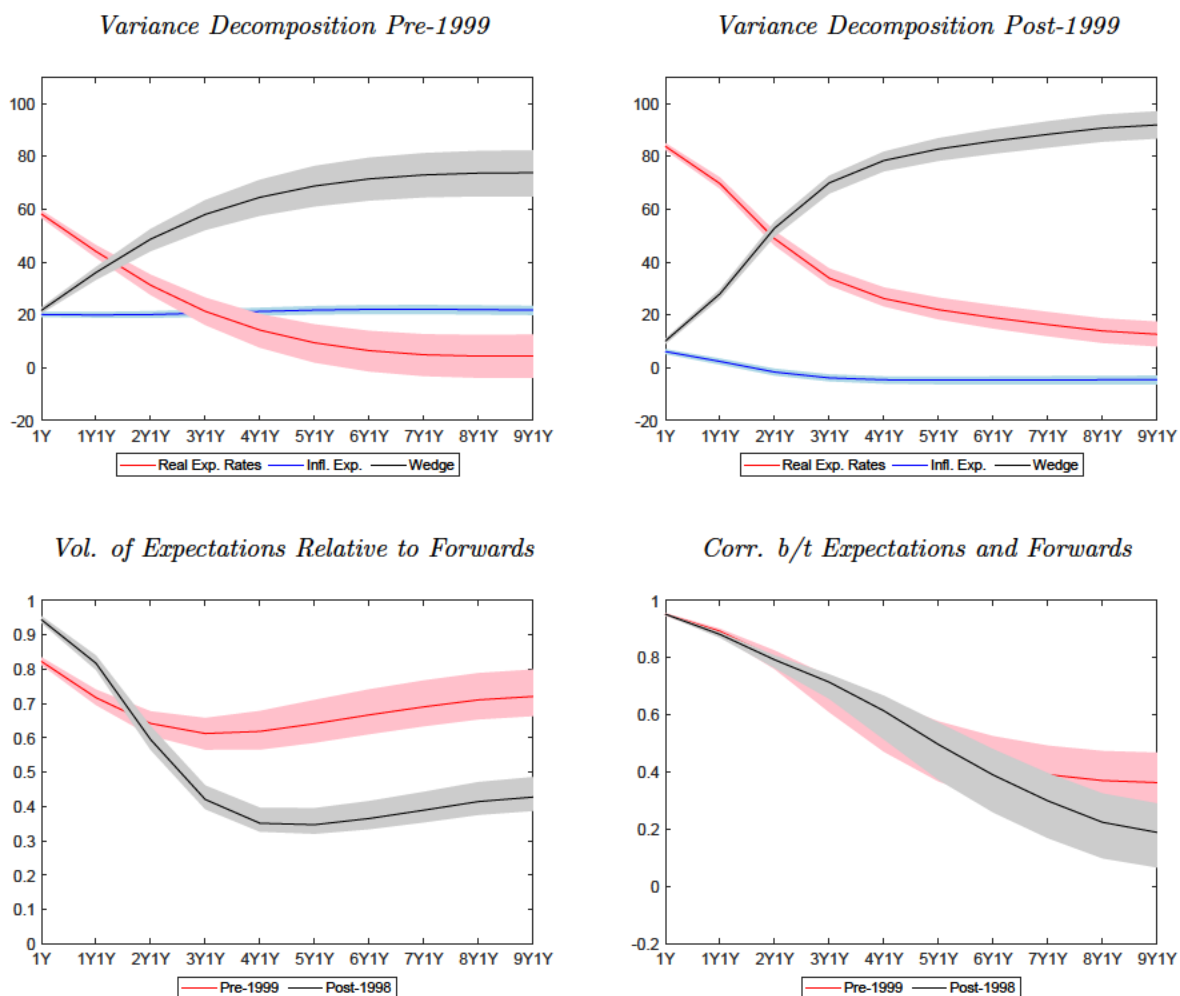


Figure SA1-3. Decomposing Forward Rates (5-Year Changes). The top panels show the variance decomposition of the 60-month changes of forward rates at different maturities in real expected rates (red line), inflation expectations (blue line) and the wedge (black line) components. The bottom left panel displays the volatility of 60-month changes in interest rate expectations relative to forwards for the pre-1999 (red line) and post-1998 (black line) sample. Solid lines denote posterior medians while shaded regions denote the range of 1,000 posterior draws. The sample period is 1983m1–2019m12.

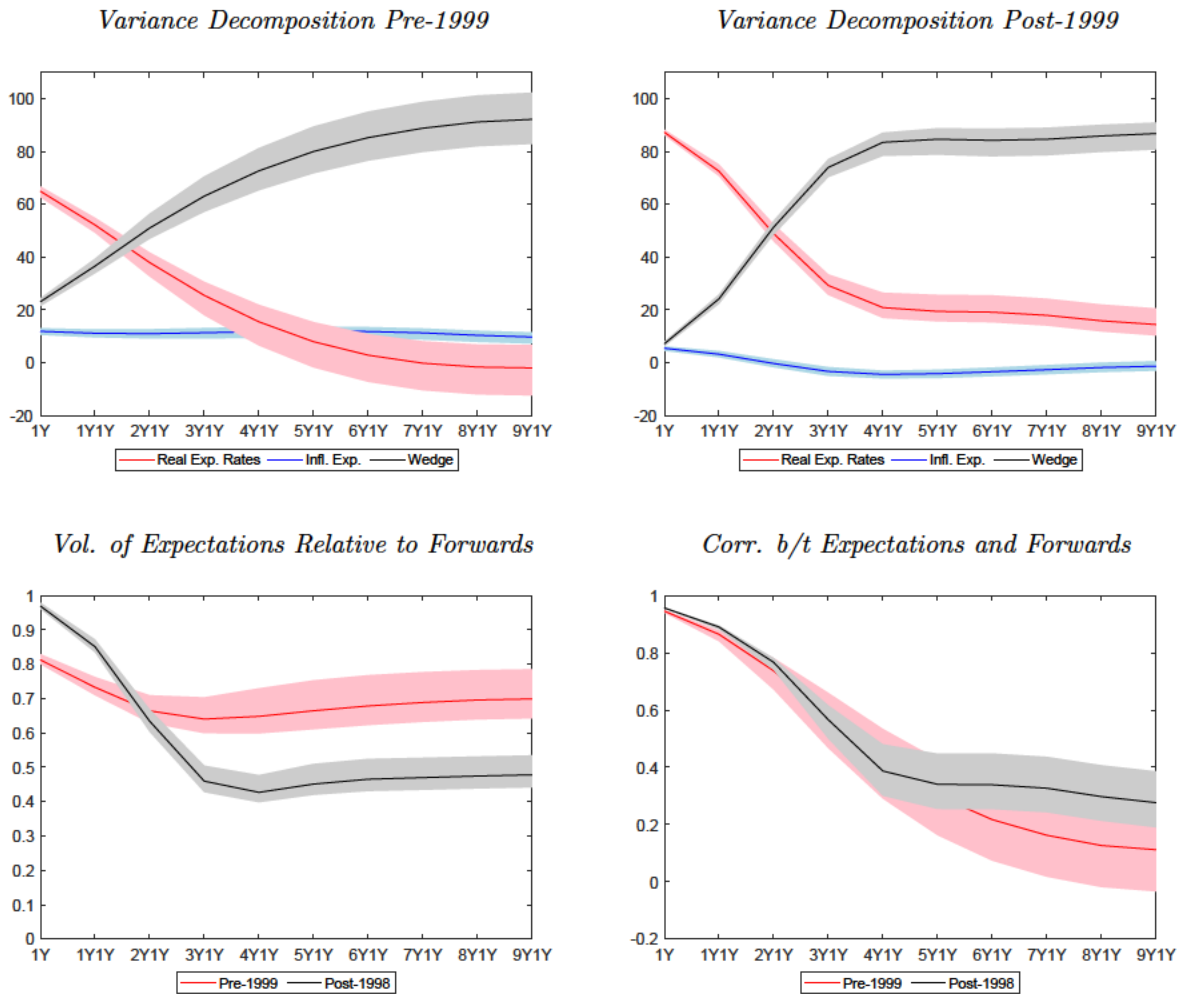
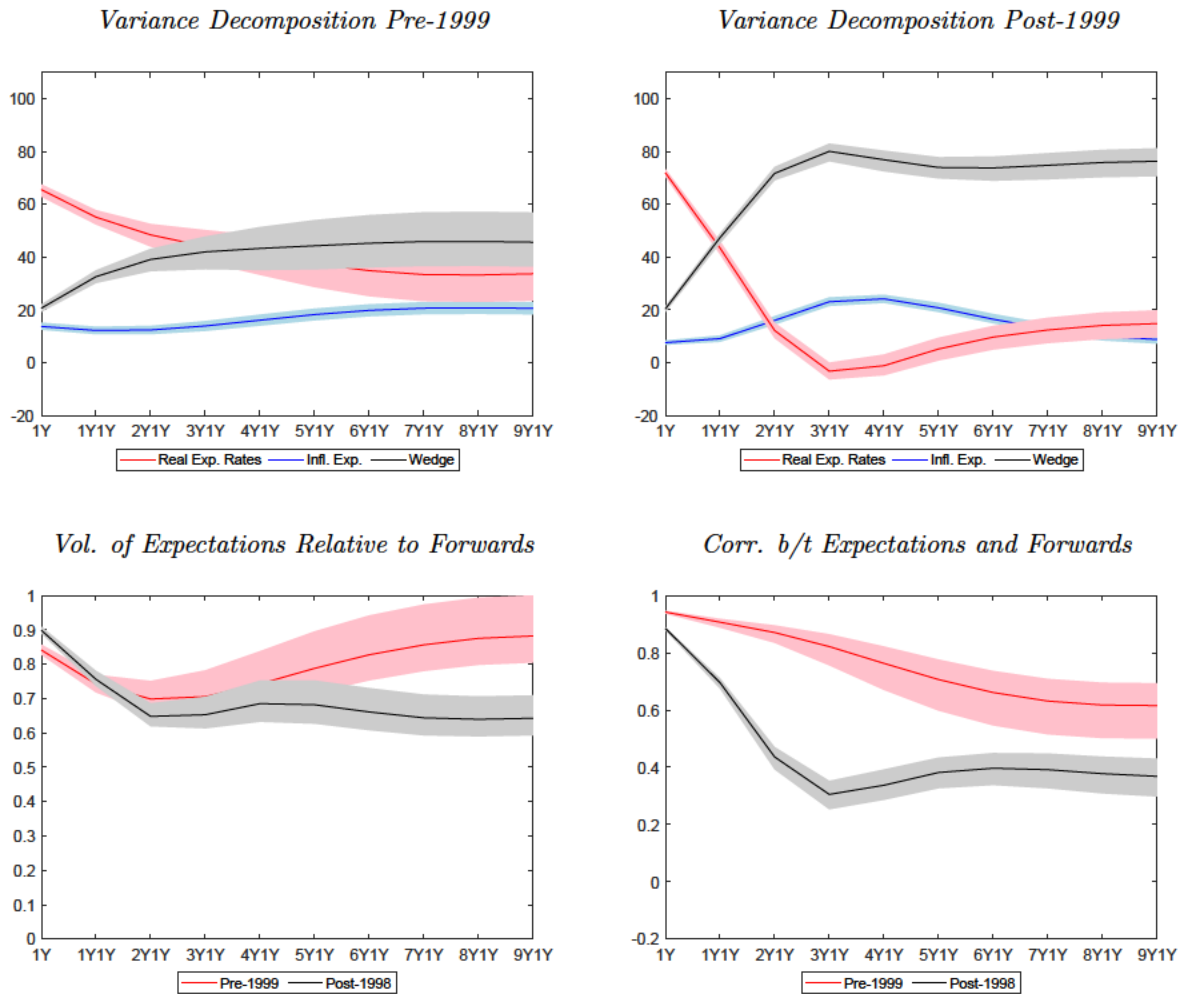


Figure SA1-4. Decomposing Forward Rates (10-Year Changes). The top panels show the variance decomposition of the 120-month changes of forward rates at different maturities in real expected rates (red line), inflation expectations (blue line) and the wedge (black line) components. The bottom left panel displays the volatility of 120-month changes in interest rate expectations relative to forwards for the pre-1999 (red line) and post-1998 (black line) sample. Solid lines denote posterior medians while shaded regions denote the range of 1,000 posterior draws. The sample period is 1983m1–2019m12.



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