CHAPTER

The term structure of expectations☆

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17.1 Introduction

Economic theory predicts that intertemporal decisions critically depend on expectations about future outcomes. Over the past two decades, a concerted research program has aimed to measure household, firm, and policymaker beliefs using numerous data sources, including surveys, asset prices, and controlled experiments. By dint of this effort, we now have invaluable data that can be used to evaluate alternative theories of expectations formation and their implications for macroeconomics and finance.

Yet the vast majority of this work has focused on expectations about *short-term* economic developments. This choice is partly driven by what data are available, as there is substantially less information on long-run forecasts. But it also reflects the common assumption in macroeconomic models that economic agents operate in a stationary environment and, consequently, that they can quickly and efficiently come to understand the long-run behavior of the economy. In these models, any information frictions that might be relevant to the expectations formation process, are only relevant to short-run economic dynamics.

These assumptions, however, belie the considerable uncertainty that confronts decision makers in practice. Indeed, direct survey evidence clearly reveals that expectations about the *long-run* values of economic and financial variables vary over time. For example, the Survey of Professional Forecasters annually queries respondents on their estimate of the nonaccelerating inflation rate of unemployment, the Federal Reserve Bank of New York's Survey of Primary Dealers includes questions on "longer-run" values of economic variables such as output, inflation, and the target interest rate, and the FOMC members themselves report, in the Survey of Economic Projections, the value that key macroeconomic variables would be expected to converge to under appropriate monetary policy and in the absence of further shocks to the economy. All of these long-run forecasts display substantial variation over time.

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Movements in long-term expectations are not without consequence. Prominent debates in macroeconomics and finance rest on the long-term behavior of the economy. The seminal contribution of Lucas (2003) argued that the economic costs of short-term fluctuations pale in comparison to the implications of long-run growth, underscoring the need to study long-term expectations and their impact on economic decisions. Among academics and policymakers there is widespread agreement that the ability of central banks and fiscal authorities to manage business cycles depends on the maintenance of long-term fiscal sustainability and stable long-run inflation expectations. And a growing literature in finance understands movements in asset prices by linking them to changes in perceived long-run risk, again highlighting the need to understand market participants' shifting views about the long run.

In this chapter we use survey measures of U.S. professional forecasters to study the term structure of expectations including long horizons. One key advantage of using professional forecasts is the wealth of available data in the U.S. and other countries. Multiple surveys covering a wide range of forecast horizons spanning "nowcasts" to the very long run are available. And unlike the growing number of new surveys of households and firms that have become available to researchers only in recent years, data on professional forecasts have been collected since at least the mid-1950s. Using these data we document the evolution of the entire term structure of expectations since the 1980s and propose a simple expectations formation mechanism that rationalizes their behavior. Armed with this framework, we evaluate some implications in a standard New Keynesian dynamic general equilibrium model.

We emphasize that professional forecasts display two important stylized facts. First, long-run expectations about economic variables such as output growth, inflation and short-term nominal interest rates fluctuate significantly over time, tracking perceived slow-moving changes in the economy such as the long-run mean of inflation or the natural rate of interest. Second, the individual components of the term structure of expectations display a clear pattern of comovement across different variables and forecast horizons. Changes in long-term expectations are tied to short-term forecast errors, consistent with an expectations formation mechanism where agents estimate unobserved trend and cycle components from available data. At the same time, agents appear to form expectations about macroeconomic variables jointly, so that, for example, policy rate forecasts are tightly linked to inflation and output growth forecasts.

Throughout the chapter we use a model of expectations formation that is consistent with these observations. While we discuss the literature on the term structure of expectations throughout the chapter, our primary aim is not to provide an exhaustive summary of existing work. Recent research covers a wide range of theories that can potentially account for some of the empirical regularities in survey data. Here we focus on a specific class of information frictions, and, therefore, a specific modeling approach, and discuss its implications for different aspects of the data.

This chapter is structured in four broad sections. Section 17.2 introduces our workhorse model of the expectations formation mechanism and the information frictions at its foundations. This is an unobserved components model of the trend and cycle which agents estimate using standard filtering methods. The model captures the key aspects of our theory and accounts for the joint term structure of expectations of output growth, inflation and the policy rate. The forecast data are based on the universe of professional forecasts for the United States in the post-war era. We argue that a drifting long-run mean is essential to capture the low-frequency adjustment in long-run beliefs. Moreover, the multivariate model provides a far superior fit when compared to a univariate model specification for each variable. This underscores that the dynamic behavior of survey forecasts of different macroeconomic variables need to be modeled jointly. Existing studies often focus on expectations about an individual variable.

Section 17.3 focuses specifically on the term structure of interest rates, the linchpin of the monetary policy transmission mechanism. We use our measure of expectations to evaluate the expectations hypothesis, stating that yields on government bonds reflect the average short rate that investors expect to prevail over the life of the bond. We compare the behavior of the term structure of consensus expectations with the U.S. Treasury yield curve. Despite the observed volatility of expectations, there remains substantial unexplained variation at the long end of the yield curve. We obtain the subjective term premium as the residual between observed yields and average expected future short rates. The survey-based measure of the term premium does not comove in any meaningful way with expected short rates, suggesting that a large share of movements in longer-maturity interest rates remains unaccounted for by changes in expectations.

The first parts of this chapter are motivated by a reduced-form model of the expectations formation process. This has the advantage of sidestepping detailed assumptions about information frictions and, in particular, taking a stand on the rationality of expectations. There are notable advantages, however, to a more structural approach. Section 17.4 presents a dynamic structural general equilibrium model where agents are boundedly rational and have to learn about a possibly changing economic environment. Subjective beliefs of households and firms are consistent with our reduced-form forecasting model based on survey evidence. However, the structural model assumes a specific deviation from the full information rational expectations setup: subjective and objective (model consistent) forecasting models differ. We discuss the implications for monetary and fiscal policy design under different assumptions about how expectations are formed. Finally, Section 17.5 concludes and provides suggestions for future directions of research.

17.2 Joint behavior of short- and long-term forecasts

In this section, we present a simple model of expectations formation. The key insight of the model—which will resonate throughout the chapter—is that agents revise their beliefs about both the trend and the cyclical components of macroeconomic variables in response to short-term forecast errors. As a result, unanticipated short-term innovations may drive the entire term structure of macroeconomic expectations.[1]

17.2.1 Motivation: a simple model of long-term drift

Market participants observe a wealth of data about the current state of the economy. These data provide signals both about short-term economic developments as well as longer-run trends. Forming expectations about economic variables at different horizons into the future therefore requires decomposing the data into transitory and persistent components. Such decompositions have a long tradition in theoretical and empirical macroeconomic research. For instance, the seminal real-business-cycle model in Kydland and Prescott (1982) assumes agents cannot perfectly observe the short- and long-term components of

[1] For a more detailed discussion of this mechanism along with additional empirical evidence, see Crump et al. (2021).

technical progress. Stock and Watson (1989) and Stock and Watson (2007) model inflation as having a trend and a transitory component. This approach has also been incorporated in countless structural models of inflation dynamics of which Cogley et al. (2010) is a prominent example. Various studies apply trend-cycle decompositions to other macroeconomic variables, showing that models which embed slow-moving time-varying drifts capture the dynamic properties of real GDP growth (Stock and Watson, 1989; Cogley and Sargent, 2005 and Laubach and Williams, 2003) and the federal funds rate (Kozicki and Tinsley, 2001 and Gürkaynak et al., 2005) well.

17.2.1.1 Modeling a drift in the long-run mean

Consider forecasting the observable variable z_t using the model

$$z_t = \omega_t + x_t \tag{17.1}$$

where

$$\omega_t = \omega_{t-1} + \epsilon_t^{\omega}, \tag{17.2}$$

$$x_t = \phi x_{t-1} + \epsilon_t^{x}, \tag{17.3}$$

with $0 < \phi < 1$, and ϵ_t^x and ϵ_t^{ω} are mutually independent $i.i.d.$ Gaussian innovations. The variables x_t and ω_t are *unobserved* by the forecaster. While x_t captures a stationary cyclical or business-cycle component of z_t, ω_t represents a slow-moving trend or drift. For example, ω_t could represent the underlying productivity trend of the economy, the implicit or explicit inflation target of the central bank, or the long-term drift in the natural rate of interest. This trend is assumed to be nonstationary, but a sufficiently persistent process would deliver essentially the same dynamics. Kozicki and Tinsley (2001) labeled the nonstationary case a "shifting endpoint" model.

Observing z_t at time t, agents estimate the trend and cycle components, $\omega_{t|t}$ and $x_{t|t}$, using the Kalman filter. The expected value of z_t for any horizon $T > t$ is then

$$E_t z_T \equiv z_{T|t} = \omega_{t|t} + \phi^{T-t} x_{t|t},$$

where the persistent and cyclical components satisfy

$$\omega_{T|t} = \omega_{t|t} = \omega_{t-1|t-1} + \eta_t, \tag{17.4}$$

$$x_{T|t} = \phi^{T-t} x_{t|t} = \phi^{T-t} \times [\phi x_{t-1|t-1} + \nu_t], \tag{17.5}$$

where $\eta_t = \kappa_{\omega} \left(z_t - z_{t|t-1} \right)$ and $\nu_t = \kappa_x \left(z_t - z_{t|t-1} \right)$ are innovations measuring the forecast "surprises." These surprises are given by the one-step-ahead or short-term forecast error scaled by the Kalman gain coefficients κ_{ω} and κ_x. The size of the Kalman gains depends on the relative volatility of the innovations in the trend component and the persistence of the stationary process (e.g., Hamilton, 1994). Given the slow-moving nature of the trend component, κ_{ω} is assumed to be relatively small.

We explore three implications of this model in the data. First, the model parameters forge a tight connection among forecasts at different horizons. For example, we show that the term structure of inflation forecasts is consistent with random-walk behavior, i.e., $\phi \approx 0$. The entire term structure of inflation expectations shifts in response to revisions in the estimate $\omega_{t|t}$. In contrast, interest rate forecasts at short horizons largely reflect a persistent cyclical component, while long-term forecasts are tied to the drift component.

Second, the model implies a tight connection between long-run forecasts and short-term forecast errors. To see this, for a forecast horizon $T^* > t$ sufficiently large that the cyclical component becomes unimportant, that is $\phi^{T^*-t} \approx 0$, so that we have

$$E_t z_{T^*} \approx \omega_{t|t}.$$

Using the law of motion for the estimated trend component in Eq. (17.4), the change in longer-term forecasts is tied to short-term forecast errors or surprises

$$E_t z_{T^*} - E_{t-1} z_{T^*} \approx \omega_{t|t} - \omega_{t|t-1} = \kappa_\omega \left(z_t - z_{t|t-1}\right).$$

A forecaster who underpredicts z_t for a few periods should revise upwards their long-term forecast, reflecting a perceived increase in the estimated unobserved drift component.

Third, the model predicts a strong, in this simple example a perfect, correlation between the updates to the trend and cycle components, as they both depend on the same forecast error: $z_t - z_{t|t-1}$. This property holds in more general models albeit with a nonzero, but not necessarily perfect, correlation (see, for example, Crump et al., 2022a and Crump et al., 2022b). Crump et al. (2022b), using a novel panel of individual professional forecasts at short and long horizons, provide evidence in favor of such a relation in the data.

17.2.2 A model to fit the term structure of expectations

Based on the theoretical framework discussed in the previous section, we now present a parsimonious reduced-form model of the term structure of expectations for three key U.S. macroeconomic variables: output growth, inflation and the short-term nominal interest rate. The model and the analysis are based on Crump et al. (2022a). The model serves three purposes. First, it permits evaluating whether our simple theory of expectations formation can account for the observed dynamics of expectations across a range of forecast horizons. Second, the model matches different surveys and different types of forecasts (i.e., fixed-horizon and fixed-event) in a coherent way. It also provides consistent proxies for missing survey observations. As a result, the model enables us to construct *a consensus measure of expectations at all horizons* that avoids unduly overweighting a particular survey. Third, since we observe fewer forecasts for short-term interest rates than we do for output and inflation, the multivariate nature of the model allows us to exploit the correlation structure across variables and time horizons to inform the term structure of expectations of the short-term interest rate.

17.2.2.1 Baseline multivariate model

The state of the macroeconomy is defined by the vector $z_t = (g_t, \pi_t, i_t)'$ representing monthly real output growth, inflation and the short-term nominal interest rate, respectively. They evolve as

$$z_t = \hat{\omega}_t + \hat{x}_t \tag{17.6}$$

where

$$\hat{\omega}_t = \hat{\omega}_{t-1} + \eta_t, \tag{17.7}$$

$$\hat{x}_t = \Phi \hat{x}_{t-1} + \nu_t, \tag{17.8}$$

and the variables $\hat{x}_t \equiv x_{t|t}$ and $\hat{\omega}_t \equiv \omega_{t|t}$ are 3×1 vectors capturing agents' estimates about the underlying unobserved states. To keep the model simple, the innovations $\varepsilon_t = \left(\eta_t', \nu_t'\right)'$ are assumed to be *i.i.d.* across time and normally distributed with variance-covariance matrix Σ_ε. Consistent with the model presented in Section 17.2.1, innovations in the drift are potentially correlated with innovations in the cyclical components of the model. The matrix Φ measures the autocorrelation properties of the stationary component $\hat{x}_t$ and consequently has eigenvalues in the unit circle. The model is defined at the monthly frequency which is the highest frequency observed across the range of surveys of professional forecasts to which we fit the model.

17.2.2.2 Data overview

We utilize the universe of professional forecasts for the United States in the post-war era, 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); (6) Goldsmith–Nagan (GN); (7) Livingston Survey (Liv.); (8) Survey of Primary Dealers (SPD); (9) Survey of Professional Forecasters (SPF). Further details about each survey are available in Crump et al. (2022a) (see also Chapter 3 in this Handbook). We focus on three sets of forecasts. For output growth, we use forecasts of real GNP growth prior to 1992 and forecasts of real GDP growth thereafter. For inflation, we use forecasts of growth in the consumer price index (CPI). We choose the CPI over alternative inflation measures such as the GDP deflator because CPI forecasts are available more frequently and for a longer history than alternative inflation measures. Finally, we use 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.[2]

Combined, these surveys provide a rich portrait of professional forecasters' macroeconomic expectations. Our results are based on 627 variable-horizon pairs spanning the period 1955 to 2019. The survey data differ in frequency, forecast timing, target series, sample availability and forecast horizons. As we make clear below, we are careful to ensure consistency between model-implied and observed forecasts with respect to variable definition and forecast horizon. Table 17.1 summarizes the survey data we use in the paper. 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. At all horizons there are relatively fewer forecasts for the 3-month Treasury bill than for output growth and inflation.

In the discussion of our results we focus on the period from the early 1980s through 2019, covering the Great Moderation, the Great Recession following the Global Financial Crisis, up to the pre-COVID period. This period includes the majority of the available survey forecasts with over 75% of the total number of series used available in this 35 year time span.

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2 For 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).

Table 17.1 Summary of Surveys.

	BCFF	BCEI	CE	DMP	EF	GN	Liv.	SPD	SPF
Survey Sample (full)									
Frequency	*Monthly*	*Monthly*	*Monthly*	*Irregular*	*Monthly*	*Quarterly*	*Biannually*	*8 per year*	*Quarterly*
RGDP:	1984–present	1978–present	1989–present	n/a	1984–1995	n/a	1971–present	2011–present	1968–present
CPI:	1984–present	1980–present	1989–present	1978–1987	n/a	n/a	1946–present	2011–present	1981–present
TBILL:	1982–present	1982–present	1989–present	n/a	1984–1995	1969–1986	1992–present	n/a	1981–present
Survey Sample (LT)									
Frequency	*Biannually*	*Biannually*	*Quarterly*	*n/a*	*n/a*	*n/a*	*n/a*	*8 per year*	*Quarterly*
RGDP:	1984–present	1979–present	1989–present	n/a	n/a	n/a	1990–present	2012–present	1992–present
CPI:	1984–present	1984–present	1989–present	1978–1987	n/a	n/a	1990–present	2011–present	1991–present
TBILL:	1983–present	1983–present	1998–present	n/a	n/a	n/a	n/a	n/a	1992–Present
Horizons (NT)									
RGDP:	Q0-Q6, Y2, Y1-5, Y2-6	Q0-Q7, Y2, Y0-4, Y1-5, Y2-6, Y1-10	Q0-Q8, Y1, Y2	n/a	Q1-Q4	n/a	Q1-2, Q3-4, Y2, Y0-9	Q0-Q2, Y1, Y2	Q0-Q4, Y2, Y0-9
CPI:	Q0-Q6, Y2, Y1-5, Y2-6	Q1-Q7, Y2, Y1-5, Y2-6	Q2-Q8, Y1, Y2	Y1-10	n/a	n/a	Q3-4, Y2, Y0-9	n/a	Q2-Q4, Y1, Y2, Y0-4, Y0-9
TBILL:	Q0-Q6, Y1, Y2, Y1-5, Y2-6	Q1-Q7, Y1, Y2, Y1-5, Y2-6	M3, M12, Y1, Y2	n/a	Q1-Q4, Y0, Y1	M3	Q0, Q2, Q4, Y1, Y2	n/a	Q1-Q4, Y1, Y2, Y0-9
Horizons (LT)									
RGDP:	Y3, Y4, Y5, Y6, Y6-10, Y7-11	Y3, Y4, Y5, Y6, Y5-9, Y6-10, Y7-11	Y3-Y10	n/a	n/a	n/a	Y0-9	Y3, LR	Y3, Y0-9
CPI:	Y3, Y4, Y5, Y6, Y6-10, Y7-11	Y3, Y4, Y5, Y6, Y5-9, Y6-10, Y7-11	Y3-Y10	Y1-10	n/a	n/a	Y0-9	Y5-10	Y0-4, Y0-9
TBILL:	Y3, Y4, Y5, Y6, Y6-10, Y7-11	Y3, Y4, Y5, Y6, Y6-10, Y7-11	Y3-Y10	n/a	n/a	n/a	n/a	n/a	Y3, Y0-9

This table provides a summary of the forecast data available from each survey: Blue Chip Financial Forecasts (BCFF), Blue Chip Economic Indicators (BCEI), Consensus Economics (CE), Decision Makers' Poll (DMP), Goldsmith-Nagan Survey (GN), Economic Forecasts: A Worldwide Survey (EF), Livingston Survey (Liv.), Survey of Primary Dealers (SPD), and the Survey of Professional Forecasters (SPF). NT refers to horizons of two years or less while LT refers to horizons including more than two years in the future. Forecasts for output growth (RGDP) are based on real GNP growth prior to 1992 and real GDP growth thereafter. M3 and M12 signify forecasts of 3-months and 12-months ahead, respectively. Q1 represents a one-quarter ahead forecast, Q2 represents a two-quarter ahead forecast and so on. Y1 represents a one-year ahead forecast, e.g., a forecast for the year 2014 made at any time in 2013. Y2 represents a two-year ahead forecast and so on. Y0-5 represents a forecast for the average value over the years ranging from the current year to five years ahead, e.g., a forecast for the average annual growth rate of GDP from 2014 through 2019 made at any time in 2014. Y1-6, Y2-7 and so on are defined similarly. Y6-10 represents a forecast for the average value over the years ranging from six years ahead to 10 years ahead, e.g., a forecast for the average annual growth rate of GDP from 2020 through 2024, made at any time in 2014. Finally, "–" indicates sequential horizons, e.g., entries of the form Q0-Q6 imply that horizons Q1, Q2, Q3, Q4, Q5, and Q6 are available.

17.2.3 Mapping the model to survey forecasts

The model defined by Eqs. (17.6)–(17.8) has the state-space representation

$$Z_t = F(\Phi) Z_{t-1} + V\varepsilon_t$$

where $Z_t = \left(z_t, z_{t-1}, z_{t-2}, z_{t-3}, z_{t-4}, \hat{x}_t, \hat{\omega}_t\right)'$. The presence of four lags in z_t facilitates mapping data definitions to model concepts, as discussed further below. The heterogeneity of available forecasts makes this a nontrivial task. Start with a simple example. Suppose each month we only observe survey forecasts at monthly horizons. For example, we might measure a forecast for the n-month-ahead inflation rate at time t. Using the model, the n-step-ahead forecast of all model variables is given by

$$E_t z_{t+n} = \hat{\omega}_t + \Phi^n \hat{x}_t,$$

where the model forecast of inflation would be the second element of the vector z_t. The larger state vector satisfies

$$E_t Z_{t+n} = F(\Phi)^n Z_t$$

and provides the observation equation. The mapping between data and model is then straightforward.

In practice, however, survey participants are rarely asked to provide monthly forecasts. Rather they are queried about different types of forecasts, which involve quarterly averages, year-over-year growth rates, and so on. When estimating our model we take care to match as closely as possible the observed forecasts with the correct model representation. The following examples help clarify how we do this. Consider the short-term interest rate. 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 annualized growth, annual average growth, and Q4/Q4 growth. Let G_{2019Q1} and G_{2019Q2} be the level of real GDP in billions of chained dollars in the first and second quarter of 2019, respectively. Then, the quarterly average annualized growth rate is defined as $100 \cdot ((G_{2019Q2}/G_{2019Q1})^4 - 1)$. Our model variables define a month-over-month (annualized) real GDP growth rate series. To map the monthly series into this specific measured quarterly growth rate, we follow Crump et al. (2014) and use

$$100 \cdot ((G_{2019Q2}/G_{2019Q1})^4 - 1) \approx \frac{1}{9}\left(g_{2019m2} + 2 \cdot g_{2019m3} + 3 \cdot g_{2019m4} + 2 \cdot g_{2019m5} + g_{2019m6}\right),$$

where, for example, g_{2019m2} represents the model-based month-over-month annualized real output growth in February 2019. This notation makes clear why lagged values of z_t appear in the state vector Z_t. Annual average growth rates follow a similar pattern. For example, let G_{2018} and G_{2019} be the average level of real GDP in billions of chained dollars in the years 2018 and 2019. The annual average growth rate is $100 \cdot (G_{2019}/G_{2018} - 1)$ which we approximate via

$$\begin{aligned}100 \cdot (G_{2019}/G_{2018} - 1) \approx \frac{1}{144}&\left(g_{2018m2} + 2 \cdot g_{2018m3} + 3 \cdot g_{2018m4} + \cdots + 12 \cdot g_{2019m1}\right.\\ &\left.+ 11 \cdot g_{2019m2} + 10 \cdot g_{2019m3} + \cdots + 2 \cdot g_{2019m11} + g_{2019m12}\right).\end{aligned}$$

Finally, Q4/Q4 growth rates are calculated, for example, by $100 \cdot (G_{2019Q4}/G_{2018Q4} - 1)$ and approximated via

$$100 \cdot (G_{2019Q4}/G_{2018Q4} - 1) \approx \frac{1}{12}\left(g_{2019m1} + g_{2019m2} + g_{2019m3} + \cdots + g_{2019m12}\right).$$

The above shows that certain short-term 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 z_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. We do so to help pin down monthly real output growth since the actual series is only available at the quarterly frequency. Finally, for simplicity, forecasts which involve averages over multiple years are mapped as simple averages over the corresponding horizons.

The mapping between unobserved states and observed forecasts is then given by the observation equation

$$\mathcal{Y}_t = H_t(\Phi) \times Z_t + o_t,$$

where $\mathcal{Y}_t$ includes the survey forecasts. The observation matrix depends nonlinearly on Φ and is time-varying, reflecting missing observations in the survey forecasts series. The vector o_t denotes measurement errors. We assume individual observation errors for each survey to be mean-zero, i.i.d. and mutually independent Gaussian innovations. To ensure a parsimonious model we impose equal variances for each target variable at similar forecast horizons (but not by the specific survey). 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.

17.2.4 Discussion

The model is designed around the central mechanism driving changes in the term structure of expectations introduced in the previous section. The time-varying long-run mean captures the observed drift in survey-based forecasts. This model feature has been exploited in the previous literature with a tight focus on inflation expectations. Kozicki and Tinsley (2012), a precursor of this approach, show this class of models fits professional forecasters' inflation expectations at different horizons, including the long-run. Chan et al. (2018) conduct a similar exercise for a wide set of countries. Aruoba (2020) fits the term structure of survey-based inflation expectations by adapting the structure of the Nelson–Siegel (NS) model of the yield curve, which summarizes the yield curve with three factors (level, slope, and curvature). In contrast to the existing literature, in our model forecasters form *joint* expectations about different macroeconomic variables.

However, for the sake of simplicity the model ignores some possibly important features of the expectations formation mechanism. First, the model parameters are time invariant. Shifts in the volatility of forecast errors might have an impact on the updating of expectations by affecting the sensitivity to forecast errors via the Kalman gain. While it has been widely documented that economic volatility has changed in the post-war U.S., this is likely less of a concern for our baseline estimation period. Other sources of structural change such as regime shifts in monetary or fiscal policy can also impact the expectations formation process that the model aims to capture. Mertens and Nason (2020) extend the framework by introducing time-varying persistence and volatility in their model of inflation expectations.[3] Carvalho et al. (2021) and Eusepi et al. (2020) allow for structural changes in the expectations formation process in general equilibrium frameworks. We revisit these ideas in Section 17.4.

Second, to what degree is the model used by our representative forecaster close to the correct data generating process? Under the common assumption of rational expectations agents use the correct model. This implies the updating equations (17.4) and (17.5) are based on the optimal filter.[4] Macroeconomic models embedding these assumptions have been used to study the response of the economy to changes in long-run productivity (Tambalotti, 2003; Edge et al., 2007); shifts in the long-run mean of inflation (Erceg and Levin, 2003); or movements in asset prices in response to long-run dividend growth (Timmermann, 1993). However, a growing literature assumes agents form expectations under bounded rationality. These models produce a wedge between subjective expectations and the model-consistent data generating process. Agents' inference and expectations updating is then no longer optimal. This literature includes models of adaptive learning (Marcet and Sargent, 1989; Evans and Honkapohja, 2001 and Eusepi and Preston, 2011), or models where expectations exhibit extrapolation bias (Fuster et al., 2010; Bordalo et al., 2020 and Angeletos et al., 2020).[5] We discuss these additional frictions in Section 17.4, where we study the term structure of expectations in a structural general equilibrium model.

17.2.5 Results

17.2.5.1 *Model fit*

The model is estimated over the period January 1983 to December 2019 using Bayesian methods and provides an excellent fit of the 627 times series, especially for the short-term nominal rate. In particular, Crump et al. (2022a) show that it strongly outperforms univariate versions of the unobserved components model for each variable. The superior fit of the multivariate model suggests that market participants form expectations about the short rate jointly with those of output and inflation.

Given the large number of series involved in the estimation, it is not straightforward to illustrate the fit of our model comprehensively in the time series domain. Fig. 17.1 offers a subset of this information, detailing three forecast horizons for each variable: the short term (two-quarters ahead); the medium term (two-years ahead); and the long term (five-years ahead and beyond). In each panel, we show a collection of survey forecasts from different sources that approximately match the appropriate forecast horizon (we use about sixty time series in total). The model does a remarkable job. Perhaps not surprisingly given the vast number of survey forecasts available for this time period, the gray areas capturing the 95% coverage interval are very tight. Moreover, the model-implied forecast values closely track the data, with a few exceptions for real GDP long-term forecasts during the late 1980s and the 2009 recession.

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3 Grishchenko et al. (2019) go beyond consensus inflation forecasts and use probability distributions of future inflation rates from several U.S. and euro-area surveys of professional forecasters to estimate a dynamic factor model featuring time-varying uncertainty.

4 Under this assumption the surprises measured by $z_t - z_{t|t-1}$ are uncorrelated with information available at $t-1$, as we assume here for convenience. In particular, the Kalman filter produces innovations to trend (η_t) and cycle (ν_t) that are *i.i.d.* across time.

5 See Angeletos et al. (2020) which offers a comprehensive discussion on the literature and introduces a model featuring both disperse information and extrapolation bias. This model reproduces the observed response of survey-based forecasts to an identified business cycle shock.

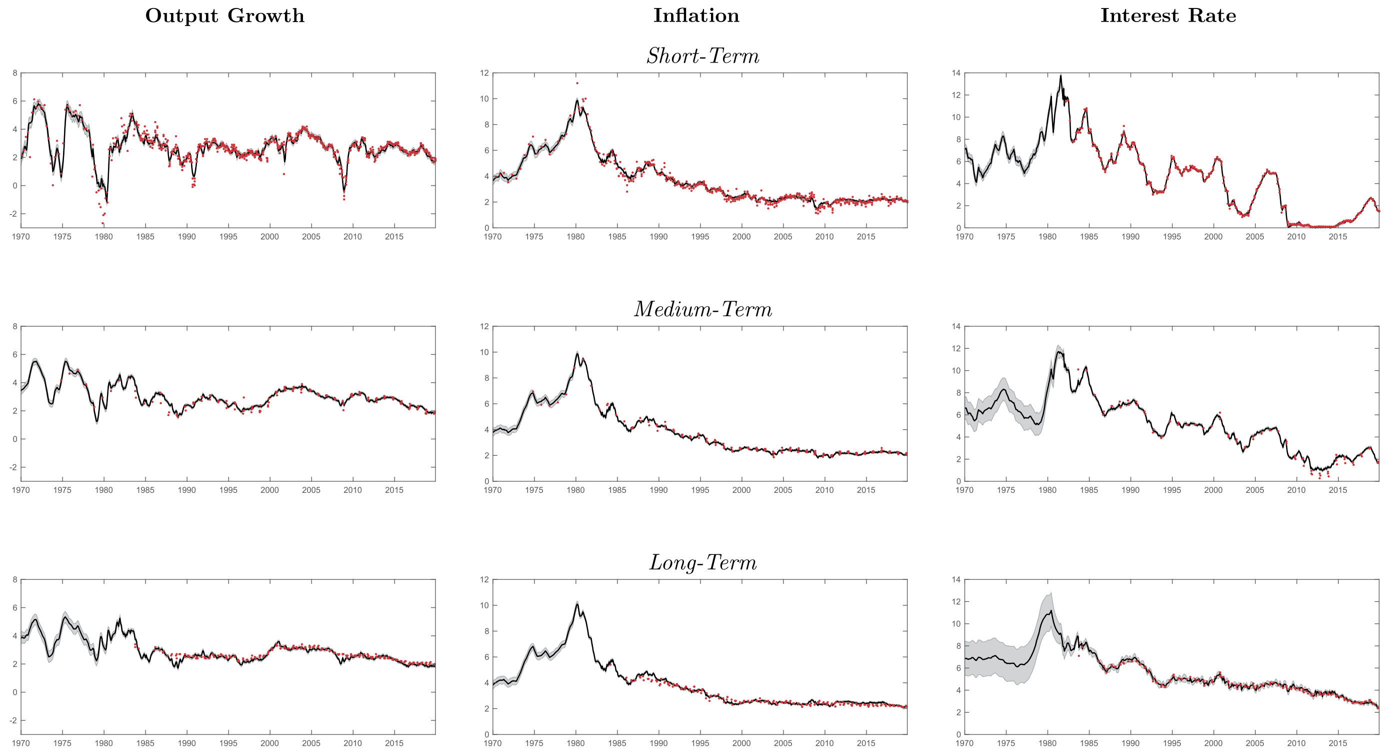


FIGURE 17.1 Fitting the Term Structure of Expectations

The panels contrast model predictions with survey data at different forecast horizons. The solid line shows median predictions and the gray shade shows the 95% coverage interval. The squares represent survey-based forecasts at short-term (two quarters ahead), medium-term (two years ahead) and long-term (five years ahead and beyond) horizons from different surveys.

In addition to fitting the observed survey forecasts over the estimation period 1983–2019, we backcast the individual model-implied forecast series and report smoothed estimates of expectations going back to 1970. Over this earlier period the availability of survey forecasts is scarce and, for longer-range forecasts, nonexistent. Therefore, there is considerable uncertainty about the term structure of forecasts. One additional caveat with this exercise is that the expectations formation mechanism has most likely undergone structural change across the full sample. As discussed in Section 17.4, the evolution of the perceived drifts has changed and has become less responsive to short-term developments over time. Also, economic volatility and, possibly, the perceived policy regime could have shifted over time.[6]

These caveats notwithstanding, the model also fits the few observed survey forecasts for output growth and inflation that are available before 1983 reasonably well. Not surprisingly, the uncertainty around the estimates increases as we move backwards in time. However, model predictions accord with conventional wisdom, with an increase in inflation and interest rate expectations over the mid-1970s, peaking in the early 1980s. While predicted long-term forecasts for real GDP are possibly too volatile, they capture the higher growth rate during that period. Overall, this simple and highly parsimonious model fits the term structure of survey-based expectations, especially after the mid-1980s, exceptionally well.

Beyond consensus expectations

Here we focus on a representative forecaster and disregard the forecast disagreement widely documented in surveys. Researchers have introduced a rich set of informational frictions that can generate plausible degrees of forecast dispersion. Models of sticky (Mankiw and Reis, 2002) or noisy information (Woodford, 2003) and models of rational inattention (Sims, 2003 and Maćkowiak and Wiederholt, 2009) assume that individual forecasters endogenously have different information sets regarding the current state of the economy. As such, they disagree in their forecasts about future economic outcomes. Coibion and Gorodnichenko (2012) show that forecast dispersion can affect the dynamic properties of consensus measures of expectations.

A few recent papers incorporate this theoretical framework to explain observed forecaster disagreement. Andrade and Le Bihan (2013) employ a multivariate setup and assume forecasters are subject to sticky *and* noisy information. Mertens and Nason (2020) capture a wider set of information frictions by allowing for infrequent forecast updating of inflation expectations by individual forecasters. This prior literature has largely focused on individual target variables, such as inflation, and shorter-term forecast horizons. However, as shown in Andrade et al. (2016) and Crump et al. (2022b), individual *long-term* forecasts show a high degree of dispersion for all variables considered and for all forecasting horizons. This is consistent with economic agents facing uncertainty about the long-run behavior of the economy. Andrade et al. (2016) show that the nature of disagreement is fundamentally different across macroeconomic variables: the term structure of disagreement is upward-sloping only for short-rate forecasts while it is flat across horizons for inflation and downward-sloping for output growth. While the primary focus here is on the consensus (mean) forecast, this model can also explain the behavior of the term

[6] A potential extension to the framework involves explicitly incorporating time variation in both the systematic and stochastic components of the model. For example, Garnier et al. (2015) estimate a model for trend inflation on different countries and allow time variation in the volatility of the trend. Primiceri (2005) and Bianchi and Ilut (2017) estimate VARs with time-varying coefficients on U.S. data in order to account for structural change.

structure of disagreement. In particular, Andrade et al. (2016) show that models of dispersed information, such as noisy and sticky information models, must be endowed with a multivariate setup along with a drifting long-run mean to match the observed behavior of forecast disagreement. Taken together, this shows that the model introduced in Section 17.2.2.1 is able match the evolution of both the first and second moments of professional forecast data.

17.2.5.2 *Evolution of the term structure of expectations*

The estimated model allows us to study the fitted expected paths of the three variables at any specific point in time. Fig. 17.2 shows a number of "hair charts" which are a convenient way to summarize the evolution of these forecast paths. The top panel displays real GDP growth whereas the middle panels show the nominal interest rate and the underlying rate of CPI inflation.[7] The black solid lines show the actual realized data while the gray lines show the expected paths of the variable over the next 10 years once every 12 months.

The forecast paths display substantial volatility over time, typically flattening (and often inverting) at the end of economic expansions and steepening in the aftermath of recessions. This pattern is starker for nominal (and real) interest rates, as professional forecasters respond to the predictable component of monetary tightening and easing cycles. For example, the term structure of short-rate expectations inverts in early 1989 when short rates reached their local peak leading into the 1990–1991 recession. A flattening and slight inversion is also observed at the end of the 2004–2006 tightening cycle. Importantly, these estimated measures of short-rate expectations based on survey forecasts, in contrast to many model-based expected short-rate paths, are consistent with a perceived zero lower bound (ZLB) on nominal interest rates. After the short rate reached the ZLB in 2008, the term structure first flattened and then steepened again as forecasters continued to expect an eventual lift-off. This "overoptimism" about lift-off that is apparent in the short-rate expectations is mirrored by overoptimistic real GDP forecasts during the same period.

While expected nominal short rates display a significant degree of volatility, the shape of the expected path of inflation (third panel) exhibits far less variation, remaining mostly flat around the prevailing level of inflation. Professional forecasters perceive the persistent component of inflation to approximately follow a random walk. An important implication is that movements in expected nominal short rates translate almost one-to-one to expected real short rates, consistent with nominal rigidities preventing prices from adjusting in the short term.

The expected ten-year paths of short rates and inflation converge to each variable's time-varying long-run mean extracted from all available surveys of professional forecasters. These long-run projections reflect forecasters' perceptions of macroeconomic fundamentals rather than cyclical variation. Long-run forecasts have all varied substantially over the past thirty years. The long-run expected nominal short rate has gradually fallen from about 8% in the mid-1980s to about 2.5% in 2019. Much of this decline is accounted for by a secular decline in the expected long-run level of inflation, which dropped from about 6% in the early 1980s to a level of around 2.5% in the late 1990s. Since then, the perceived inflation target has remained quite stable, only showing a small dip around the Great Recession and over the last two years in our sample.

[7] In order to smooth the high volatility in this series we plot the model-based measure of underlying CPI inflation which does not include transitory shocks which are captured by an observation error.

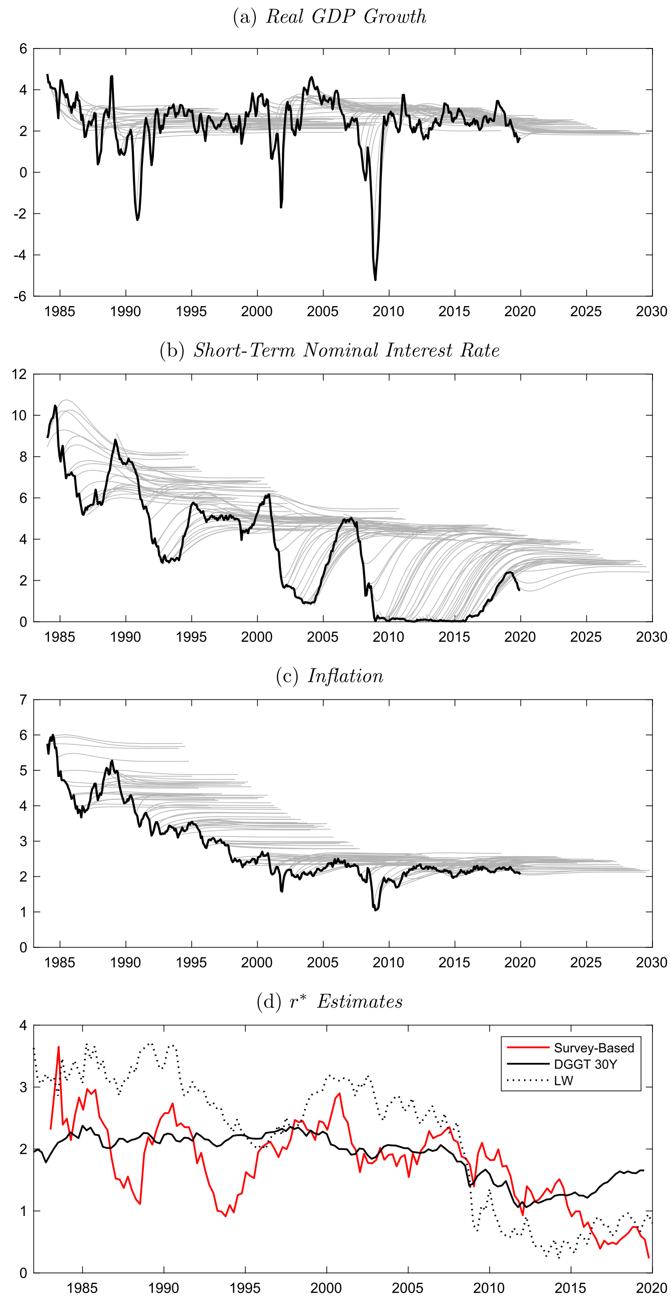


FIGURE 17.2 Estimated Forecast Paths

The figure shows fitted survey-based expectations for real output growth, the short-term nominal interest rate, inflation, and the short-term real interest rate. The top three panels show the actual variable along with the fitted survey-based forecast path up to the ten-year horizon. The bottom panel shows the long-term forecast of the real short rate (i.e., the perceived natural rate of interest) along with r^* estimates from Del Negro et al. (2018) and Laubach and Williams (2003).

Using the survey-implied term structures of expectations for the nominal short rate and inflation, the final panel shows the evolution of the long-term forecast of the real short rate (i.e., the perceived natural rate of interest).[8] The long-term expected real short rate has remained fairly stable around 2% over the 30 year period starting in 1983, but has begun to decline after 2010, falling below 1% by the end of 2014. This is consistent with long-run real GDP growth forecasts which have fallen modestly over the past 10 or so years, reaching slightly below 2% by the end of the sample. It is also in line with recent evidence on the decline of the natural real rate of interest. Summers (2014), Johannsen and Mertens (2021), Holston et al. (2017), Del Negro et al. (2018), Crump et al. (2022a) among others, have argued that long-run equilibrium real rates in the U.S. have seen a secular decline over the past decades. This chart also compares the perceived natural rate of interest based on survey data with two other estimates – those of Laubach and Williams (2003) and Del Negro et al. (2018).[9] All three estimates share a similar broad pattern – a fairly stable natural rate around 2% up until the financial crisis followed by a marked decline.

17.3 Expectations and the term structure of interest rates

Monetary policy affects the aggregate economy primarily via the term structure of interest rates. While central banks have tight control over short-term rates, the efficacy of monetary policy depends on the ability to affect longer-maturity interest rates which drive the saving and investment decisions of households and firms. Standard macroeconomic models assume that the transmission mechanism of monetary policy is given by the expectations hypothesis: yields on longer-term government bonds reflect the average short rate that investors expect to prevail over the life of the bond.

We now use the fitted term structure of expectations to evaluate how well movements in future short rate expectations explain long-term yields. We do this by decomposing observed government bond yields into an expectations hypothesis component and a residual component which we interpret as a measure of the subjective term premium perceived by professional forecasters. Because our survey-based term premiums represent the residual between yields and expected short rates, we can remain agnostic about what specifically they represent. For example, they might reflect shifts in investor risk attitudes leading to time variation in expected excess bond returns, differences between the expectations of the marginal investor and consensus expectations, or frictions in the bond market which prevent the elimination of arbitrage opportunities. Hereafter we will refer to this measure as the "term premium" for simplicity.

17.3.1 Decomposing the term structure of interest rates

We obtain zero coupon U.S. Treasury yields from the Gurkaynak et al. (2007) dataset available on the Board of Governors of the Federal Reserve's research data page.[10] The sample period is March

[8] In particular, since our model is at the monthly frequency we define the real rate as the current interest rate less the one-month ahead forecast of inflation.

[9] Data available at https://www.newyorkfed.org/research/policy/rstar and https://github.com/FRBNY-DSGE/rstarBrookings2017.

[10] See https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html.

1983–December 2019. Let $y_t(n)$ be the continuously compounded yield on an n-month discount bond and i_t the risk-free nominal short rate at time t. 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-month bond maturing in $n+m$ months:

$$f_t(n,m) = \frac{1}{n}[(n+m)y_t(n+m) - my_t(m)]. \tag{17.9}$$

Because our empirical model of expectations is estimated at the monthly frequency, we construct annual forward rates as the annual average of monthly forward rates. For example, a 4Y1Y forward would set $n = 12$ and $m = 48$. We then define forward term premiums as the difference between $f_t(n,m)$ and the expected nominal short-term rate over the n months from m months hence, which we can further decompose into the expected real short rate and expected inflation:

$$\begin{aligned} tp_t^{fwd}(n,m) &= f_t(n,m) - \frac{1}{n}\sum_{h=m+1}^{n+m} \mathbb{E}_t\left[i_{t+h}\right] \\ &= f_t(n,m) - \frac{1}{n}\sum_{h=m+1}^{n+m} \mathbb{E}_t\left[r_{t+h} + \pi_{t+h+1}\right]. \end{aligned} \tag{17.10}$$

In other words, the forward term premium is the difference between observed forwards and what would be the yield predicted by the expectations hypothesis, i.e., the average expected future short rate over the n months beginning in m months. 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 term premiums.

Fig. 17.3 uses Eq. (17.10) to decompose nominal Treasury forward rates into expected future real short rates, expected future inflation, as well as the forward term premium. The figure displays the 1Y1Y, 4Y1Y, and 9Y1Y forward horizons in the top, middle, and bottom panel, respectively. All three components of bond yields contribute to the secular decline in Treasury yields observed over the past several decades, albeit to different degrees and with different timing. At the 1Y1Y horizon, the term premium declined from about 3% in the early 1980s and stabilized around zero in the early 2000s, mimicking the path of expected inflation. At longer maturities, forward term premiums display a similar pattern, falling over the 1980s and 1990s and stabilizing in the 2000s. Since about 2010, however, longer-maturity forward term premiums again declined together with the expected real short rate. Term premiums have remained at negative levels since 2010, except for a brief uptick around the "taper tantrum" episode of 2013.

Overall, forward term premiums account for more than half of the secular decline in longer-maturity forwards. This finding of a secular decline in term premiums 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 economies have experienced sizable and persistent declines between 1990 and mid-2009. He attributes this decline to a broad-based reduction of inflation uncertainty. Our survey-based decomposition shows that even when one takes full account of the expected short rate path of well-informed economic agents (professional forecasters), there is a secular decline of term premiums. Cao et al. (2021) offer one potential explanation based on heterogeneous beliefs about short rates.

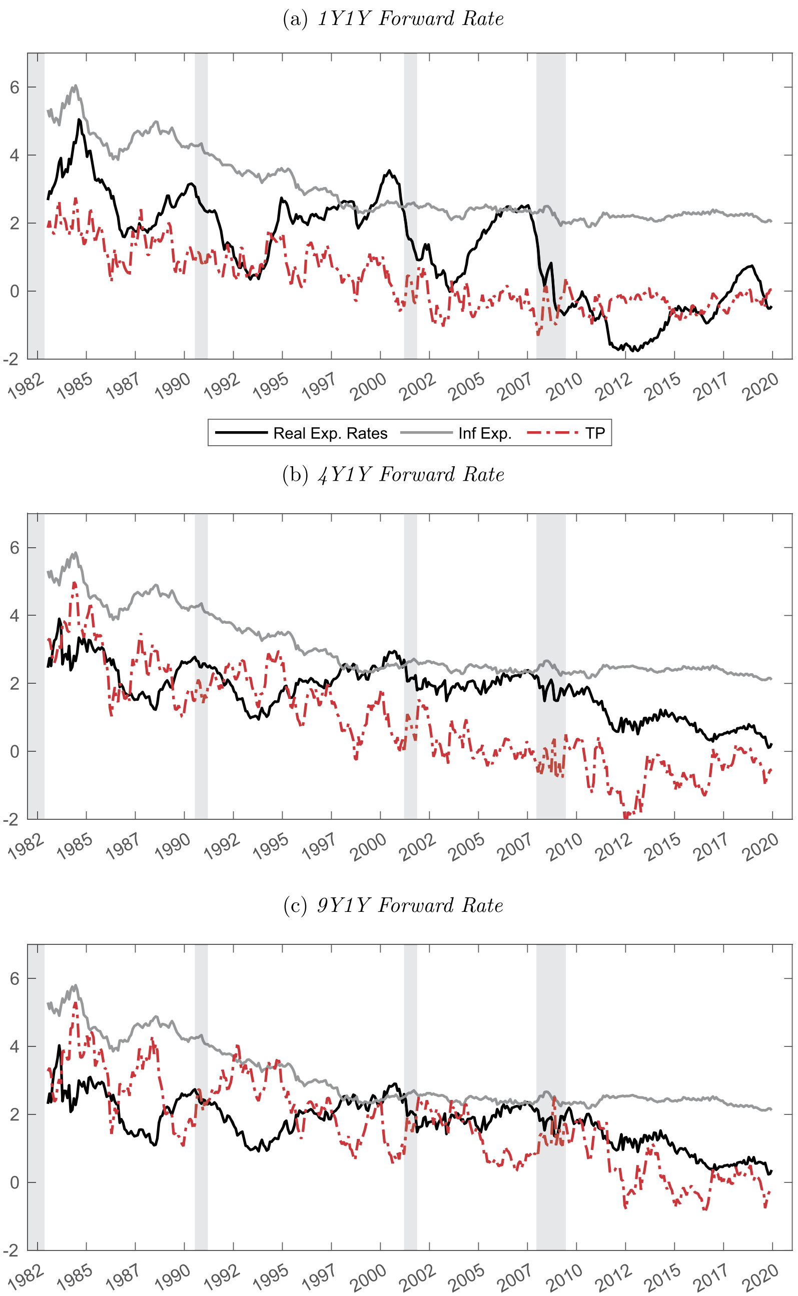


FIGURE 17.3 The Components of Treasury Forward Rates

This figure shows the decomposition of Treasury forwards into the expected short-term real interest rates ("Real exp. rates"), expected inflation ("Infl Exp.") and the nominal forward term premium ("TP"). The top panel reports results for the 1Y1Y forward rate, the middle panel for the 4Y1Y forward rate, and the bottom panel for the 9Y1Y forward rate. Treasury forwards are based on the zero coupon bond yields from Gurkaynak et al. (2007). The sample period is March 1983–December 2019.

Term premiums and survey forecasts: existing literature

Our measure of the term premium is model-free, in the sense that we simply obtain it as a residual from observed yields and observed or tightly fitted expected short rates. A few other studies have estimated term premiums using information from surveys of professional forecasters. However, they all obtain term premium estimates from no-arbitrage term structure models, fitted using observed yields and some survey forecasts of interest rates. For example, Kim and Wright (2005) and Kim and Orphanides (2012) employ survey forecasts of the nominal short rate at select horizons to discipline their estimates. Similarly, Piazzesi et al. (2015) combine survey forecasts of the short rate, inflation, and of longer-term Treasuries to distinguish subjective beliefs (i.e., surveyed forecasters), objective beliefs (i.e., those of a statistician endowed with full-sample information) and subjective risk premiums. All these models assume a small-scale stationary VAR governing the dynamics of short rates and term premiums and, therefore, do not explicitly allow for low-frequency variation in expected short-rate paths which we have shown is a key element of actual short-rate expectations. In more recent work, Cieslak and Povala (2015), Bauer and Rudebusch (2020), and Feunou and Fontaine (2021) incorporate shifting endpoints for macroeconomic variables into models of the term structure of interest rates.

Variance decomposition of forwards

Fig. 17.3 shows that at higher frequencies, forward term premiums and expected real rates feature significant variability across all maturities. Crump et al. (2022a) perform a variance decomposition of the components to quantify their relative contributions. They highlight the pivotal role of term premiums in accounting for yield variation. Expected real rates explain about 60% of the variance of the one-year yield while expected inflation and the term premium account for about 30% and 10%, respectively. Expected real rates also explain just shy of 50% and 30% of forward rates at the one- and two-year maturity. However, their importance then declines sharply at longer maturities, accounting for less than 20% at forward horizons beyond four years. In contrast, term premiums only explain a small amount of variation at the very short end, but account for about 50% of the variation in forward rates at intermediate and longer maturities. The share of variance explained by expected inflation is relatively stable at around 30% across the maturity spectrum.

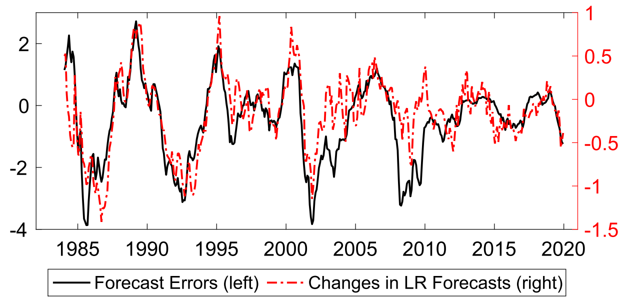
Since yields and forward rates are quite persistent, it is instructive to investigate the decomposition of their *changes*. The contribution of term premiums to the variation of monthly changes in forward rates is substantial at all horizons and increases from 75% at the one-year forward horizon to over 90% at longer forward horizons. In contrast, expected real short rates only account for 20% of the month-to-month variation at the one-year forward horizon, and this contribution quickly drops to zero at longer maturities. Expected inflation also accounts for a negligible share of the variance of forward rate changes across maturities.

Given the considerable volatility of expected short rates, how can we explain the dominant role of term premiums in accounting for the variability of longer-maturity bond yields? Crump et al. (2022a) show that this is driven by the fact that changes in expectations *co-move very little* with changes in yields, except at short forecast horizons.

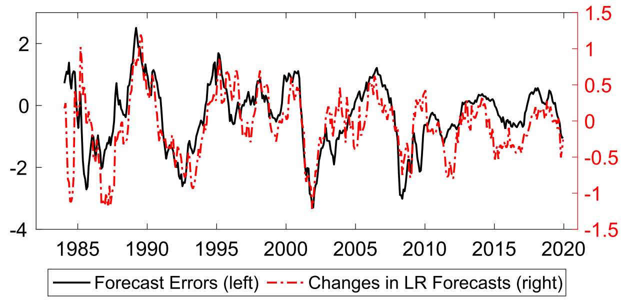
Short-run forecast errors and the components of yields

To gain further intuition about the determinants of longer-term interest rates we return to the simple model of Section 17.2.1. Revisions in long-term expectations should be positively related to short-term forecast errors. The top two panels in Fig. 17.4 show this is indeed the case for both nominal

(a) *Nominal short rate forecast errors vs. Revisions in Long-run (9Y1Y) Forecasts*



(b) *Real short rate forecast errors vs. Revisions in Long-run (9Y1Y) Forecasts*



(c) *Nominal short rate forecast errors vs. Changes in the 9Y1Y Term premium*

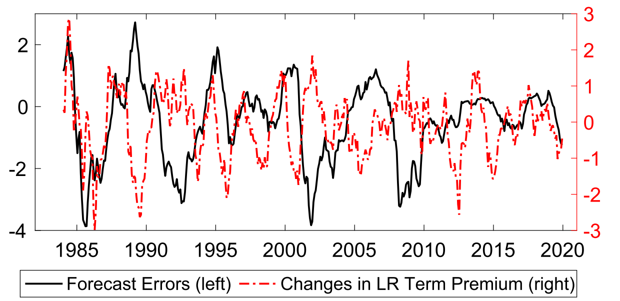


FIGURE 17.4 Short Rate Forecast Errors vs. Changes in Long-Run Forecasts

This figure compares forecast errors with changes in long-run expectations and term premiums. Nominal and real short-rate forecast errors are calculated as the 12-month ahead forecast error. Revisions to long-run forecasts and changes in term premiums are defined as changes relative to 12 months ago. The sample period is January 1984–December 2019.

and real short rates. The comovement is striking with correlations of 74% and 63%, respectively. This implies that market participants update their views about the long-term mean of the nominal and real short rate in response to new information captured by forecast surprises. In contrast, the bottom panel showing both short-term forecast revisions and our measure of the term premium shows no discernible relation; furthermore, the correlation of only −15% clearly indicates that forces other than forecast errors determine the behavior of term premiums.

Cross-sectional comovement of the components of yields

We have discussed the weak comovement of expected short rates and forward rates in the time dimension. Next, we uncover another important difference by looking across bond maturities. A long literature in finance has documented that government bond yields feature substantial comovement across maturities (e.g., Garbade, 1996; Scheinkman and Litterman, 1991). This is also true in our sample: the first two principal components extracted from one-year forward rates, from zero-to-nine-years ahead, explain 97% and 3% of their joint variation. The loadings of these principal components confirm the common interpretation as level and slope of the yield curve.

Based on our decomposition of forwards into expected short rate and term premium components, we can parse out the sources of the strong cross-sectional correlation. Almost half of the variance of the level factor is explained by term premiums, one third by expected inflation and the remaining 20% by expected real short rates. Also consistent with the variance decompositions for individual forwards, almost 90% of the month-to-month variation in the level factor and more than three quarters of the year-over-year variation are explained by term premiums. The expectations components are somewhat more important for the slope factor: 85% of its variation is accounted for by expected real short rates, about 10% by expected inflation, and the remainder by term premiums. However, more than two-thirds of the month-to-month variation of the slope factor is explained by term premiums, in line with the above finding that only a small share of the yield curve variation at higher frequencies is driven by expectations.

Fig. 17.5 visualizes the importance of term premiums for the strong comovement across maturities. It shows 12-month changes in short- and long-maturity forward rates (top panel), expected rates (middle panel), and forward term premiums (bottom panel) for the 1Y1Y and 9Y1Y forward maturities. The figure documents that across maturities survey-based term premiums comove much more strongly than survey-based expected future short rates or even forwards themselves. Twelve month changes in expected rates at short and long horizons are only weakly correlated, whereas changes in forward term premiums comove in lockstep, at least until the mid to late 2000s.

Note that the strong comovement of term premiums is a feature of the data and is not imposed in any way in our analysis as term premiums are obtained as residuals between observed forwards and expected average short rates. Term premiums equal average expected short-term excess holding period returns over the life of a bond, see, for example, Cochrane and Piazzesi (2008). Hence, our finding of a strong comovement of term premiums across maturities is consistent with a strong factor structure in expected excess returns as also documented by Cochrane and Piazzesi (2005). Interestingly, we observe a break in this comovement around the financial crisis. This might be capturing the unconventional monetary policy actions undertaken during that period, with particularly strong effects on term premiums of longer-term bonds.

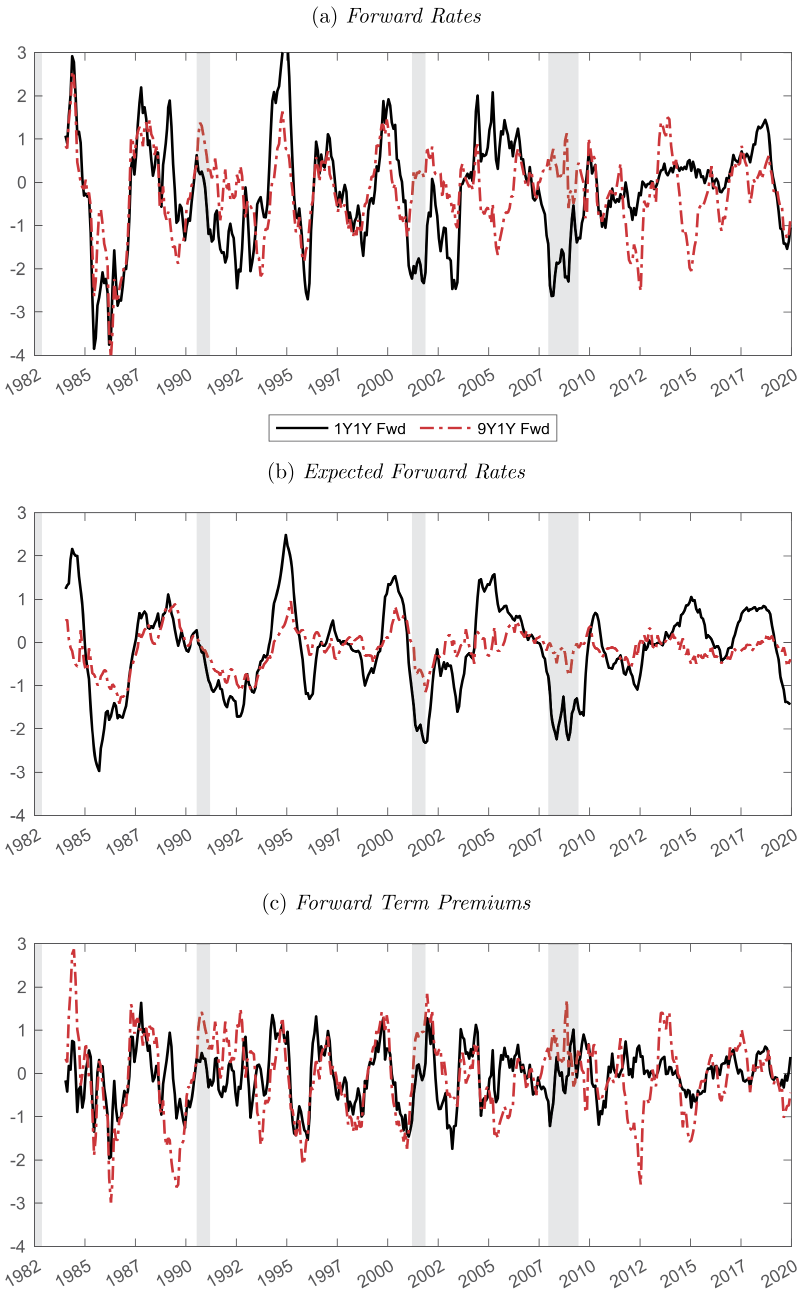


FIGURE 17.5 Comovement of Expected Rates and Term Premiums

This figure shows 12-month changes in forward rates (top chart), expected forward nominal short-term rates (middle chart) and the forward term premium (bottom chart) for the 1Y1Y and 9Y1Y forward maturities. The sample period is January 1984–December 2019.

Forecast accuracy

The previous results based on the decomposition of longer-term interest rates into expected short rate paths and term premiums rely on the quality of survey-based short-rate forecasts as representative measures of expectations. While a formal forecast evaluation is beyond the scope of this chapter, we illustrate the precision of survey-based short-rate expectations by visually comparing them with the expected short rates implied by the forward curve.[11] As discussed above, these expected short-rate paths are consistent with the expectations hypothesis in the absence of any term premiums.

In fact, forward rates are often interpreted as market-based (or risk-neutral) expectations and used as an alternative to professional surveys. Cochrane (2017) argues that "risk-neutral probabilities are a good sufficient statistic to make decisions." Crump et al. (2022a) show that forward-based short-rate paths display very different dynamics compared to survey-based short-rate expectations. They are typically steeper and lie above those of surveys, in line with the notion of a time-varying term premium that is positive on average. Fig. 17.6 compares the forecast performance, as measured by the difference of squared errors over time for different forward horizons. The main takeaway is that our survey-based measure of short-rate expectations has on average performed substantially better in predicting short rates than the forward curve, and the performance gap widens with the forecast horizon. This finding is consistent with the notion that forecasters do not simply report risk-neutral expectations extracted from the forward curve when being surveyed about short rates, a conclusion also shared by Adam et al. (2021) and Chapter 16 in this Handbook. At the same time both measures have come closer in the past 20 or so years, reflecting the overall decline of term premiums. In addition, forward rates appear to have performed somewhat better at intermediate horizons since around 2010: this is consistent with the notion that professional forecasters were more optimistic about the normalization process at that time, while terms premiums where compressed. For a more general discussion of forecasts based on market prices, see Chapter 14 in this Handbook.

Summing up, we offer two conclusions. First, we document that the term structure of short-rate expectations is fairly volatile and its behavior is consistent with market participants frequently updating their beliefs about the medium- to long-term evolution of the policy rate. Second, we show that the term structure of interest rates is only partly driven by short-rate expectations. The residual component, the term premium, plays a key role in determining the evolution of interest rates at longer maturities. This component is often left unaccounted for in standard macroeconomic models used for monetary policy analysis.

17.4 The term structure of expectations in structural models

So far, our analysis of the term structure of expectations has yet to take a stand on the rationality of expectations. We now develop a dynamic structural general equilibrium model in which the subjective

[11] Crump et al. (2011) study the forecast accuracy of professional forecasts for the federal funds rate based on BCFF data. They show that forecast accuracy is negatively correlated with the variation in the federal funds rate (i.e., forecast accuracy is generally worse during easing and tightening cycles). Moreover, they show that forecast accuracy has been consistently improving across tightening cycles over their sample period (1982 through mid-2011). In contrast, there is no such improvement when the forecast evaluation is restricted to easing cycles. Cieslak (2018) and Schmeling et al. (2021) investigate the relationship between short-rate forecast errors and the dynamics of returns on fixed-income assets.

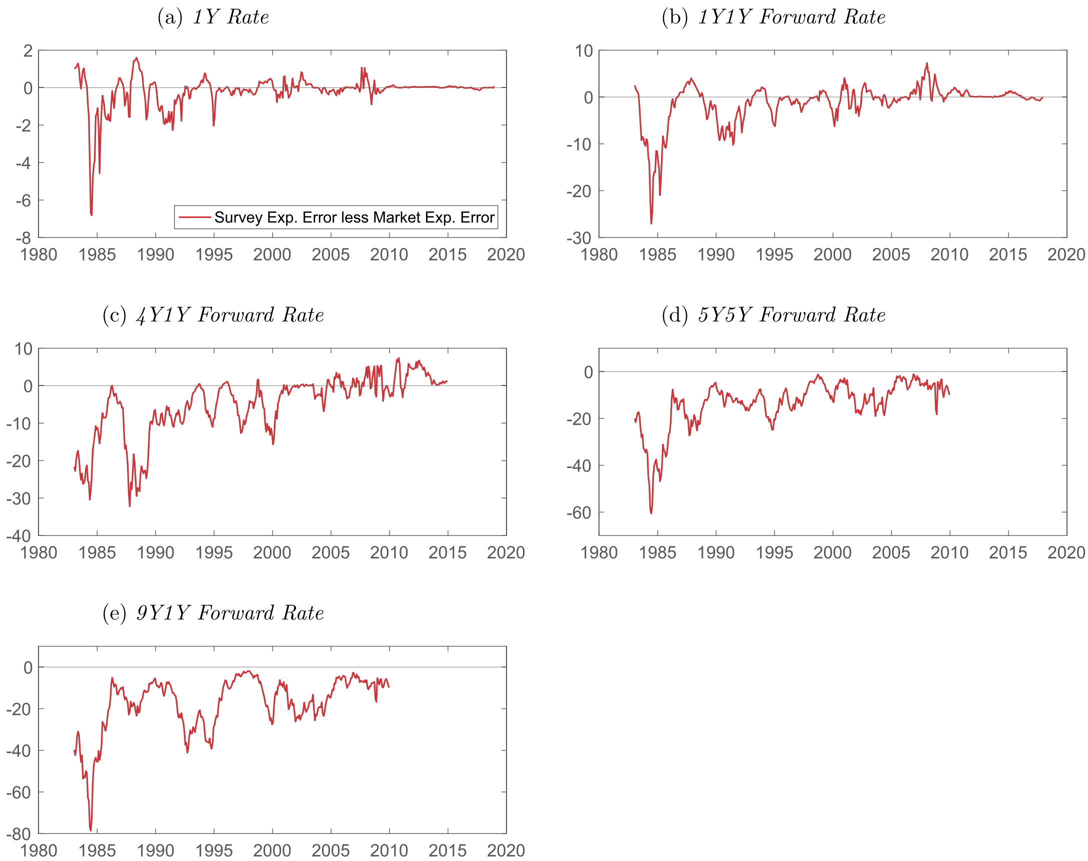


FIGURE 17.6 Forecast Errors

This figure shows the difference between the mean-square forecast error (MSFE) of survey expectations and the MSFE of market expectations. Values below zero indicate that survey expectations have a lower MSFE. The sample period is January 1983–December 2019.

beliefs of households and firms are consistent with our reduced-form forecasting model. The structural model has the equilibrium property that subjective beliefs are more persistent than the true data generating process. Household and firm expectations exhibit extrapolation bias, consistent with empirical and laboratory evidence. That subjective and objective forecasting models differ represents a departure from full-information rational expectations.

An advantage of a structural model is that we can estimate how different economic shocks determine forecast errors and the term structure of expectations. In principle, this permits addressing some earlier questions—such as the determinants of real neutral rates and inflation expectations—left unanswered by the reduced-form model. Having a structural theory of long-term expectations allows the analysis of important practical policy questions that rational expectations models cannot answer. For example, we argue that our framework provides a coherent definition of expectations anchoring, and clear predictions of the economic conditions in which expectations will be anchored or un-anchored. We show this has important implications for monetary and fiscal policy.

17.4.1 A general structural model

Dynamic stochastic general equilibrium (DSGE) models describe the behavior of economic agents solving infinite-horizon intertemporal decision problems in a market economy.[12] The equilibrium behavior of the economy therefore depends on the expected future path of aggregate variables such as prices, quantities and policy variables. The log-linear solution of a typical DSGE model can be expressed as

$$A_0 z_t = \sum_{s=1}^{n} A_n \left(E_t \sum_{T=t}^{\infty} \lambda_s^{T-t} z_{T+1} \right) + A_{n+1} z_{t-1} + A_{n+2} \varepsilon_t,$$

where the vector z_t collects all model variables in deviation from their nonstochastic steady-state values; the vector ε_t collects exogenous innovations; $\lambda_s \in 1, \ldots, n$ are discount factors resulting from the agents' decisions rules; A_i for $i \in 1, \ldots, n+2$ coefficient matrices; and

$$E_t = \int_0^1 E_t^i di$$

average beliefs across agents. This representation holds for arbitrary beliefs, including rational expectations.[13] Under rational expectations, the model has the equilibrium solution

$$z_t = \Psi z_{t-1} + \Psi_\varepsilon \varepsilon_t.$$

The matrix Ψ measures the transitional dynamics around the steady state, and Ψ_ε captures the economy's impact response to innovations. Agents are fully informed about the economy's steady-state; they face no information frictions leading to fluctuating long-run beliefs.

Now introduce an information friction to this full information benchmark. Consistent with our simple model in Sections 17.2.1 and 17.2.2 agents are uncertain about the long run. Expectations are then formed using the forecasting model

$$z_t = S\omega_t + \Psi z_{t-1} + \nu_t, \tag{17.11}$$

$$\omega_t = \omega_{t-1} + \eta_t, \tag{17.12}$$

where both the drift ω_t and the innovations ν_t are unobserved by agents.[14] Reflecting the perceived slow-moving drift we further assume agents' priors imply $E\left[\eta_t \eta_t'\right] = \kappa_\omega^2 \times E\left[\nu_t \nu_t'\right]$ where $0 < \kappa_\omega \ll 1$.

[12] For a discussion of using survey data to help estimate DSGE models, see Chapter 18 in this Handbook.

[13] See Eusepi et al. (2020) for a detailed example and derivations. For an analysis of real-business-cycle theory, see Eusepi and Preston (2011).

[14] For simplicity we assume the matrix Ψ which governs short-run dynamics is known to agents.

The matrix S is a selection matrix which maps the set of drifts to a larger vector with the same dimension as z_t.[15] This signal extraction problem delivers the now familiar Kalman filter updating

$$\begin{aligned}\hat{\omega}_{t+1} &= \hat{\omega}_t + \kappa_\omega S' \left(z_t - S\hat{\omega}_t - \Psi z_{t-1}\right) \\ &= \hat{\omega}_t + \kappa_\omega S' \left(z_t - z_{t|t-1}\right),\end{aligned} \tag{17.13}$$

where $z_t - z_{t|t-1}$ denotes the short-term forecast error. Given the estimate $\hat{\omega}_t$, forecasts at any horizon $T > t$ are determined as

$$E_t z_T = \Psi^{T-t} z_t + \sum_{j=0}^{T-t} \Psi^j S\hat{\omega}_t \tag{17.14}$$

while their estimate of the time-varying mean is

$$\lim_{T\to\infty} E_t z_T = (I - \Psi)^{-1} S\hat{\omega}_t. \tag{17.15}$$

As before, beliefs are characterized by a "shifting end-point" model.

Evaluating expectations in the structural equations and combining with the belief updating equation gives the true data-generating process:

$$z_t = \Gamma(\Psi) S\hat{\omega}_t + \Psi z_{t-1} + \Psi_\varepsilon \varepsilon_t, \tag{17.16}$$

$$\hat{\omega}_{t+1} = \left[I + \kappa_\omega S' \left(\Gamma(\Psi) - I\right) S\right] \hat{\omega}_t + \kappa_\omega S' \Psi_\varepsilon \varepsilon_t, \tag{17.17}$$

$$z_t - z_{t|t-1} = (\Gamma(\Psi) - I) S\hat{\omega}_t + \Psi_\varepsilon \varepsilon_t, \tag{17.18}$$

where the matrix $\Gamma(\Psi)$ is a composite of structural parameters Ψ. Provided $\hat{\omega}_t$ is stationary, the rational expectations equilibrium represents a limiting case of this model with $\kappa_\omega \to 0$.[16]

Comparison with the reduced-form model of earlier sections reveals three new properties of structural models. First, forecast errors are determined by long-run drifts and model innovations. This permits giving a structural interpretation to the economic determinants of the term structure of expectations. Second, because economic decisions depend on the estimated drifts, dynamics exhibit self-referentiality. Beliefs affect realized data, and the data in turn affect beliefs. The matrix $\Gamma(\Psi)$ determines the extent to which equilibrium outcomes depend on beliefs.[17] Third, and related, the model displays *extrapolation bias* as an equilibrium property.[18] Subjective beliefs have a unit root, while the true data-generating process implies beliefs evolve as a stationary vector autoregressive process, with eigenvalues determined by the matrix

$$I + \kappa_\omega S' \left(\Gamma(\Psi) - I\right) S.$$

15 For example, if agents observe purely exogenous shocks, these elements of z_t will have no drift.

16 That is, the eigenvalues of $I + \kappa_\omega S' (\Gamma(\Psi) - I) S$ are inside the unit circle.

17 In the case that $\Gamma(\Psi) = I$, the model would have a self-confirming equilibrium (see Sargent 1999). In general, $\|\Gamma(\Psi)\| < 1$ so that beliefs are only partially self-fulfilling. This implies beliefs in equilibrium are stationary variables.

18 See Fuster et al. (2010), Piazzesi et al. (2015), and Bordalo et al. (2020) along with the discussion in Section 17.2.4.

The wedge between subjective and objective beliefs provides a metric of the importance of the information friction from belief formation. The use of a structural model permits understanding how structural shocks and economic policy affect this wedge.

17.4.2 The New Keynesian model

To give some context for these properties, consider the simple New Keynesian model given by the aggregate demand and supply equations:

$$x_t = E_t \sum_{T=t}^{\infty} \beta^{T-t} \left[(1-\beta)\, x_{T+1} - \left(i_T - \pi_{T+1} - r_T^n\right)\right], \tag{17.19}$$

$$\pi_t = E_t \sum_{T=t}^{\infty} (\xi\beta)^{T-t} \left[\kappa x_T + (1-\xi)\, \beta \pi_{T+1}\right], \tag{17.20}$$

where π_t is inflation, x_t the output gap, i_t is the one-period nominal interest rate, the instrument of monetary policy, and r_t^n the natural rate of output, an exogenous first-order autoregressive process. The parameters $0 < \beta, \xi < 1$ are the household discount factor and the probability that the firm cannot re-optimize their price in any given period. These parameters determine the slope of the aggregate supply curve as $\kappa \equiv (1-\xi\beta)(1-\xi)/\xi > 0$. The model is closed with the assumption that the central bank adopts the simple rule

$$i_t = \varphi \pi_t, \tag{17.21}$$

where $\varphi > 1$ is a policy parameter.

Under rational expectations, there is a unique bounded equilibrium of the form

$$z_t = \Psi r_{t-1}^n + \Psi_\epsilon \epsilon_t^n,$$

where $z_t = (\pi_t, x_t, i_t)'$ and ϵ_t^n the innovation to the natural rate of interest. Under imperfect information beliefs are given by Eqs. (17.11) and (17.12) with $\omega_t = \left(\omega^\pi, \omega^x, \omega^i\right)$, S an identity matrix, and lagged state vector replaced by the natural rate of interest, so that $z_{t-1} \equiv r_{t-1}^n$. With this replacement, Eq. (17.13) continues to determine the updating of beliefs and Eqs. (17.16), (17.17) and (17.18) the true data-generating process.

Extrapolation bias

Extrapolation bias is an equilibrium property of the model driving a wedge between subjective and objective beliefs. To illustrate in the case of interest rates, consider an economy where prices are nearly flexible, that is $\xi \to 0$, and monetary policy is understood to be implemented using the simple rule so that beliefs satisfy $\omega^i = \varphi\omega^\pi$. Long-term interest rate forecasts are revised in response to short-term forecast errors according to

$$\begin{aligned} \hat{\omega}_{t+1}^i &= \hat{\omega}_t^i + \kappa_{\omega_i} \left(i_t - \hat{\omega}_t^i - \Psi_i r_{t-1}^n\right) \\ &= \hat{\omega}_t^i + \kappa_{\omega_i} \left(i_t - i_{t|t-1}\right), \end{aligned} \tag{17.22}$$

where Ψ_i is the element of Ψ corresponding to the rational expectations solution for the interest rate. Shocks to the natural rate of interest induce interest rate surprises leading to shifts in long-term beliefs—indeed, the whole term structure of expectations.

Taking the difference between subjective interest-rate forecasts, $\hat{E}_t$, and model-consistent projections under the true data-generating process, E_t, gives the wedge in any future period $T > t$

$$\begin{aligned}\hat{E}_t i_T - E_t i_T &= \left(1 - \frac{\varphi^{-1} - \beta}{1 - \beta}\right) \hat{\omega}_t^i \\ &= \kappa_{\omega_i} \left(1 - \frac{\varphi^{-1} - \beta}{1 - \beta}\right) \sum_{j=0}^{\infty} \left(1 - \kappa_{\omega_i} \frac{1 - \varphi^{-1}}{1 - \beta}\right)^j \epsilon_{t-1-j}^n,\end{aligned} \tag{17.23}$$

where the second equality follows from writing current interest rate beliefs as a function of the entire past history of natural rate innovations. Both the size of the learning gain and monetary policy regulate the degree of extrapolation bias. Depending on the expectations formation mechanism and monetary policy, transitory natural-rate shocks may have long-lived effects. For example, a sequence of positive shocks to the natural rate leads to an increase in the wedge, leading to a steeper path of the interest rate compared to that path which would be expected under the true data-generating process. This wedge has empirical and policy implications.

Implications for aggregate dynamics

Eusepi et al. (2020) explore the empirical and policy implications of extrapolation bias in general equilibrium. They estimate a medium-sized DSGE model using U.S. macroeconomic data, including the term structure of interest rate and inflation expectations from professional forecasters. The wedge between subjective and objective beliefs is central to understanding the evolution of macroeconomic data and therefore U.S. monetary history and to understanding the ability of the Federal Reserve to pursue active stabilization policy.[19]

Fig. 17.7 summarizes some relevant results. The top and middle panel plot the model-implied five-to-ten (black solid line) and one-to-ten year (blue dashed–dotted line) expectations for both inflation and nominal short-term interest rates along with survey measures of long-term expectations from Blue Chip Financial Forecasts and Blue Chip Economic Indicators (red dots and blue squares, respectively). The gray solid lines show the actual quarterly realizations of inflation and short-term interest rates. The DSGE model matches the behavior of long-term expectations well, while at the same time also fitting shorter-term survey forecasts (not shown).[20] Low frequency movements in long-term expectations provide a compelling theory of trend inflation. At higher frequencies, long-term expectations display cyclical variation and are clearly correlated with inflation and short-term interest rates. The estimates reveal that monetary policy shocks explain the sustained rise in long-term inflation and interest rate expectations over the 1970s.

The bottom panel plots the *subjective* one-to-ten-year-ahead expectation for the short-term nominal rate (black solid line) together with the *model-consistent* expectation (blue dashed line) held by an

19 See Giannoni and Woodford (2004).

20 See Eusepi et al. (2020) for further details. The estimation allows a structural break in the learning gain at the end of the 1990s.

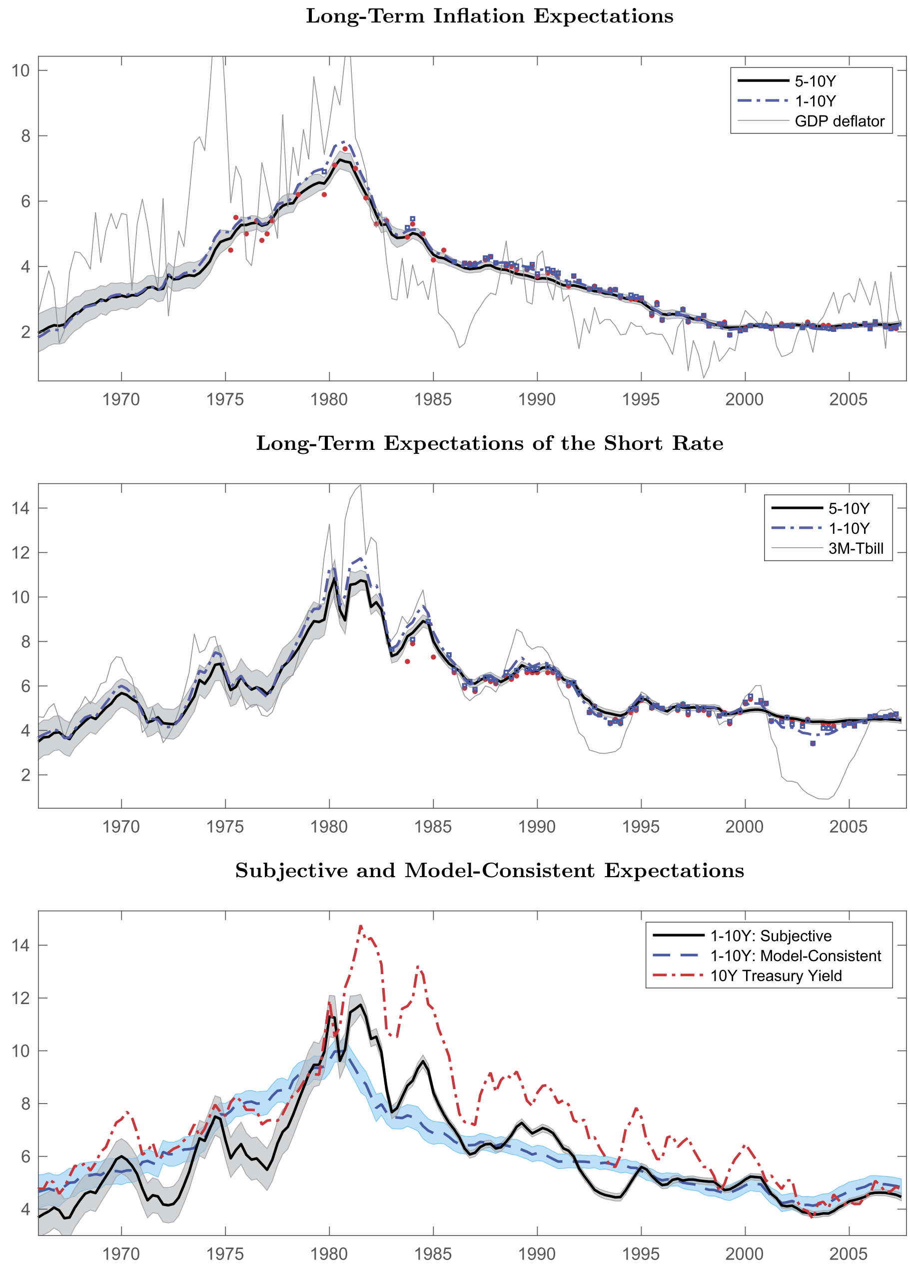


FIGURE 17.7 Long-Term Expectations from a DSGE model

The top and middle panels show the evolution of long-term survey expectations data for inflation and the short-term nominal rate of interest. Actual variable (gray), survey expectations for 5 to 10 year average and 1 to 10 year average (red dots and blue squares, respectively), the model implied 1–10 year average expectations (the blue dashed–dotted line), and the model implied 5–10 year average expectations with 95% coverage interval (black solid line and gray shaded area). The bottom panel shows the subjective (black solid) and model consistent expectations (blue dashed) with 95% coverage interval (gray shaded area). Then red dashed–dotted line defines the 10-year Treasury yield.

outside observer knowing the true data-generating process. Because of extrapolation bias subjective expectations display weaker mean reversion and higher volatility compared to objective expectations. This wedge has economic content. Model consistent expectations would correctly predict short-term rates to fall more quickly from the peak of the Great Inflation over the subsequent Great Moderation period: a lower expected path of the short-term rate in turn would deliver lower equilibrium long-term interest rates. Similarly, at the beginning of the sample, loose monetary policy flattens the term structure of interest rates and forecasters systematically under-predicted the significantly higher interest rates observed over the 1970s. These discrepancies result in excessive stimulus to real activity in the 1970s and excessive restraint in the 1980s.

The figure also illustrates that the wedge between subjective and objective expectations varies over time: over the last decade of the sample this wedge shrinks significantly as long-term expectations stabilize. Furthermore, ten-year Treasury yields (red dash-dotted line) move together with yields implied by subjective expectations, but still leave a significant residual, consistent with the reduced-form model of Section 17.3. Finally, note that the new Keynesian model satisfies the expectations hypothesis of the yield curve. The fact that subjective yields differ markedly from objective yields represents a strong rejection of the expectations hypothesis under rational expectations. As shown by Sinha (2016), learning models can explain rejections of the expectations hypothesis of the yield curve identified by Campbell and Shiller (1991). Econometric tests that assume rational expectations are misspecified when financial market participants are Bayesian, learning about the long-run.

17.4.3 Implications for monetary and fiscal policy

The previous example adduces further evidence that long-term movements in expectations of inflation and interest rates are tied to short-term forecast errors. Eusepi et al. (2020) show that these properties of long-term expectations have implications for monetary policy. In contrast to a full-information rational expectations model, a central bank cannot fully stabilize the macroeconomy, even in the case of demand shocks. The degree to which stabilization policy is compromised depends on how sensitive long-term expectations are to short-run forecast errors. As long-term expectations become less stable, aggressive aggregate demand management becomes infeasible: large movements in policy rates translate into volatility in long rates and therefore aggregate demand. However, when long-term expectations are quite stable, model predictions are much closer to those of a rational expectations analysis. The constraint posed by the term structure of interest rate expectations is quantitatively important.

That activist stabilization policy is undesirable contrasts with earlier papers by Ferrero (2007), Orphanides and Williams (2007), and Molnar and Santoro (2013). These papers emphasize how departures from rational expectations can alter the short-run trade-off in the new Keynesian Phillips curve and conclude that optimal policy should be more aggressive than a rational expectations analysis. However, this literature makes the assumption that the central bank can directly control aggregate demand. Accounting for the transmission mechanism of monetary policy turns this result on its head, because aggressive adjustment of overnight rates creates volatility in the term structure of interest rate expectations.

These papers assume a single constant gain. Building on work by Marcet and Nicolini (2003), Milani (2014), and Cho and Kasa (2015), Carvalho et al. (2021) develop a theory in which the sensitivity of long-run inflation expectations to short-run inflation surprises depends on recent forecasting performance. Firms do not know the inflation target and must learn it from observed inflation data. In response to large and persistent forecast errors, firms doubt the central bank's commitment to the inflation target. They switch from a decreasing gain algorithm to a constant gain algorithm to better track changes in the inflation target. Because the forecasting model is endogenous, the sensitivity of long-term expectations to forecast errors depends on historical forecasting performance. The relationship between short-run forecast errors and long-run expectations is time varying. In this way the model gives a coherent definition of "anchored" inflation expectations as a situation in which expectations display declining sensitivity to forecast errors. The model fits professional forecast data exceptionally well both in the United States and a range of other countries. Importantly, the empirical model predicts various periods of poorly anchored expectations. Gáti (2021) considers optimal monetary policy in this environment, confirming the insights of Eusepi et al. (2020): better anchored expectations permit aggressive monetary policy.

Building on Eusepi et al. (2020), Eusepi et al. (2021) explore the implications for optimal monetary policy at the zero lower bound. Their model addresses the common practical concern that long-term inflation expectations might become un-anchored and drift downwards in response to a large negative demand shock. They show learning about the long run complicates monetary policy requiring an extended period of zero interest policy because expectations themselves, if sufficiently pessimistic, can cause the zero lower bound to be a constraint on policy actions. The optimal forward guidance policy is front-loaded and displays an insurance principle: aggressive responses to a negative demand shock are required to support inflation expectations in the case of a persistent deterioration in economic conditions. However, policy is too stimulative in the case of transitory disturbances. These policy implications are strikingly different to Eggertsson and Woodford's (2003) rational expectations analysis.

Introducing fiscal and debt management policy further complicates inflation control in this class of models. Eusepi and Preston (2012) and Eusepi and Preston (2018) show that when households are uncertain about their long-run tax obligations, modeled in the same way as uncertainty about long-run inflation or interest rates, then Ricardian equivalence fails to hold, even when the fiscal authority has access to lump-sum taxation. Movements in expectations about taxes, inflation, and interest rates generate shifting valuations of the public debt and the expected tax burden attached to that debt. The resulting wealth effects on aggregate demand complicate stabilization policy, fundamentally changing the economy's response to different kinds of disturbances. These effects are larger for higher levels of debt and for moderate debt maturities, and quantitatively important for debt levels observed for the United States and other countries since the Great Recession. These results are relevant for analyzing inflation policy over the coming decade, given the substantial debt-financed stimulus packages in response to the global pandemic.

17.5 Conclusions and further directions

This chapter has provided a simple expectations formation mechanism to fit and study the term structure of expectations. Observed survey-based measures of expectations are consistent with forecasters frequently revising their long-term outlook. In particular, these revisions are partly associated with their short-term forecast errors, as predicted by standard statistical models of trend and cycle decomposition. This holds not only for the consensus term structure of expectations but also for individual forecasts. In addition to fitting consensus expectations, the proposed model provides valuable insights into the sources of forecast dispersion from short to long horizons.

In the final section, we consider the implications of this expectations formation mechanism in DSGE models. Here additional information frictions are imposed. In particular, economic agents are boundedly rational and do not know the correct data generating process: consistent with much empirical evidence, they tend to overextrapolate from recent developments. Having estimated the models using the term structure of expectations, we show that the proposed expectations formation mechanism has profound implications for monetary and fiscal policy design when compared with the benchmark of rational expectations.

The work explored also suggests interesting future avenues of investigation. First, both reduced-form and structural models should allow for time-varying components in the expectations formation process. As discussed in the last section, agents' model validation process can lead to state-dependent sensitivity of revisions of long-term expectations to short-term forecast errors. But time- and state-dependence of information frictions can be more general. For example, the agents' ability or willingness to process information likely depends on the associated costs and benefits which may change with the state of the economy.

Second, while models of information frictions with dispersed information are now ubiquitous in macroeconomics, these models mostly focus on forecast dispersion over the short-term. Incorporating learning about the long run in structural models of dispersed information could deliver important implications for both business cycle analysis and policy design.

Third, our measure of consensus expectations suggests that the term structure of interest rates is driven only partly by the term structure of policy rate expectations. An overwhelming majority of monetary models used for policy analysis instead assumes that the only transmission channel of monetary policy is via short rate expectations. The results in this chapter help better quantify the importance of this channel but also highlight the importance of additional channels, including variation in term premiums, forecast dispersion or failure of equilibrium asset pricing restrictions grounded on the assumption of perfect information and rational expectations.

Finally, while the reduced-form framework we have introduced offers a fairly flexible specification that is able to provide a tight fit to the observed survey data, when incorporating the expectations formation mechanism in a DSGE setup we made specific assumptions about information frictions. While the literature has made remarkable progress in using survey data to select among competing theories of expectations formation, the jury is still out. The properties of the term structure of expectations that this chapter summarizes can be used to make further gains in selecting the models that best describe the data, for example, by studying the dynamic response of the term structure of expectations to specific macroeconomic shocks.

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