

Crump, Richard K.; Eusepi, Stefano; Moench, Emanuel

Working Paper

The term structure of expectations and bond yields

Staff Report, No. 775

Provided in Cooperation with:

Federal Reserve Bank of New York

Suggested Citation: Crump, Richard K.; Eusepi, Stefano; Moench, Emanuel (2016) : The term structure of expectations and bond yields, Staff Report, No. 775, Federal Reserve Bank of New York, New York, NY

This Version is available at:

<https://hdl.handle.net/10419/146674>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Federal Reserve Bank of New York
Staff Reports

The Term Structure of Expectations and Bond Yields

Richard K. Crump
Stefano Eusepi
Emanuel Moench

Staff Report No. 775
May 2016



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 authors 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 authors.

The Term Structure of Expectations and Bond Yields

Richard K. Crump, Stefano Eusepi, and Emanuel Moench

Federal Reserve Bank of New York Staff Reports, no. 775

May 2016

JEL classification: D84, E44, G12

Abstract

How much do term premiums matter for explaining the dynamics of the term structure of interest rates? A lot. We characterize the expected path of nominal and real short-rates as well as inflation using the universe of U.S. surveys of professional forecasters covering more than 500 survey-horizon pairs. We obtain term premiums as the simple difference between observed government bond yields and survey-based expected average short rates. Our term premiums measured directly based on expectations accommodate perceived structural change and learning effects, are consistent with a lower bound on nominal interest rates, and uncover a number of important facts: 1) the bulk of the variation in medium- and long-term bond yields is driven by term premiums, not expected short rates or inflation; 2) term premiums co-move more strongly across maturities than expected short rates or even yields themselves; 3) the term premium, not the term spread or the expected path of future short rates, predicts quarterly real output growth; 4) macroeconomic factors are important drivers of term premiums, with demand shocks playing the most prominent role; and 5) the secular decline of U.S. long-term bond yields over the past thirty years is primarily the result of a decline of expected inflation and term premiums while expected future real rates have fluctuated around 2 percent.

Key words: term premiums, expectations formation, survey forecasts, monetary policy, business cycle fluctuations

Crump, Eusepi: Federal Reserve Bank of New York (e-mail: richard.crump@ny.frb.org, stefano.eusepi@ny.frb.org). Moench: Bundesbank (e-mail: emanuel.moench@bundesbank.de). The authors thank Tobias Adrian, Nina Boyarchenko, Carlos Carvalho, Dean Croushore, Domenico Giannone, David Lucca, Monika Piazzesi, Jonathan Wright, and participants at the 2015 CIRANO Real-Time Workshop and PUC-Rio University for helpful comments and discussions. Kirby Fears and Matthew Yeaton provided excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve System, the Bundesbank, or the Eurosystem.

1 Introduction

The term structure of interest rates is a key object of study in both macroeconomics and finance. Not only is it the centerpiece of the monetary policy transmission mechanism, but also has important implications for fiscal policy such as the choice of the optimal maturity structure of government debt. Furthermore, understanding the market pricing of the term structure can reveal important information about market participants' economic outlook and their attitude towards risk.

The simplest model of the term structure of interest rates is the expectations hypothesis. According to this model, movements in yields on default-free government bonds reflect variations in the average short rate that investors expect to prevail over the life of the bond. While the expectations hypothesis still plays a prominent role in many macroeconomic models, a large body of work in finance, starting with [Fama and Bliss \(1987\)](#) and [Campbell and Shiller \(1991\)](#), has challenged its empirical validity. It is now a widely accepted tenet that bond yields can be decomposed into investors' expectations about the path of future short-term interest rates as well as a time-varying term premium. Correctly distinguishing the role of these two components for the behavior of yields has important implications for many key issues in economics.

Crucially, the existing literature treats these two components as unobservable and uses statistical models to decompose yields into their constituent components. Therefore, their measurement is inevitably model-specific. Perhaps unsurprisingly, then, the literature has drawn starkly different conclusions regarding the driving forces behind bond yields. At one side of the spectrum, changes in the expected path of short-term interest rates are seen as the primary driver of variation in longer-term bond yields. On the opposite side, time varying term premiums are viewed as playing a pivotal role for understanding movements in the term structure of interest rates. Furthermore, the conclusions about the relative importance of expected rates and term premiums vary dramatically depending on the state variables used to model bond yields and the statistical method employed.

In this paper, we propose a decomposition of the yield curve which relies explicitly and solely on observed measures of expected short-term nominal and real interest rates. We obtain term premiums as the simple difference between observable yields on Treasuries and the average consensus expected short rate over the life of the bond. To characterize the latter component we use the entire term structure of expectations for output growth, inflation and the short-term nominal interest rates from the universe of surveys of professional forecasters in the U.S. Specifically, we collect monthly survey forecasts for the 3-month T-bill interest rate, CPI inflation, and real GDP growth corresponding to over 500 survey-horizon pairs.

Since term premiums are defined as a residual, we can remain agnostic about what specifically they represent. For example, they might reflect shifts in investors’ risk attitudes, differences between the expectations of the marginal investor and consensus expectations, or frictions in the bond market which prevent the elimination of arbitrage opportunities.

Since the available data on professional forecasts come from multiple surveys covering different sets of forecast horizons and variables, we rely on a parsimonious parametric model to obtain “consensus” term structures of expectations. We show that a simple monthly vector autoregression (VAR) with time-varying long-term means approximates the multivariate term structure of professional forecasts surprisingly well.¹ The model highlights that structural changes and learning by the forecasters are an important feature of expectations formation. In particular, it captures the challenge forecasters face of parsing temporary shocks from changes in underlying trends.²

While our term structures of expectations are constructed for the post-war period, our subsequent analysis focuses primarily on the sample 1983–2014 for which we have a wealth of survey information especially at longer forecast horizons. As our approach relies on using all observable data on professional forecasters’ expectations, it provides measures of the expected path of future policy rates and term premiums which, by construction, are consistent with a lower bound on nominal interest rates in the U.S. Moreover, they accommodate perceived structural change and learning effects and, as surveys are available in real time, do not get revised. We find that expectations of short-term interest rates over this sample feature some interesting regularities. Most notably, medium- to long-term expectations exhibit a significant slow-moving drift throughout the sample. At higher frequencies we observe that the expected path steepens towards the end of a monetary easing cycle and flattens at the end of tightening cycles. As professional forecasters perceive the persistent component of inflation to (approximately) follow a random walk, expected nominal and real rates move in lockstep, consistent with nominal rigidities preventing prices from adjusting in the short term. We also find evidence for the standard transmission mechanism of monetary policy where current changes to policy via real interest rates are transmitted along the term structure of real short-term rate expectations. Furthermore, short-term real rates are positively related to current and expected inflation, suggesting monetary policy followed an activist monetary policy over this period (see, e.g., [Clarida et al. \(2000\)](#)).

Decomposing yields into their expectations and term premium components, we find that the secular decline of long-term bond yields in the U.S. over the past several decades has

¹For univariate examples of this result see, for example, [Kozicki and Tinsley \(2012\)](#), [Edge et al. \(2007\)](#). To our knowledge the only multivariate example is [Andrade et al. \(2014\)](#).

²[Andrade et al. \(2014\)](#) show that this mechanism plays a prominent role in explaining disagreement across professional forecasters.

primarily been driven by lower expected inflation and term premiums whereas expected future real interest rates have fluctuated around 2% since the early 1980s. In contrast, we find that shorter maturity bond yields are driven by all three components—expected inflation, expected future real rates and term premiums—with the real rate playing the primary role and term premiums being the least important. Moreover, using TIPS yields we find that, across the maturity spectrum, nominal risk premiums are primarily driven by movements in real risk premiums.

We then ask the question: how important are term premiums for explaining yield curve dynamics and how do they relate to macroeconomic dynamics? We find that term premiums are very important. In particular, while expected real rates play some role in explaining the level and variation of bond yields with maturity up to three years, at longer horizons term premiums explain the bulk of the variation in the level of bond yields and over 90% of their variation in changes. Of note, inflation expectations explain roughly one-third of the variation in the level of yields across maturities, while they play only a minor role in explaining changes in yields—consistent with the interpretation that expected inflation acts as a level factor (see, e.g., [Diebold et al. \(2006\)](#) and [Ang et al. \(2008\)](#)).

We document that term premiums are tightly connected with macroeconomic conditions in two different empirical exercises. First, we find that fluctuations in term premiums have significant predictive power for quarterly growth rates of real output growth, income growth, and consumption up to two years in the future—a difficult feat given the small amount of serial correlation in these series. Moreover, this finding is all the more remarkable as the yield spread has, at best, only marginal predictive power for future output growth over this period (as opposed to earlier samples). This potentially reflects a higher degree of activism in monetary policy as suggested by [Clarida et al. \(2000\)](#) and [Estrella \(2005\)](#). Our results show that since the early 1980s the predictive content in yields for future economic outcomes can be attributed to term premiums rather than expectations about short-term interest rates.

Our results also emphasize the role of macroeconomic variables in explaining movements in the yield curve. We construct impulse responses of the constituent components of yields to a host of structural macroeconomic shocks studied in the literature. We consider policy shocks, which include measures of monetary and fiscal surprises; “demand” shocks comprising shocks to financial conditions and uncertainty; and “supply” shocks, which cover oil shocks and news about total factor productivity. Our evidence indicates that, over our sample period, policy and demand shocks have significant and long-lasting effects on term premiums. Financial shocks, in particular, are shown to have sizable effects even in the pre-crisis sample. A tightening of financial conditions as measured by an innovation to financial spreads tends to *compress* term premiums across the maturity spectrum—possibly reflecting a shift in

preferences toward “safer” assets. Interestingly, unexpected tightening of monetary policy also leads to a reduction in term premiums consistent with lower inflation risk. In contrast, the effects of supply shocks appear to have shorter duration. Our results resonate with the recent macroeconomic literature which highlights the role of financial shocks for shaping business cycles (e.g., [Gilchrist and Zakrajšek \(2012\)](#), [Justiniano et al. \(2010\)](#), and [Christiano et al. \(2014\)](#)). Moreover, they also suggest that the dominant paradigm in which term premiums are driven by shocks which drive inflation and output in opposite directions (e.g., supply shocks) and according to which surprise inflation represents “bad news” may be less representative for the last 30 years of the U.S. economy ([Piazzesi and Schneider \(2007\)](#) and [Rudebusch and Swanson \(2012\)](#)).

We believe that our findings have important implications for both macroeconomics and finance. Most structural macroeconomic models such as dynamic stochastic general equilibrium (DSGE) models used for monetary and fiscal policy analyses do not explicitly model term premiums. Instead, they assume the expectations hypothesis to hold, at least to a first-order approximation. Our findings suggest that incorporating time varying term premiums is extremely important if one would like to have any hope of explaining the variation of long-term bond yields. Introducing term premiums in such models, even when they only have second and higher effects on economic activity, can provide useful information about the underlying shocks buffeting the economy. More importantly, in models with financial frictions, time variation in term premiums may be of first order and can significantly alter the monetary transmission mechanism and the response of the economy to shocks.

A large literature has attempted to decompose observable government bond yields into their expectations and term premium components. The modeling approaches used run the gamut from arbitrage-free term structure models to structural general equilibrium models.

In the finance literature, term structure models are often used to characterize the joint evolution of government bond yields. These models frequently impose the absence of arbitrage opportunities and explicitly allow for time variation term premiums (see [Duffie \(2001\)](#), [Piazzesi \(2003\)](#), [Singleton \(2006\)](#) and [Gürkaynak and Wright \(2012\)](#) for surveys). While this literature finds that models featuring time-varying term premiums provide a better in-sample fit and more accurate forecasts of bond yields, the plausibility of the expected path of future policy rates implied by these models is rarely scrutinized. Although many term structure models are solely based on the information in yields (e.g., [Duffie and Kan \(1996\)](#), [Dai and Singleton \(2000\)](#), [Duffee \(2002\)](#), [Cochrane and Piazzesi \(2005\)](#), [Joslin et al. \(2011\)](#), [Adrian et al. \(2013\)](#)), another strand of the literature introduces macroeconomic variables in these models (see, e.g., [Ang and Piazzesi \(2003\)](#), [Wright \(2011\)](#), [Joslin et al. \(2014\)](#)).

In the macroeconomics literature there have been a few recent contributions focussing on

explaining the behavior of yields both with statistical models and in a general equilibrium framework. Two examples for the latter are [De Graeve et al. \(2009\)](#) and [Rudebusch and Wu \(2008\)](#) who find an important role for the expectations hypothesis in explaining the variation of yields using DSGE models. [Dewachter and Lyrío \(2008\)](#), [Dewachter and Lyrío \(2011\)](#) estimate a DSGE model where learning is explicitly modeled and show that movements in the expected path of interest rates capture a substantial fraction of the variation in long-term rates. An alternative literature utilizes time-varying coefficients to accommodate perceived structural changes or learning effects in the data generating process. [Cogley \(2005\)](#) investigates time variation in yields using a state space model with time-varying parameters while [Laubach et al. \(2007\)](#) adopt a VAR model where the coefficients are estimated using a constant-gain algorithm. [Kozicki and Tinsley \(2001\)](#), [Kozicki and Tinsley \(2005\)](#) and [Fuhrer \(1996\)](#) focus on a monetary policy rule with time varying coefficients. In general, these papers tend to find a much larger role for the expectations hypothesis in explaining movements in bond yields.

Our paper is also linked to the literature using actual expectations data to inform and discriminate between economic models (see [Manski \(2004\)](#) for an overview). For example, survey data have been used to discriminate between models of information frictions (see, e.g., [Mankiw et al. \(2003\)](#), [Patton and Timmermann \(2010\)](#), [Coibion and Gorodnichenko \(2012\)](#), [Andrade and Le Bihan \(2013\)](#), [Andrade et al. \(2014\)](#)), inform models of investment decisions ([Gennaioli et al. \(2015\)](#)), and to estimate the elasticity of intertemporal substitution ([Crump et al. \(2015\)](#)). There is also a literature which uses survey data to understand the behavior of asset prices (see, e.g., [Froot \(1989\)](#), [Frankel and Froot \(1987\)](#), [Greenwood and Shleifer \(2014\)](#), [Barberis et al. \(2015\)](#)).

Seminal works using survey data for understanding the term structure of interest rates are [Friedman \(1979\)](#) and [Froot \(1989\)](#). In response to prior work, these authors emphasize that regression-based tests of the expectations hypothesis are, in fact, joint tests of the expectations hypothesis and rational expectations. To bypass this concern they use survey data of expected interest rates. [Friedman \(1979\)](#) finds that the expectations hypothesis alone does not explain the short end of the yield curve, but instead that term premiums exist and also vary. [Froot \(1989\)](#) uses survey data on near-term rate expectations and finds that the expectations hypothesis fails at short maturities but cannot be rejected at medium-term maturities.

Only a few other papers have used survey data on expected future short rates to inform the model-implied path of policy expectations. Specifically, [Kim and Wright \(2005\)](#), [Kim and Orphanides \(2012\)](#), and [Piazzesi et al. \(2015\)](#) use affine term structure models to jointly fit government bond yields and survey forecasts of short rates. The primary difference between

these approaches and ours is that (1) they use information from yields across the maturity spectrum to inform the models; (2) they utilize a stationary VAR to govern the dynamics of their variables; (3) they use only a small subset of available survey data. Furthermore, in [Kim and Wright \(2005\)](#), [Kim and Orphanides \(2012\)](#), and [Piazzesi et al. \(2015\)](#) survey data and yields are modeled with a small number of state variables and allow for substantial deviations of model-implied expectations from observed policy rate expectations. We show that the implications for the behavior of expected rates and term premiums are very different in these models, despite the commonality of using survey data to understand decomposition of yields.

The paper proceeds as follows. Section 2 discusses the data while Section 3 introduces the model used to extract the “consensus” term structures of survey expectations. Section 4 is concerned with the decomposition of real and nominal US Treasury yields and Section 5 links these decompositions to the broader macroeconomy. Section 6 concludes. A Data Appendix is provided with further details about the survey data and construction and a Supplementary Appendix provides additional results.

2 Data

In this paper we use, to the best of our knowledge, the universe of professional forecasts for the United States in the post-war era. Our forecast data are obtained from eight 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) Goldsmith-Nagan (GN)³; (6) Livingston Survey (Liv.); (7) Survey of Primary Dealers (SPD); (8) Survey of Professional Forecasters (SPF). We focus on three variables – output growth, inflation and the short-term interest rate. 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 CPI over alternative inflation measures such as the GDP deflator for two reasons. First, Treasury Inflation Protected Securities (TIPS) have coupon and principal payments indexed to the CPI. Second, 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.⁴

We use essentially all available forecasts for these three variables covered in the eight

³We thank Kenneth Froot for sharing the Goldsmith-Nagan survey data.

⁴For example, forecasts of the Federal Funds rate, the target rate of US monetary policy are only available in two of the eight surveys we consider (BCFF and SPD).

surveys.⁵ To provide a sense of the wealth of survey data used, our results are based on 521 variable-horizon pairs spanning the period 1955 to 2014. In the Data Appendix we give more explicit details about each individual survey, however, we want to emphasize here that the survey data differ in frequency, forecast timing, target series, sample availability and forecast horizons.

To ease notation we use the following conventions. 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. Within each of these sub-categories the exact form of the target variable may vary. For example, a forecast for the year 2014 may be queried based on annual average growth or Q4/Q4 growth. Throughout the paper we ensure that the survey data are treated in a consistent manner with respect to the target variable to ensure that all comparisons are appropriate. See the Data Appendix for further details.

Table 1 provides a bird’s eye view of the survey data series 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 (target period is 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 1983–2014, representing the great moderation and recession. This period includes the majority of the available survey forecasts with over 70% of the total number of series used available in this 30 year time span. Although there are survey forecasts for the TBILL spanning short-, medium- and long-term horizons, they are still underrepresented in the sample as compared to GDP and CPI forecasts. More details about each survey are provided in the Data Appendix.

⁵We exclude some series for technical reasons discussed in the Data Appendix.

3 Model and Estimation

We assume that the true state of the macroeconomy is captured by the random vector $z_t = (g_t, \pi_t, i_t)'$ representing real output growth, g_t , inflation, π_t , and the short-term interest rate i_t . z_t evolves according to,

$$z_t - \bar{z}_t = x_t \quad (3.1)$$

$$x_t = \Phi x_{t-1} + \nu_t, \quad (3.2)$$

or alternatively,

$$z_t - \bar{z}_t = \Phi (z_{t-1} - \bar{z}_{t-1}) + \nu_t, \quad (3.3)$$

where x_t represents the factors driving the short to medium-term fluctuations in the economy with *i.i.d.* Gaussian innovations, $\nu_t \sim \mathcal{N}(0, \Sigma^\nu)$. In contrast, \bar{z}_t represents the factors driving the long-term, slow-moving aspects of the economy represented by $\bar{z}_t = (\bar{g}_t, \bar{\pi}_t, \bar{i}_t)'$. The first two elements are assumed to follow the multivariate random walk,

$$\begin{pmatrix} \bar{g}_t \\ \bar{\pi}_t \end{pmatrix} = \begin{pmatrix} \bar{g}_{t-1} \\ \bar{\pi}_{t-1} \end{pmatrix} + \eta_t, \quad (3.4)$$

with *i.i.d.* Gaussian innovations, $\eta_t \sim \mathcal{N}(0, \Sigma^\eta)$ and the third element, \bar{i}_t , is a linear function of long-run growth and inflation via the Fisher equation,

$$\bar{i}_t = s \log(\beta^{-1}) + \sigma \bar{g}_t + \alpha \bar{\pi}_t. \quad (3.5)$$

where s is a scaling parameter (e.g., $s = 400$ for annualized percent) and $\beta \in (0, 1)$ denotes the time-invariant discount factor. The parameter σ allows a connection between the real interest rate and the growth rate of the economy: it can be interpreted as the inverse of the intertemporal elasticity of substitution. The parameter α equals one in theory, but we estimate it as an additional check on our specification. This relationship between the real interest rate and long-term output growth commonly emerges from dynamic general equilibrium models with intertemporal optimizing households.

Throughout the paper let a superscript “A” or “S” denote variables related to actual or survey forecasts, respectively. The observed data are related to the true state of the economy via,

$$\begin{pmatrix} y_t^A \\ y_t^S \end{pmatrix} = \begin{bmatrix} H_t^A \\ H_t^S \end{bmatrix} Z_t + \begin{pmatrix} \varepsilon_t^{y,A} \\ \varepsilon_t^{y,S} \end{pmatrix}, \quad Z_t = F Z_{t-1} + V \begin{pmatrix} \nu_t \\ \eta_t \end{pmatrix} \quad (3.6)$$

where $Z_t = (z_t, z_{t-1}, z_{t-2}, z_{t-3}, z_{t-4}, x_t, \bar{z}_t)'$ is the 18×1 state vector, $F = F(\Phi, \sigma, \alpha)$ is the 18×18 transition matrix and $V = V(\sigma, \alpha)$ is an 18×5 matrix which maps the 5 underlying shocks to the appropriate elements of the state vector. The presence of the four lags in the state vector are essential for mapping monthly growth rates to quarterly growth rates. This is because quarterly growth in variables such as GDP or CPI are measured as the growth rate of the average value of the variable in the current quarter as compared to the average value of the variable in the previous quarter. This measure of the growth rate is well approximated by a weighted average of the past 5 monthly growth rates.

We now discuss the state-space model features in detail. First, y_t^A contains quarter-over-quarter annualized real GDP growth (available once a quarter), month-over-month annualized CPI inflation (available monthly), and the 3-month TBILL rate (available monthly).⁶ We assume that the true state of real output growth and inflation are measured with error whereas interest rates are perfectly observed. The measurement error in output growth and inflation accounts for the presence of publication lags and data revisions which prevents forecasters from perfectly observing these variables in real time. Moreover, when making predictions forecasters aim to filter from the actual data the underlying, persistent factors as evidenced by the fact that forecasts, even at very short horizons, are considerably less volatile than realized variables.

Thus we assume $\varepsilon_t^{y,A} = (\varepsilon_t^{g,A}, \varepsilon_t^{\pi,A}, 0)'$ where $\varepsilon_t^{g,A}$ and $\varepsilon_t^{\pi,A}$ are mean-zero, *i.i.d.*, mutually independent Gaussian innovations. For both the actual and the survey data we make repeated use of the linear approximation of different measures of growth rates to the underlying monthly annualized growth rates.⁷ We assign the observation of real GDP growth to the last month of the quarter which ensures that forecasters in the model have the largest information set when they observe the noisy measure of g_t . Thus, in the last month of each quarter when all three variables are observable, H_t^A is of the form

$$H_t^A = \begin{bmatrix} \frac{1}{9} & 0 & 0 & \frac{2}{9} & 0 & 0 & \frac{3}{9} & 0 & 0 & \frac{2}{9} & 0 & 0 & \frac{1}{9} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

The second set of observable variables includes all survey forecast data discussed in Section 2 corresponding to the 521×1 vector y_t^S . We assume individual observation errors for each survey to be mean-zero, *i.i.d.*, mutually independent Gaussian innovations. To

⁶We obtain real GDP growth from the Bureau of Economic Analysis, headline CPI inflation from the Bureau of Labor Statistics and the 3-month Treasury bill rate from the H.15 release of the Federal Reserve Board.

⁷This can be formally justified via a Taylor series expansion. See the Appendix and [Crump et al. \(2014\)](#) for further details and examples.

ensure a parsimonious model we group the variances of these Gaussian variables 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. To populate the matrix H_t^S we require the target variable, the specific transformation (e.g., annual average growth), the forecast horizon, and the parameters Φ , α , and σ .

To illustrate how H_t^S is formed, consider the example of an annual average growth forecast for real GDP in the year 2013 (i.e., the average value of the level of real GDP in 2013 as compared to 2012) formed in January 2012. This can be approximated by the linear combination,

$$\sum_{j=1}^{23} w_j \hat{g}_{\tau+j}, \quad \hat{g}_{\tau+j} = e_g' F^j Z_\tau$$

where $e_g = (1, 0, \dots, 0)'$ selects the appropriate row of the forecasted state and the weights, w_j , are “tent-shaped” of the form $w_j = \min(j, 24 - j)/24$. Here, g_τ is the annualized monthly real GDP growth rate in January 2012 and $\hat{g}_{\tau+j}$ is the model-implied forecast for real GDP growth j periods ahead. Thus, the corresponding row in H_t^S for this survey forecast series is equal to $\sum_{j=1}^{23} w_j e_g' F^j$. As an additional example, the SPD surveys respondents on their forecasts of “longer-run” real GDP growth, i.e., \bar{g}_t . In this case the corresponding row of H_t^S is simply $e_{\bar{g}} = (0, \dots, 0, 1, 0, 0)'$, i.e., a vector with all elements equal to zero except for a one corresponding to the first element of \bar{z}_t . For additional details see the Data Appendix.

3.1 Discussion of Model

The purpose of our paper is to use all available surveys of professional forecasters in the U.S. to characterize the term structures of consensus expectations for real output growth, inflation, and the short term interest rate. In practice, survey expectations are available from a number of different surveys at some forecast horizons whereas at other horizons no survey forecasts are observed.⁸ In order to trace out the full path of consensus expectations at all horizons and to not unduly overweight a particular survey, we rely on a simple parametric model to fit all available survey data. The model thus serves three purposes. First, it allows us to assess whether a relatively simple multivariate time-series model can capture the joint dynamics of survey forecasts across the three major macroeconomic variables. Second, by using a model we can provide consistent proxies for the missing observations and/or horizons

⁸Kozicki and Tinsley (2012) use a univariate version of our model to fit the term structure of inflation expectations. More recently, Aruoba (2016) performs a similar exercise for inflation expectations in a different modeling framework.

for each survey and are thus able to extract the common information across different surveys in a coherent way. Finally, since we observe fewer forecasts for short-term interest rates than we do for output and inflation, a multivariate model allows us to exploit the dependence structure across variables and horizons to inform the term structure of forecasts of the short-term interest rate.

Importantly, while our model is simple and parsimonious, it allows for time-variation in the long-run mean. This feature has been shown to capture well the dynamic properties of both actual economic variables as well as survey expectations.⁹ Moreover, there is direct survey evidence that expectations of longer-run values for economic and financial variables vary over time. For example, the SPF annually queries respondents on their value of NAIRU, the SPD includes questions on “longer-run” values of 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 these predicted long-run values show some degree of time variation. A multivariate forecasting model featuring time-varying long-run means is also consistent with evidence from the cross-section of professional forecasters. In fact, [Andrade et al. \(2014\)](#) show that both the multivariate specification and shifting endpoints are essential to matching the empirical properties of forecaster disagreement.

The shifting endpoints $(\bar{g}_t, \bar{\pi}_t, \bar{i}_t)$ also play a crucial role in matching survey forecasts at all horizons in our model. Intuitively these time-varying means capture perceived structural changes in the economy alongside the learning process, more generally. In addition to time variation in the long-run means, our model features the mean-reverting component x_t which captures cyclical deviations from the trend. The expectations-formation process that we model thus implies that forecasters filter from the observed data temporary factors as well as slow-moving changes in fundamentals. Meanwhile, the observation errors in real output growth and inflation (equation (3.6)) have two potential interpretations: first, they capture an informational constraint as market participants have imperfect information about the true state z_t of the macroeconomy due to data revisions and publication lags; second, agents endeavor to filter out the very high-frequency fluctuations in output and inflation that are not useful for forecasting their evolution beyond one quarter ahead. In sum, forecasters appear to decompose observed data in trend, cycle, and noise. Such a decomposition squares well with forecaster commentary which often highlights the importance of disentangling very short

⁹See, for example, [Stock and Watson \(1989\)](#), [Cogley and Sargent \(2005\)](#), [Laubach and Williams \(2003\)](#), [Stock and Watson \(2007\)](#), [Cogley et al. \(2010\)](#), [Kozicki and Tinsley \(2001\)](#), [Kozicki and Tinsley \(2005\)](#), [Gürkaynak et al. \(2005b\)](#); [Edge et al. \(2007\)](#); [Kozicki and Tinsley \(2012\)](#), [van Dijk et al. \(2014\)](#), and [Andrade et al. \(2014\)](#).

term, cyclical, and trend components.

3.2 Estimation

The model is estimated at the monthly frequency for the sample starting in January 1955 and ending in December 2014 using maximum likelihood. Recall that the observation equation (equation (3.6)) has time-varying coefficients to account for missing observations in actual and survey data.

3.3 Model Fit

While the estimated parameter values are provided in Table 2, we emphasize three important features here. First, the volatility of the two drifts is significantly smaller than the volatility of the short-term shocks, consistent with fundamentals changing slowly over time. Second, the estimated relationship between the drifts for the nominal short-rate, output growth and inflation is: $\bar{i}_t = .99\bar{\pi}_t + .75\bar{g}_t$. Thus, consistent with the Fisher-equation the estimated coefficient on the inflation drift is very close to one.¹⁰ In contrast, the coefficient of the output growth drift, which we can loosely relate to the intertemporal elasticity of substitution parameter in dynamics optimization models is modestly above one and not inconsistent with values commonly assumed in the macroeconomics and finance literature. Finally, the time-invariant discount rate β is set to one consistent with values commonly used in the calibration of macroeconomic models.

Our parsimonious model captures the behavior of survey-based expectations surprisingly well, as evidenced by the good fit of the model to the 521 forecast series. While we document the fit of the model series by series in the Supplementary Appendix, Figure 1 shows actual and fitted survey forecasts for selected forecast-horizons. We group these into short-term, medium-term and long-term forecasts, respectively. As shown by the figure, the model is flexible enough to simultaneously match survey-based forecasts at very different horizons. This is also confirmed by the small magnitudes of the observation error variances shown in Table 2.

4 Decomposing Nominal and Real Yields

In this section we are going to construct and analyze the behavior of expected short rates and term premiums, using the data on expectations as discussed in the previous sections.

¹⁰As a robustness check we also considered models which explicitly set $\alpha = 1$ which produce very similar results.

We start from the following identity:

$$y_t(n) = \frac{1}{n} \mathbb{E}_t [i_t + i_{t+1} + \dots + i_{t+n-1}] + tp_t(n), \quad (4.1)$$

where $y_t(n)$ is the continuously compounded yield on an n -month discount bond, i_t is the risk-free nominal short rate at time t , and $tp_t(n)$ is the nominal term premium. The term premium is thus simply given by the difference between observed yields and what would be the yield predicted by the expectations hypothesis, i.e. the average expected future short rate over the life of the bond.

In order 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:

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

Since the model is estimated at a monthly frequency, we construct annual forward rates as the annual average of monthly forward rates. We then define forward term premiums as the difference between $f_t(n, m)$ and the consensus expected short-term rate over the n years m years hence (i.e., a forward version of equation (4.1)):

$$tp_t^{fwd}(n, m) = f_t(n, m) - \frac{1}{n} \sum_{i=m+1}^{n+m} \mathbb{E}_t [i_{t+i}]$$

For example, the 9Y1Y forward term premium, i.e., the term premium embedded in a one-year bond, nine years in the future, would be defined as:

$$tp_t^{fwd}(12, 108) = f_t(12, 108) - \frac{1}{12} \sum_{i=109}^{120} \mathbb{E}_t [i_{t+i}]$$

Furthermore, since we collect data on inflation expectations we can further decompose expected nominal future short rates into expected real short rates and expected inflation,

$$tp_t^{fwd}(n, m) = f_t(n, m) - \frac{1}{n} \sum_{i=m+1}^{n+m} \mathbb{E}_t [r_{t+i} + \pi_{t+i+1}],$$

where r_t is the *ex-ante* real short rate, i.e., $i_t = r_t + \mathbb{E}_t [\pi_{t+1}]$. In the next section, we describe the evolution of expected rates and term premiums and evaluate their relative importance in explaining the variation of observed yields.

4.1 Expected Nominal and Real Short Rates

Our data allows us to study the expected paths of future nominal and real rates as well as inflation at any specific point in time. Figure 2 displays a number of “hair charts” which are a convenient way to summarize the evolution of these expected paths over time. Specifically, in each chart the black solid lines show the actual nominal or real short-term rates and the persistent component of inflation, π_t , respectively, and the grey lines show the expected path of each of the three variables over the next ten years. By the design of the model that we use to extract the term structures of professional forecasts, the expected paths converge to the variable’s predicted long-run mean, which drifts slowly over time.

The top panel of Figure 2 shows the evolution of expected nominal short rate paths, the middle panel the evolution of expected paths of the persistent component of inflation, and the bottom panel the evolution of expected real short rate paths. As discussed above, for the sample 1965-1983 we have limited survey data and, in particular, very little information about medium-to-long-term forecasts. We thus exclude this sample period in our analysis here and in the following sections.

The figure reveals several interesting facts about the term structures of consensus expectations. The shapes of the nominal and real expected paths varied substantially over the past thirty years; at times they are upward sloping, downward sloping, convex and concave. In contrast, the shape of expected inflation has shown far less variation. A common behavior of forecasts across all sample periods is the steepening of the expected nominal short-rate path at the beginning of monetary tightenings, and the flattening at the end of tightening cycles. This pattern translates almost one to one in expected real rates, as professional forecasters perceive the persistent component of inflation to approximately follow a random walk. It is also consistent with nominal rigidities preventing the rapid adjustment of prices to movements in the policy rate. Third, focusing at the last few years of our sample, we see that survey-implied expected nominal short rate paths are consistent with the zero lower bound.¹¹ Over this part of the sample, forecasters have repeatedly predicted that the short rate would take about five years to return to its long-term mean, the level of which they perceived to be little changed relative to before the financial crisis. Real rates, in turn, were expected to remain negative as far out as 2017 as of the end of 2014. Similar to nominal rates, expected short-term real rates in the far future have remained fairly stable in recent years. Hence, the low level of expected real rates at the end of the sample was perceived to be reflecting temporary (albeit quite persistent) factors.

Figure 3 shows the relationship between the short-term ex ante real interest rate and

¹¹As we use a linear model to fit the entire term structure of survey forecasts, very short-term expectations are in some instances negative, but never below ten basis points.

expected inflation (top panel) as well as with long-term expected real rates (bottom panel). We see a positive correlation between the ex-ante real interest rate and expected inflation, consistent with the “Taylor principle” being satisfied. That is, the short-term nominal interest rate responds more than proportionally to (expected) inflation, see [Clarida et al. \(2000\)](#). Over our sample we thus see no evidence of the [Mundell \(1963\)](#) and [Tobin \(1965\)](#) effect which predicts a negative correlation between real rates and (expected) inflation.¹²

Changes in the short-term real rate also display a strong positive correlation with movements in the average expected real rate over the next five years, suggesting that monetary policy decisions, implemented through the short-term nominal rate, affect the entire path of expected real rates. This is consistent with the standard monetary transmission mechanism, for example in the new Keynesian framework, see [Woodford \(2003\)](#).

These findings suggest that professional forecasters respond to the business cycle, and the behavior of their forecasts is consistent with conventional views about monetary policy.¹³

4.2 Nominal and Real Term Premiums

Having documented the time series dynamics of expectations, we now turn to the relative importance of each component for the variation of yields at different maturities. Figure 4 provides a decomposition of several nominal Treasury forward rates into the components predicted by the expectations hypothesis alone as well as the forward term premium. The chart shows that at the one-year, one-year (1Y1Y) maturity, expected short rates explain much of the low-frequency variation in the forward rate while the term premium mainly contributes to variation at higher frequencies. This is quite different from the behavior at the four-year, one-year (4Y1Y) forward and nine-year, one-year (9Y1Y) forward maturities, shown in the middle and lower panel. In fact, at these intermediate and long horizons, the expectations components of rates contribute to the secular decline of rates, but term premiums explain most of the variation at higher and medium-term frequencies.

Based on the fitted monthly time series of expected nominal and real short rates, we can further decompose Treasury yields and forwards into the expected path of future inflation, the expected path of future real short rates, and term premiums. Figure 5 shows these components for the 1Y1Y, 4Y1Y and 9Y1Y forward horizons from 1983 through 2014. Focusing

¹²See also [Ang et al. \(2008\)](#) for a discussion.

¹³While the primary objective of our paper is to characterize the term structures of expectations and term premiums, there are a number of papers which have evaluated the accuracy of those forecasts relative to statistical models. In fact, [Ang et al. \(2007\)](#), [Croushore \(2010\)](#), and [Faust and Wright \(2013\)](#) among others document that professional forecasters’ inflation predictions outperform those implied by a wide range of time series models at various forecast horizons. Similarly, [Cieslak and Povala \(2014\)](#) argue that professional forecasts of short-term interest rates cannot be outperformed by a number of different statistical models.

first on the 1Y1Y forward in the top panel of Figure 5, we see that all three components have contributed to the decline in short-term Treasury yields observed over the past several decades, albeit in different ways. First, average expected inflation over the next ten years decreased from about six percent in the early 1980s to about 2–2.5 percent in the late 1990s, and has since leveled out. Second, average expected real short rates one-to-two years out have fluctuated around two percent for most of the sample, but have displayed a pronounced decline in the aftermath of the financial crisis. Third, the 1Y1Y forward term premium has declined from about two percent in the early 1980s to around zero in the early 2000s and has hovered around that level since.

The middle and bottom panel of Figure 5 provide the same time series decompositions for the one-year forward rates four and nine years out, respectively. While these largely mirror the evolution of the yield curve components at the one-year forward just described, there are also some noteworthy differences. Expected inflation behaves very similarly at medium-term and long-term forward horizons, highlighting that professional forecasters perceive the persistent component of inflation to be close to a random walk. Conversely, real short rate expectations and term premiums at intermediate and long maturities behave quite differently than those at the shorter horizon. While the movements in expected real rates explain the bulk of variation in the 1Y1Y forward, the opposite is true for the 4Y1Y and the 9Y1Y forwards where most of the variation is accounted for by the term premium. The expected long-run real rate has fluctuated around two percent over the entire sample even in the aftermath of the financial crisis.

Table 3 provides variance decompositions for both the level (upper panel) and the monthly changes (lower panel) of one-year forward rates from one through nine years out.¹⁴ The decompositions reveal several interesting facts. First, expected real rates are the most important driver of (the level of) forward rates up to three years out (i.e., the 1Y1Y and 2Y1Y forward rates), explaining 60 percent of the variation at the one-year ahead forward horizon and about 30 percent at the two-year ahead forward horizon, but their importance declines sharply going out the maturity spectrum. At the nine-year ahead forward horizon, they only explain a meager four percent of the variation in forward rates. In contrast, while term premiums only explain a small amount of variation at the short end, they account for close to 60 percent of the variation in forward rates at long maturities. The share of variance explained by expected inflation is relatively stable across the maturity spectrum, ranging from 31 percent at the one-year to 39 percent at the nine-year forward horizon. Combined, these shares reinforce our previous evidence that expected inflation acts like a level factor

¹⁴For each maturity, the variance decomposition is obtained by computing the ratio of the covariance of the forwards with their individual components, divided by the variance of the forwards.

while expected real rates and term premiums act like slope factors with opposite signs.

Since forward rates are very persistent, it is instructive to also look at the decomposition of monthly changes of forward rates into the three components. While expected real rates also make up for the largest share in the month-to-month variation in the one-year forward rate, that fraction declines sharply for longer maturities, implying that only three (one) percent of the monthly changes in forward rates are explained by expected real rate movements at the four (nine) year forward horizon. In contrast, the contribution of term premiums to the variation of monthly changes in forward rates is substantial at all horizons and increases from 73 percent at the one-year forward horizon to 93 percent at the nine-year forward horizon. Lastly, expected inflation explains only a small fraction of the observed changes in forward rates, across the maturity spectrum.

The importance of term premiums for variations in Treasury yields is not driven by the recent financial crisis and the large-scale asset purchases undertaken by the Federal Reserve. In Table 4, we repeat the variance decompositions ending the sample in December 2007. Interestingly, term premiums played a slightly larger role in the 1983–2007. In sum, these variance decompositions show that when expectations about future real rates and inflation are fully taken into account, term premiums are the most important driver of medium to long-term interest rates. As Treasury yields directly affect the rates at which firms and consumers lend and borrow, our results suggest that term premiums might have important effects on economic activity. This is investigated in Section 5.

While Table 4 shows that the relative importance of term premiums for explaining the variation in yields varies across maturities, the left column of Figure 6 documents that survey-based term premiums co-move much more strongly than survey-based expected future short rates across maturities. In fact, four quarter changes in long- and short-term expected rates are only weakly correlated (top panel) whereas changes in term premiums are almost perfectly correlated (bottom panel).¹⁵ Note that this strong co-movement in term premiums is not the outcome of any parameter restrictions, as it would be in a standard term structure model. Since term premiums equal average expected short-term excess returns over the life of a bond this finding is, however, consistent with a strong factor structure in expected excess returns as has been argued by [Cochrane and Piazzesi \(2005\)](#).¹⁶ Interestingly, we observe a break in this co-movement after the last recession. This might be capturing both the effects of the zero lower bound on the short-term nominal rate and, possibly, the unconventional monetary policy actions undertaken during that period, with their effects particularly on

¹⁵A principal components analysis on the four-quarter changes of the 9 forward term premiums shows that the first principal component explains 89% of the variation in these changes.

¹⁶[Cochrane and Piazzesi \(2005\)](#) use this factor structure to construct a bond return forecasting factor (the “CP factor”) as a linear combination of forward rates.

term premiums of longer-term bonds.

Using yields from Treasury inflation protected securities (TIPS) and our survey-based inflation expectations, we can further decompose the survey-based term premium into a real term premium and an inflation risk premium. Unfortunately, this decomposition is only possible starting in 1999 when the TIPS data became available.¹⁷ The right-hand column of Figure 6 suggests that during this recent period, most of the variation in medium and long-term forward term premiums was due to movements in real term premiums. Abstracting from illiquidity, the charts imply that inflation risk premiums have been close to zero at the 4Y1Y horizon and slightly positive at the 9Y1Y horizon during this period.¹⁸

4.3 Comparison with Statistical Models

In the previous section we have discussed the decomposition of yields into expected rates and term premiums based on survey expectations. As already mentioned in the Introduction, a large literature has instead decomposed yields using statistical models of the term structure of interest rates. Here, we compare the survey-based term premium and expected rates components with those from a few different statistical models. Figure 7 displays the time series of expected average nominal short rates at the 1Y1Y, 4Y1Y and 9Y1Y forward horizons. In each of the panels, the gray solid lines represent the expected average short rates implied by the survey data. In order to highlight the importance of accounting for changes in the expected long-run mean of the short rate, we contrast the results from the previous section with those obtained from a stationary VAR in the level, slope, and curvature factors of the yield curve¹⁹ and an additional VAR augmented with measures of real activity and inflation.²⁰

This stationary VAR is a useful benchmark because standard affine term structure models are largely unconstrained VARs in the model factors (see Joslin et al. (2013)), and hence short rate expectations and term premiums implied by such models can essentially be derived

¹⁷Note that during the first four years of the sample liquidity factors make inflation compensation difficult to interpret. In the graphs we show 4Y1Y and 9Y1Y forwards note in Figure 6 for TIPS because liquidity in the TIPS market is concentrated in those maturity ranges.

¹⁸The finding that the bulk of the variation in nominal term premiums is driven by real term premiums is consistent with the results in Abrahams et al. (2015) who obtain such a decomposition using an affine term structure model fitted to both nominal Treasury yields and TIPS yields.

¹⁹Following e.g. Diebold and Li (2006) and Diebold et al. (2006), we define the level factor as the three-month TBill ($y(3)$), the slope factor as the ten-year Treasury note ($y(120)$) minus the three-month TBill, and the curvature factor as $((y(120) - y(3)) - (y(60) - y(3)))$. These three factors are highly correlated with the first three principal components of nominal Treasury yields.

²⁰Following Joslin et al. (2014) we use the three-month moving average of the Chicago Fed National Activity Index as an indicator of real activity. As a measure of inflation we use year-over-year core CPI inflation.

from such a VAR. The short rate expectations implied by a VAR thus crucially depend on the estimated long-run mean as well as the speed of mean reversion of the yield factors. As the factors are typically quite persistent, these parameters are difficult to pin down and their estimates might thus differ across samples. We therefore provide VAR-based short rate expectations for two samples. The blue dashed line represents expected average nominal short rates implied by a VAR estimated over the full sample 1968–2014, the purple dash-dotted line instead represents those forecasts implied by a VAR estimated over the subsample 1990–2007. We choose this specific subsample as it is the one used by e.g. [Wright \(2011\)](#) and [Joslin et al. \(2014\)](#), two prominent references for term premium estimates obtained from macro-finance affine term structure models.

As the figure shows, both VAR specifications estimated over the subsample imply medium to long-term average expected short rates that are nearly constant, consistent with a substantial degree of mean reversion in the short rate. In contrast, the VAR using only yields, estimated over the full sample, implies medium-to-long-term forecasts of the average short rate that are substantially more volatile and essentially mimic the evolution of the short rate itself. In contrast, the VAR which additionally includes macroeconomic variables, displays very different dynamic properties for different forecast horizons. At short horizons, during the zero-bound period, the model-based forecast is for sharply negative short-term rates, which is largely influenced by the marked decline in real activity at that time. At longer horizons, forecasts for short-term rates appear to be fairly stable around a constant value of about 4.5% showing no evidence of the downward trend displayed by the yields-only VAR.

These findings underscore that the specific choice of sample period and the choice of state variables matter immensely for the average expected short rate implied by statistical models. What is more, the long-run predictions of the short rate from surveys have deviated sizably from those implied by these models. This is especially true in the early 1980s, in the early 2000s, and in the zero lower bound period where survey-based and model-implied expected long-term future short rates have differed by up to two percentage points. This comparison demonstrates that survey-based expected rates display very different behavior as compared to constant parameter VAR models where the estimated degree of persistence and the estimated long-run mean of the short rate can vary substantially.

In Figure we show the term premiums corresponding to these models of expected rate paths.²¹ In the top panel of each column we show the implied term premiums for the 1Y1Y maturity. Survey-based term premiums are much more volatile than all of their VAR-based counterparts and can differ markedly in level. For example, at the height of the financial

²¹In Figure 14 in the Supplementary Appendix we also compare to the two publicly-available yield curve decompositions based on [Kim and Wright \(2005\)](#) and [Adrian et al. \(2013\)](#).

crisis, the VAR supplemented with macroeconomic data implies an almost 400 basis point difference. At intermediate and longer maturities (middle and bottom panel) there are also noteworthy differences—especially at the beginning and the end of the sample when rates were particularly high and low. Moreover, the economic implications of the term premiums can be very different even in the middle of the sample. For example, survey-based term premiums at intermediate maturities were comfortably negative during the early 2000s which was not the case for their VAR counterparts. All that said, term premiums based on surveys or those based on statistical models do show some commonalities: they are broadly trending down over the sample and they roughly co-move at business-cycle frequencies.^{22,23} This is hardly surprising in light of the results in Section 4.2 where we have shown that expected short rates play a minor role in explaining the variation in intermediate- and longer-term yields.

We have documented earlier that our survey-based term premiums correlate stronger across maturities than the expected rate components. An alternative is to study the co-movement between the two components themselves. The top panel of Figure 9 provides the correlations between monthly change in the expected rate path and term premium at the 1Y1Y, 4Y1Y and 9Y1Y forward horizons, respectively. The charts show a modest negative correlation between the two components at all three horizons. We also compute these correlations for the statistical models considered above. Maybe not surprisingly, there are notable difference between the models also in terms of the comovement between the yield curve components. While the yields-only VAR model implies a positive correlation at short and intermediate horizons, the sign of the co-movement changes at long horizons. Except for the [Kim and Wright \(2005\)](#) model which features strongly positive correlations at all horizons, the remaining statistical models considered imply varying degrees of negative co-movements.

²²Combined, the common trend and the co-movement at business cycle frequencies imply that survey-based and VAR model-based expected bond returns are positively correlated both in levels and in changes. This is in contrast to [Greenwood and Shleifer \(2014\)](#) who find that model- and survey-based equity risk premiums co-move negatively. See also [Cieslak and Povala \(2015\)](#) and [Kojen et al. \(2015\)](#).

²³Using factors extracted from a large cross-section of macroeconomic variables to predict bond yields and returns, [Moench \(2008\)](#) and [Ludvigson and Ng \(2009\)](#) also find that they are strongly countercyclical. [Ghysels et al. \(2014\)](#) document substantially less countercyclicality in expected excess bond returns when using real-time instead of final revised macroeconomic variables or factors.

5 Expected Rates, Term Premiums and Real Activity

5.1 Predictive Regressions

A long-standing strand of the literature in macroeconomics and finance has shown that the yield curve is informative about future economic activity and inflation – see for example [Mishkin \(1990\)](#), [Estrella and Hardouvelis \(1991\)](#), [Estrella and Mishkin \(1998\)](#) and [Rudebusch et al. \(2007\)](#). In particular, a decline of the term spread between long- and short-term yields has been documented to predict a decline in inflation and a decline in economic activity.²⁴ While there is no general consensus in the literature as to why term spreads predict future economic activity and inflation, the predictive power has mainly been attributed to movements in the expected path of the short term rate (i.e. the expectations hypothesis). More precisely, a falling term spread is viewed as reflecting lower expected short-term rates in the future, i.e. a monetary policy easing, in response to low expected economic activity.

In this spirit, [Estrella \(2005\)](#) obtains a predictive relation between term spreads and economic activity and inflation in a simple New-Keynesian framework. In his model the strength of the relationship between the current term spread and future economic activity depends on the monetary policy regime in place. Specifically, monetary policy rules that respond weakly to inflation and economic activity imply a tight relationship between term spreads and the macroeconomy, as such policies produce pronounced business fluctuations where economic activity and inflation deviate for long periods of time from their long-run means. This in turn creates a link between the expected policy rate and economic activity. In contrast, a monetary authority which responds actively to deviations of inflation and economic activity from their objectives breaks this relationship by limiting economic fluctuations. For example, under this policy expected rates would move but economic activity would be fairly stable over time. As the model does not feature time-variation in prices of risk, its predictions for the relation between term spreads and economic activity are entirely based on the expectations hypothesis. In line with this channel, some studies (see, for example, [Ang et al. \(2006\)](#) and [Rosenberg and Maurer \(2008\)](#)) have found that only the expected rates component predicts economic activity but not term premiums.²⁵

Using our survey-based decompositions of Treasury yields, we now reassess which of the components of Treasury term spreads predicts economic activity. We start by decomposing

²⁴Some of this literature has focused on predicting recessions, some on forecasting real GDP growth.

²⁵[Hamilton and Kim \(2002\)](#), using ex-post term observed short rates as a measure of expected short rates, and [Favero et al. \(2005\)](#), using various different statistical models, also find some evidence that the term premium predicts economic activity in the earlier part of our sample.

the term spread of a bond of maturity n as:

$$TS_t(n) \equiv y_t(n) - i_t = \left(\frac{1}{n} \sum_{i=1}^n \mathbb{E}_t [i_{t+i}] - i_t \right) + tp_t(n),$$

where, in the second equality, we have decomposed the term spread into the average expected short rate over the next n periods less the current short rate (an “expected” term spread) and the n -period term premium. We can further decompose the expected future path of nominal short rates into the expected future path of real short rates and the expected future path of inflation:

$$\left(\frac{1}{n} \sum_{i=1}^n \mathbb{E}_t [i_{t+i}] - i_t \right) = \left(\frac{1}{n} \sum_{i=1}^n \mathbb{E}_t [r_{t+i}] - r_t \right) + \left(\frac{1}{n} \sum_{i=1}^n \mathbb{E}_t [\pi_{t+1+i}] - \pi_t \right),$$

We then run regressions of the form:

$$\Delta g_{t+h} = \beta_0 + \beta_1 \cdot tp_t(120) + \beta_2 \cdot \left(\frac{1}{n} \sum_{i=1}^{120} \mathbb{E}_t [i_{t+i}] - i_t \right) + \zeta_{t+h}^g, \quad (5.1)$$

as well as

$$\Delta g_{t+h} = \beta_0 + \beta_1 \cdot tp_t(120) + \beta_2 \left(\frac{1}{n} \sum_{i=1}^{120} \mathbb{E}_t [r_{t+i}] - r_t \right) + \beta_3 \cdot \left(\frac{1}{n} \sum_{i=1}^{120} \mathbb{E}_t [\pi_{t+1+i}] - \pi_t \right) + \xi_{t+h}^g, \quad (5.2)$$

where Δg_{t+h} , represents the rate of growth of real GDP from period $t + h - 1$ to period $t + h$, and ξ_{t+h}^g is an innovation. In contrast to much of the literature on the predictive power of the term spread for future activity and inflation, we choose to use marginal rates of growth as inference in regressions with overlapping dependent variables may be fraught with difficulties (see, e.g., [Hodrick \(1992\)](#), [Valkanov \(2003\)](#), [Müller \(2014\)](#), and [Cattaneo and Crump \(2014\)](#)).

Table 5 shows the results of the predictive regressions of real GDP growth on the 10-year/three-month Treasury term spread and its components using our measures of expected rates and expected inflation.²⁶ The table has two panels: the upper panel covers the sample period from 1984-2014, the bottom panel the sample period from 1984-2007.²⁷ In each

²⁶In the Supplementary Appendix, we show the corresponding results using real gross domestic income and personal consumption expenditures as measures of economic activity. These results are very similar.

²⁷For these regressions, we restrict ourselves to the sample period starting in 1984 as this is when the coverage of survey data is particularly strong. In unreported results for the full sample from 1964 onwards, we confirm the widely documented result that the term spread has had strong predictive power for future real growth.

panel, we report predictive regressions for horizons ranging from $h \in \{1, 2, 3, 4, 6, 8, 12\}$ quarters for three specifications. The first row shows the results of simply regressing on the 10-year/three-month term spread (labeled $TS10Y$), the second for regressing on the term premium ($TP10Y$) and the expected path of future nominal short rates (“risk-neutral term spread”, $RNTS10Y$), and the third for regressing on the term premium, the expected path of future real short rates (“real risk-neutral term spread”, $RRNTS10Y$) as well as the expected path of future inflation ($INFTS10Y$). For each regressor, coefficients are reported in the first column and t -statistics in the second.

Starting with the sample from 1984-2014 (upper panel), we see that the predictive power of the term spread itself has largely faded. At all forecast horizons, the predictive coefficients are not distinguishable from zero and the R^2 s are very small. This is in line with recent research (e.g., [Schrimpf and Wang \(2010\)](#)) which has shown that the predictive power of the term spread has weakened significantly in the post-1983 sample. As monetary policy is characterized by a more active monetary policy stance in this period (see for example [Clarida et al. \(2000\)](#)), this finding is also consistent with the New Keynesian model by [Estrella \(2005\)](#) discussed above.

Looking at the predictive regressions on the expected rate path and term premium components of the term spread, however, we find that the term premium strongly predicts future economic activity up to six quarters ahead. This is documented by the sizable and statistically highly significant coefficients but also by the sharp increase in the adjusted R^2 s in the regressions on the two components. This finding is in contrast to [Ang et al. \(2006\)](#) who attribute the dominant role to the expectations hypothesis component in similar regressions, albeit for the sample period 1964-2001. As their term spread decomposition results from an affine model with constant coefficients, it is subject to similar criticism as the VAR-based models studied above.²⁸

Our approach allows us to further decompose the expectations hypothesis component of the term spread into the expected path of future real short rates and the expected path of future inflation. The coefficients and corresponding t -statistics for these two components are provided in the last four columns of the table. They show that there is some predictive power for future real growth embedded in expected future real rates at horizons from two to four quarters ahead, while expected future inflation does not enter significantly.

Given the relatively stark deviations of the survey-based term premium from the model-based ones in the latter part of the sample, one might wonder if the strong predictive power of the term premium component is driven mainly by the last few years in the sample. We

²⁸In unreported results, we find that this is robust to including the level of the nominal short rate in the predictive regressions, as suggested by [Ang et al. \(2006\)](#).

address this question in the second panel of Table 5 by ending the sample in 2007 and thus excluding the zero lower-bound period. While both the predictive coefficients on the term premium and the regression R^2 s are somewhat smaller in magnitude over this sample, the results are very similar to the full post-1983 sample. Specifically, the term premium remains a strongly statistically significant predictor of future real growth up to six quarters ahead and the expected path of future real rates up to four quarters ahead.

Interestingly, in all regressions the term premium predicts future real growth with a positive sign. There are several potential explanations for this finding. First, as banks' and other financial intermediaries' business models rely on short-term borrowing to finance long-term lending, all else equal, a decline of term premiums might result in the compression of the net interest margin that they earn. Hence, declining term premiums might go hand in hand with a decline in the supply of credit to the real economy, which in turn could lead to lower future economic activity. This explanation has been brought forward by [Adrian et al. \(2010\)](#). Another potential explanation is that when investors expect a future downturn, there is a "flight to quality" or "flight to safety" as they invest more in safe and liquid Treasury bonds. To the extent that their predictions materialize, one would then see a positive relationship between term premiums and future real growth.

Combined, our results thus show that the term premium obtained from survey expectations is economically important as it captures predictive information about future real growth even when the overall term spread does not. This suggests that there is valuable information in term premiums for the design and evaluation of macroeconomic models.

5.2 Macroeconomic Shocks

In the previous section we have shown that term premiums have predictive power for economic activity. We next investigate the economic driving forces affecting their dynamics. Specifically, we assess how term premiums and short rate expectations respond to different structural macroeconomic shocks that have been identified in the literature. While most general equilibrium macroeconomic models ignore term premiums, a few approaches have recently emerged that explicitly accommodate their role in structural models. This is typically done either by exploring alternative specifications of risk preferences or by introducing financial frictions.²⁹ In both frameworks, term premiums respond to macroeconomic shocks and,

²⁹[Rudebusch and Swanson \(2008\)](#) and [Christoffel et al. \(2011\)](#) find a role for term premiums by introducing consumption preferences with habit formation, [Piazzesi and Schneider \(2007\)](#), [Rudebusch and Swanson \(2012\)](#) and [van Binsbergen et al. \(2012\)](#) instead rely on Epstein and Zin recursive preferences. In models such as [Chen et al. \(2012\)](#), [Gertler and Karadi \(2013\)](#), and [Carlstrom et al. \(2014\)](#) term premiums arise because of financial frictions that drive a wedge between short-term deposits collected from households and long-term lending rates.

in turn, changes in term premiums contain predictive information about economic activity.

In order to evaluate the impact of macroeconomic shocks on the components of the yield curve, we estimate impulse responses of both expected short-term rates and term premiums using the approach in [Romer and Romer \(2004\)](#) and [Romer and Romer \(2010\)](#). Precisely, we estimate the equation

$$tp_t = a + \sum_{i=0}^N b_i \epsilon_{t-i} + \sum_{j=1}^M c_j tp_{t-j} + e_t \quad (5.3)$$

where ϵ_t denotes the structural shocks and e_t captures an unobserved disturbance, and similarly for expected short rates. The lag lengths denoted by N and M are chosen using the Bayesian information criterion (BIC). To ensure that our conclusions are not unduly influenced by the flexibility of the specification in Equation (5.3), we also provide results from a more parsimonious (nested) model given by $c_1 = -1$, $c_j = 0$, $\forall j \neq 1$ in the Supplementary Appendix, and show that these results imply similar effects as the impulse responses from Equation (5.3).³⁰

We group the macroeconomic shocks into three broad categories: “policy”, “demand” and “supply shocks”. The first category comprises both monetary and fiscal policy shocks. In the second category, we consider financial and uncertainty shocks which in many economic models have “demand-like” features as they induce a positive comovement between inflation and economic activity. In contrast, supply shocks are generally viewed as having opposite effects on inflation and economic activity. Here we focus on oil and total factor productivity (TFP) shocks as typical examples of supply shocks.

Figures 10–13 display the responses of expected future short rates and term premiums to each of these shocks. In more detail, they show impulse responses to a one standard deviation shock on the expected rates and term premium components of the one-year rate one-year and nine-years forward, respectively. In addition, the Supplementary Appendix reports impulse responses for the four- and seven-year forwards. In each chart, the black line represents the median impulse response, while the shaded areas display the nominal coverage rates of 68, 90 and 95 percent, respectively.

An important feature of our survey-based expected rates and term premiums is that they can display quite different responses to shocks at different horizons. This is because the model we use to fit the term structures of consensus expectations allows independent variation of short-term components from long-term trends. Note that this is generally not

³⁰Specifically, we estimate the equation

$$\Delta tp_t = a + b\epsilon_t + e_t, \quad (5.4)$$

and similarly for expected short rates.

the case for standard VAR models with constant long-run means. Indeed, we verified that expected rates and term premiums implied by these models display fairly uniform responses at short- and long-term maturities. We do not show these results here to conserve space.

Policy shocks We consider monetary policy shocks based on [Kuttner \(2001\)](#) who uses surprises in federal funds futures on FOMC announcement days. The measure is the only shock series with a monthly frequency and is available from November 1988 onwards; to avoid issues with the zero lower bound period we only consider it through December 2007. Figure 10 shows that a contractionary monetary policy shock has large and persistent effects on the one-year forward expected short rate but leaves the one-year forward expected short rate nine years out essentially unchanged. Interestingly, as shown in Figure 15 in the Supplementary Appendix, the monetary policy shock affects short rate expectations strongly even four years out, suggesting that medium-term expectations are not time-invariant as assumed in most macroeconomic models. This point has been made in [Gürkaynak et al. \(2005b\)](#) who, however, use forward rates that are unadjusted for term premiums.

Figures 10 and 15 further show that term premiums decline across all horizons, with stronger and more persistent impulse responses at long maturities. This result accords with the theoretical predictions of, e.g., [Rudebusch and Swanson \(2012\)](#). In their model a contractionary monetary policy shock implies a decline in both economic activity and inflation and leads to a lower term premium. Intuitively, by lowering both expected consumption growth and inflation, an increase in the policy rate raises the payoff of nominal bonds precisely in periods when consumption growth is expected to be low and thus marginal utility is high. Therefore, investors require less compensation for holding these bonds.

The decline in term premiums subsequent to a contractionary monetary policy shock contradicts the VAR evidence in [Gertler and Karadi \(2015\)](#). These authors instead attribute the bulk of the positive response of long-term rates to a contractionary monetary policy shock to an increase in term premiums. Of note, their estimates of short rate expectations and term premiums are based on a constant parameter VAR. Interestingly, when they add a measure of short-term survey forecasts of the three-month Treasury bill rate to the VAR, they find a stronger reaction of short-term expectations to the monetary shock, consistent with our results. An increase in term premiums following a Kuttner shock is also found by [Abrahams et al. \(2015\)](#). Using an affine term structure model and daily data on nominal Treasury yields and TIPS, these authors decompose term premiums into real term premiums and inflation risk premiums and find that while the inflation risk premium declines slightly in response to a contractionary monetary policy shock, this is offset by an increase in the real term premium. [Abrahams et al. \(2015\)](#) interpret their findings as consistent with the

risk-taking channel of monetary policy according to which financial intermediaries reduce their risk-taking when faced with a tightening funding conditions. Potential reasons for the differences of our results with respect to those in [Abrahams et al. \(2015\)](#) are their relatively short sample which starts in 1999 due to the availability of TIPS data and the fact that they use daily as opposed to monthly data.

In the Supplementary Appendix we also consider as alternative monetary policy shocks the “target” and “future policy path” factors, as suggested by [Gürkaynak et al. \(2005b\)](#) — GSS henceforth.³¹ While the effects of a target shock are very similar to those of the Kuttner shock, we find that the GSS path shock affects short-term and medium-term yields entirely through the expected rates channel, and does not move term premiums or long-term short rate expectations.

In terms of fiscal shocks, we use the [Mertens and Ravn \(2012\)](#) modification of the [Romer and Romer \(2010\)](#) measure of exogenous tax changes relative to GDP which is constructed using a narrative analysis of US tax policy in the post-war period and excludes anticipated tax changes. The impulse responses in Figure 10 show that the fiscal shock induces a statistically significant and fairly persistent decline in term premiums at medium and long-term maturities but does not significantly affect the expected path for the short-term rate.³² While this finding could reflect a diminished risk to the fiscal outlook, to our knowledge no structural model discusses the implications of tax changes for term premiums. That said, [Dai and Philippon \(2006\)](#) and [Laubach \(2009\)](#), among others, show that fiscal deficits raise term premiums using reduced form affine term structure models.

In the Supplementary Appendix, we consider a second fiscal shock due to [Ramey \(2011\)](#), which captures unexpected changes in the present discounted value of federal government defense spending that are due to foreign political events, relative to GDP. This measure, which is available for the sample period 1959Q1–2010Q4, is constructed using narrative analysis from newspaper and magazine articles and has very few non-zero observations over the sample we consider in this paper. Not surprisingly, our results show no significant effects on either expected rates or term premiums across the maturity spectrum.

Demand Shocks. A recent macroeconomic literature has emphasized the importance of “financial shocks” for explaining business cycle dynamics (e.g., [Gilchrist and Zakrajšek \(2012\)](#), [Justiniano et al. \(2010\)](#), and [Christiano et al. \(2014\)](#)). Here, we label such innova-

³¹Their decomposition implies that unexpected changes in federal funds futures up to a maturity of one year are driven by both a target rate shock as well as a shock to the expected path of policy rates that is independent of changes in the current funds rate target.

³²The Supplementary Appendix also includes the impulse responses to the original [Romer and Romer \(2010\)](#) shock, which deliver similar results.

tions “demand shocks” as they typically move output and inflation in the same direction. We consider two measures of such shocks, which are both meant to capture exogenous changes to corporate spreads. The first is derived from a VAR which includes the excess bond premium described in [Gilchrist and Zakrajšek \(2012\)](#).³³ The second measure is given by the spread shocks identified using the DSGE model in [Del Negro et al. \(2013\)](#).³⁴ As can be seen from Figure 11 and from Figures 18, 22, and 23 in the Supplementary Appendix, both shocks produce a persistent decline in expected rates up to four years ahead and of term premiums across all maturities.³⁵ The effects on the term premium are consistent with theoretical predictions: by inducing a positive co-movement between economic activity and inflation the financial shocks lower the term premium. The difference with respect to monetary policy shocks is that expected rates fall as the monetary authority reacts to the negative demand shock.³⁶ An alternative explanation for the observed decline in term premiums involves investors’ risk attitudes: a negative demand shock may trigger “flight-to-quality” flows as investors switch from risky assets to safer government bonds. Consistent with this view, term premiums decline across different maturities.

We consider two additional “demand” shocks which are based on different measures of macroeconomic uncertainty. The first is due to [Jo and Sekkel \(2016\)](#) and is derived from SPF survey forecast errors for various macroeconomic indicators such as real GDP, the unemployment rate, industrial production and housing starts.³⁷ The second uncertainty shock is obtained from [Basu and Bundick \(2015\)](#) who identify it using a VAR including the Chicago Board of Options Exchange Volatility Index (VXO) as a measure of uncertainty, in addition to selected macroeconomic variables.³⁸ As Figure 12 shows, an unexpected increase

³³The VAR includes the growth rate of private consumption expenditures and real business investment growth and real GDP, together with inflation measured by the GDP deflator, the excess bond premium, the excess return on the stock market, the ten-year Treasury yield and the effective federal funds rate. The model is estimated at the quarterly frequency over the sample 1973Q1–2010Q3 and uses a recursive identification scheme.

³⁴The model uses the following observables: real GDP and total hours worked (both in per capita terms), the core PCE deflator, the labor share, the federal funds rate and a spread between the BAA ten-year corporate rate and the ten-year Treasury yield. The shock series is available for the sample period 1983Q1–2014Q4.

³⁵The Supplementary Appendix further shows that the impulse responses obtained using the pre-crisis sample are very similar, documenting that this finding is not driven by the financial crisis.

³⁶Interestingly, the impulse response of term premiums does not appear consistent with financial frictions as modeled in [Carlstrom et al. \(2014\)](#) in which a negative financial shock increases the term premium.

³⁷Specifically, uncertainty shocks are obtained as *innovations* to the conditional, time-varying standard deviation of a factor that is common to the forecast errors for the different indicators. This shock measure is available at a quarterly frequency for the sample 1968Q4–2014Q1. We thank Soojin Jo and Rodrigo Sekkel for providing this series. This measure of uncertainty is shown to have comparable effects on economic activity as the one recently proposed in [Jurado et al. \(2015\)](#), who compute a measure of uncertainty from a stochastic volatility model estimated in a data-rich environment.

³⁸Specifically, they use real GDP, consumption, investment, hours worked, the GDP deflator, the M2

in both measures of uncertainty implies a decline in the term premium on impact. Although the impulse responses for the term premium are qualitatively similar to those obtained for the spread shocks, they are less precisely estimated and display considerably less persistence. This may partly reflect the small number of sizable uncertainty events over our sample. A notable difference between the two uncertainty shocks is that the one by [Basu and Bundick \(2015\)](#) implies a significant and persistent decline in expected short term rates both at short and longer term maturities.

Supply Shocks. As “supply” shocks we consider two oil shock measures and a total factor productivity (TFP) shock which are often discussed in the macro literature. The first supply shock, discussed in [Hamilton \(1996, 2003\)](#) defines positive oil *price* shocks as the difference between the current price of oil and the maximum price over the past twelve months. In other periods the shock is set to zero. The series we use is quarterly and is available from 1951Q1–2007Q4.³⁹ The second measure we use is the oil *supply* shock series computed in [Kilian \(2008\)](#), which measures exogenous oil production disruptions across OPEC countries. This measure is available at the quarterly frequency for the sample 1971Q1–2004Q3.

Figure 13 provides the impulse responses to a positive oil price shock based on [Hamilton \(1996, 2003\)](#) and a positive oil quantity shock from [Kilian \(2008\)](#). Both supply shocks imply a significant response of medium-to-long maturity term premiums on impact. Specifically, the term premium declines when a negative oil supply shock hits. That said, both impulse responses are imprecisely estimated beyond the first quarter and, in the case of the price shock, the median response predicts that the initial increase is offset in the following quarters. As in the case of uncertainty shocks above, this lack of precise estimates might reflect the small number of sizable shocks observed in our sample. Turning to expected rates, the quantity measure does not imply any significant response, while the price shock appears to affect positively medium and long-term rate expectations.

The last supply shock we consider measures news about future TFP and is taken from [Barsky and Sims \(2011\)](#). These authors use a VAR including non-durable and services real consumption expenditures, real GDP, per-capita hours worked and a measure of TFP adjusted using capacity utilization. They identify the news shock as the innovation that best explains future TFP at a ten year horizon and is orthogonal to current TFP shocks.⁴⁰ The shock series is available at a quarterly frequency for the sample period 1983Q3–2007Q3

money stock, and a measure of the stance of monetary policy and use a recursive identification with the VXO ordered first. The shock series is available for the period 1986–2014. We thank Susanto Basu and Brent Bundick for providing this series.

³⁹We thank Olivier Coibion for providing this shock series.

⁴⁰We use the same shock series as in [Coibion and Gorodnichenko \(2012\)](#).

which roughly spans the Great Moderation. As can be seen from Figure 13, a positive news shock produces a decline in the term premium at medium-to-long maturities on impact. However, as in the case of the oil shocks the effect is not statistically significant beyond the first quarter.⁴¹

In sum, we find that negative (positive) supply shocks result in an increase (decrease) in the term premium on impact. This is consistent with the models of e.g. Piazzesi and Schneider (2007) and Rudebusch and Swanson (2012) who argue that shocks which imply a positive response of consumption growth and a negative response of inflation should lower the term premium. Our finding that the term premium does not react significantly to supply shocks beyond the first quarter may suggest a diminished importance of supply shocks in our sample period. In contrast, financial shocks have large and persistent effects on term premiums, which complements the finding discussed above that such shocks play a dominant role in explaining business cycle dynamics over the past several decades.

6 Conclusion

A long literature has used statistical models fitted to the term structure of interest rates to decompose bond yields into the expected path of future short rates and term premiums, treating both as unobserved. In this paper, we obtain term premiums as the simple difference between government bond yields and survey-based expected average short rates. Specifically, we characterize the expected path of nominal and real short-rates as well as inflation using the universe of U.S. macroeconomic survey forecasts covering over 500 survey-horizon pairs. Our survey-based term premiums accommodate perceived structural change and learning effects, are consistent with a lower bound on nominal interest rates, and are available in real time. Given the decomposition of bond yields into expected future short rates and term premiums, we document a number of important facts for the sample period from 1983 through 2014: (1) the bulk of the variation in medium- and long-term bond yields is driven by term premiums, not expected short rates or inflation; (2) term premiums co-move more strongly across maturities than expected short rates or even yields themselves; (3) the term premium, not the term spread or the expected path of future short rates, predicts quarterly real output growth; (4) macroeconomic factors are important drivers of term premiums with demand shocks playing the most prominent role; (5) the secular decline of U.S. long-term bond yields over the past 30 years is primarily due to a decline of expected inflation and

⁴¹In the Supplementary Appendix, we also consider technology shocks identified as in Galí (1999) from a VAR including changes in labor productivity, in hours and in the GDP deflator with the restriction that only technology shocks have long-run effects on labor productivity. This shock, which is not obtained using direct estimates of TFP, appears to have some impact on expected rates but not on term premiums.

term premiums while expected future real rates have fluctuated around two percent.

Our findings have important implications for both macroeconomics and finance. The vast majority of structural macroeconomic models do not include term premiums, but instead assume the expectations hypothesis to hold, at least to a first-order approximation. Our results suggest that incorporating time varying term premiums is necessary in order to account for the observed variation of long-term bond yields. Even in the absence of financial frictions, introducing term premiums in macro models can provide useful information about the underlying shocks buffeting the economy. More importantly, in models where financial frictions are present, time variation in term premiums can significantly alter the monetary transmission mechanism and the economic response to shocks.

7 Data Appendix

In this section we provide additional details about the survey data we use in the paper. Table 1 provides a succinct summary of the surveys, variables and horizons which are available. In general, we use all available professional survey data for our three candidate variables of interest. Any exception is listed in this Data Appendix. To proceed we will first provide greater detail on how we map survey forecasts to our modeling framework discussed in Section 3. 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. 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, the quarter average 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 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,

$$100 \cdot (G_{2013}/G_{2012} - 1) \approx \frac{1}{24} (g_{2012m2} + 2 \cdot g_{2012m3} + 3 \cdot g_{2012m4} + \cdots + 12 \cdot g_{2013m1} \\ + 11 \cdot g_{2013m2} + 10 \cdot g_{2013m3} + \cdots + 2 \cdot g_{2013m11} + g_{2013m12}).$$

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). 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. We now briefly discuss the individual surveys:

Blue Chip Economic Indicators The Blue Chip Economic Indicators (BCEI) is a survey of professional forecasters that has been running since 1976. The survey is typically released on the 10th of each month, and is based on 50-plus responses that have been collected during the first week of the same month. The survey focuses primarily on economic variables such as those in the NIPA tables, but also includes forecasts for the unemployment rate, total industrial production, housing starts, and vehicle sales as compared to the Blue Chip Financial Forecasts Survey but also includes forecasts for the 3-month Treasury bill. The participants

of the survey range from large commercial banks, broker dealers, insurance companies, large manufacturers, economic consulting firms, GSEs and others. Quarterly forecasts of the 3-month TBILL are the average yield in the quarter. Quarterly forecasts of CPI and GNP/GDP are quarter average annualized growth rates. Annual forecasts for the 3-month TBILL are the annual average yield in the year and annual forecasts of CPI and GNP/GDP are annual average growth rates. Beginning in March 1979, BCEI began querying respondents on their forecasts for a selection of variables over the following five years. Later that year, these special questions included longer horizons including 6-to-11 years ahead. These biannual questions have generally been conducted in the March and October surveys. Blue Chip Economic Indicators is owned by Wolters Kluwer.

Blue Chip Financial Forecasts The Blue Chip Financial Forecasts Survey (BCFF) is a monthly survey of about 50 professional forecasters that has been running since 1982. The survey is typically released on the first day of the month, and is based on participants' responses that have been collected during the last week of the previous month. The survey focuses primarily on financial variables such as interest rates (as compared to the BCEI) but also includes forecasts for major macroeconomic variables (such as output and inflation). The participants of the survey range from broker-dealers to economic consulting firms and the identity of the participants is linked to their shorter-term forecasts (out to as much as six-quarters ahead). For longer horizons the consensus (i.e., mean) forecast is provided for each variable. Quarterly forecasts of the 3-month TBILL are the average yield in the quarter. Quarterly forecasts of CPI and GNP/GDP are quarter average annualized growth rates. Annual forecasts for the 3-month TBILL are the annual average yield in the year and annual forecasts of CPI and GNP/GDP are annual average growth rates. Beginning in 1983, BCFF began querying respondents on their forecasts for a selection of variables over the following five years (once in 1983 and twice in 1984 and 1985). Starting in 1986 these biannual special questions included longer horizons including 6-to-11 years ahead. Between March 1986 and March 1996 longer-run forecasts are provided in the March and October surveys. From December 1996 onward, long-run forecasts are provided in the June and December releases. The only exception to this rule is that long-run forecasts were provided in the January 2003 survey instead of the December 2002 survey. Blue Chip Financial Forecasts is owned by Wolters Kluwer.

Consensus Economics The Consensus Economics survey is a monthly survey of professional forecasters that has been running since 1989. The survey respondents range from Economists at financial institutions to those at non-financial firms or universities. In addition to the United States, the data includes simultaneous surveys for Canada, Mexico, China, Japan, and over fifty other countries in Europe, Asia, and Latin America. The identity of the participants is linked only to their shorter-term annual forecasts; quarterly forecasts and longer-term forecasts only report summary statistics. Annual forecasts for real GDP and CPI inflation are annualized growth rates. Since 1993, the survey also reports quarter average annualized growth rates for these two variables. Forecasts for the TBILL are provided for horizons of 3-months and 12-months ahead along with additional quarterly forecasts which represent the end of quarter value (the additional quarterly forecasts begin in 1990). Longer-term forecasts out as far as 10 years ahead are available for real GDP growth and CPI inflation and are currently released four times per year. Consensus Economics is a management-owned company.

Decision-Makers Poll The Decision-Makers Poll is a survey that began in September 1978 and was conducted initially by Richard B. Hoey. The survey was discontinued in March 1991 but then reinstated for only five months in March 1993. The survey did not have a fixed frequency but starting in 1981 it was conducted at least four times a year and included participants from various firms. The number of respondents varied

from 175 to 500 according to [Levin and Taylor \(2013\)](#). We do not have access to the full data set; however, we obtain the data available from 1978 to 1987 from [Havrilesky \(1988\)](#). Early papers which used these data include [Holland \(1984\)](#), [Darin and Hetzel \(1995\)](#), [Levin and Taylor \(2013\)](#).

Goldsmith-Nagan The Goldsmith-Nagan survey is a quarterly survey that began in September 1969 and ended in 1986. The survey participants were executives and economists at banks and other financial institutions and only the consensus expectation for various interest rates and maturities (e.g., 3-, 6-, and 12-month T-bills) are reported according to [Prell \(1973\)](#). The surveys were conducted at the end of each quarter and the Q1 forecast represents the end of quarter value for the following quarter. We do not include the Q2 forecasts as they appear excessively volatile. Early papers which used these data include [Prell \(1973\)](#), [Friedman \(1979\)](#), [Friedman \(1980\)](#), and [Froot \(1989\)](#)

Livingston Survey The Livingston Survey was begun in June 1946 by Joseph Livingston, but was taken over in 1990 by the Federal Reserve Bank of Philadelphia.⁴² The survey is conducted twice a year in June and December and was conducted when Livingston worked at the *Philadelphia Inquirer*. He sent his survey to professional Economists. The survey queries respondents on all three of our variables. Annual real GDP forecasts are annual average growth rates. Note that the target CPI measure is the index value in the last month of the quarter. Prior to 2004, the survey asked for the value of the not seasonally adjusted index; however, restricting the estimation to data which is not affected by this issue does not materially change our results. For some horizons the base year used by the forecasters are unclear and so we exclude all forecasts where the forecasters' base year is unknown. Quarterly and annual forecasts for the TBILL are end of period forecasts.

Survey of Primary Dealers The Survey of Primary Dealers (SPD) is conducted by the the Trading Desk of the New York Fed one to two weeks before each regularly scheduled Federal Open Market Committee meeting.⁴³ As the name implies the survey respondents are the current (at the time of the survey) Primary Dealers to the Federal Reserve Bank of New York.⁴⁴ The survey began in 2004; however, we use only the publicly available data which begins in 2011 and has included questions on quarterly and annual real GDP growth and 5-year/5-year (Y6-10) forward CPI inflation.⁴⁵ Annual GDP forecasts are requested for Q4/Q4 growth rates to match the convention used in the FOMC's Summary of Economic Projections (SEP). In addition, the survey includes forecasts on "longer-run" real GDP growth which corresponds to the variable \bar{g}_t (see Section 3). The public data report median rather than mean values as the central tendency of the cross-section of forecasts and so we use this measure. We have verified, using non-public data, that the median and mean values are similar.

SPF The Survey of Professional Forecasters (SPF) is conducted on a quarterly basis by the Federal Reserve Bank of Philadelphia (FRBP). The survey began in the fourth quarter of 1968 and, at that time, was conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) before being taken over by the FRBP in the second quarter of 1990.⁴⁶ The forecasts are anonymous

⁴²For more details on the survey see <https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/livingston-survey/livingston-documentation.pdf?la=en>.

⁴³For more details on this survey see [Golay et al. \(2013\)](#).

⁴⁴See https://www.newyorkfed.org/markets/pridealers_current.html for more information.

⁴⁵See http://www.newyorkfed.org/markets/primarydealer_survey_questions.html.

⁴⁶For more details on the survey see <https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf?la=en>.

but are given specific industry identifiers which were updated in 2007. The survey includes forecasts of all three variables we consider and, more recently, has included longer-term forecasts over the next 10 years for real GDP, CPI and the TBILL starting in the early 1990s; however, forecasts whose target period start in 3 or more years were introduced for CPI in 2005 and real GDP and TBILL in 2009. Growth rates for real GDP are based on average levels across variables and real GNP was not explicitly surveyed before the third quarter of 1981. Unlike the other surveys, annual CPI inflation is measured as Q4/Q4 growth rates rather than annual average growth. Following the discussion in the documentation of the survey we drop the appropriate observations in 1986Q1, 1990Q1 and 1990Q2. We assign the survey period during the middle month of each quarter based on the description in SPF documentation.

References

- Abrahams, M., Adrian, T., Crump, R. K., Moench, E., 2015. Decomposing real and nominal yield curves. Staff Report 570, Federal Reserve Bank of New York.
- Adrian, T., Crump, R. K., Moench, E., 2013. Pricing the term structure with linear regressions. *Journal of Financial Economics* 110, 110–138.
- Adrian, T., Estrella, A., Shin, H. S., 2010. Monetary cycles, financial cycles and the business cycle. Staff Report 421, Federal Reserve Bank of New York.
- Andrade, P., Crump, R. K., Eusepi, S., Moench, E., 2014. Fundamental disagreement. Staff Report 655, Federal Reserve Bank of New York.
- Andrade, P., Le Bihan, H., 2013. Inattentive professional forecasters. *Journal of Monetary Economics* 60, 967–82.
- Ang, A., Bekaert, G., Wei, M., 2007. Do macro variables, asset markets, or surveys forecast inflation better? *Journal of Monetary Economics* 54, 1163–1212.
- Ang, A., Bekaert, G., Wei, M., 2008. The term structure of real rates and expected inflation. *Journal of Finance* 63, 797–849.
- Ang, A., Piazzesi, M., 2003. A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables. *Journal of Monetary Economics* 50, 745–787.
- Ang, A., Piazzesi, M., Wei, M., 2006. What does the yield curve tell us about GDP growth? *Journal of Econometrics* 131, 359–403.
- Aruoba, S. B., 2016. Term structures of inflation expectations and real interest rates. Working Paper 16-09, Federal Reserve Bank of Philadelphia.
- Barberis, N., Greenwood, R., Jin, L., Shleifer, A., 2015. X-CAPM: An extrapolative capital asset pricing model. *Journal of Financial Economics* 115, 1–24.
- Barsky, R. B., Sims, E. R., 2011. News shocks and business cycles. *Journal of Monetary Economics* 58, 273–289.

- Basu, S., Bundick, B., 2015. Uncertainty shocks in a model of effective demand. Tech. Rep. 12-15, Federal Reserve Bank of Boston, working paper.
- Campbell, J. Y., Shiller, R. J., 1991. Yield spreads and interest rate movements: A bird's eye view. *Review of Economic Studies* 58, 495–514.
- Carlstrom, C. T., Fuerst, T. S., Paustian, M., 2014. Targeting long rates in a model with segmented markets, working paper.
- Cattaneo, M. D., Crump, R. K., 2014. HAC corrections for strongly autocorrelated time series: Comment. *Journal of Business and Economic Statistics* 32, 324–329.
- Chen, H., Cúrdia, V., Ferrero, A., 2012. The macroeconomic effects of large-scale asset purchase programmes. *Economic Journal* 122, F289–F315.
- Christiano, L. J., Motto, R., Rostagno, M., 2014. Risk shocks. *American Economic Review* 104, 27–65.
- Christoffel, K., Jaccard, I., Kilponen, J., 2011. Government bond risk premia and the cyclical policy. Tech. Rep. 1411, European Central Bank.
- Cieslak, A., Povala, P., 2014. Expecting the Fed, working paper.
- Cieslak, A., Povala, P., 2015. Expected returns in Treasury bonds. *Review of Financial Studies* 28, 2859–2901.
- Clarida, R., Galí, J., Gertler, M., 2000. Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics* 115, 147–180.
- Cochrane, J., Piazzesi, M., 2005. Bond risk premia. *American Economic Review* 95, 138–160.
- Cogley, T., 2005. Changing beliefs and the term structure of interest rates: Cross-equation restrictions with drifting parameters. *Review of Economic Dynamics* 8, 420–452.
- Cogley, T., Primiceri, G. E., Sargent, T. J., 2010. Inflation-gap persistence in the US. *American Economic Journal: Macroeconomics* 2, 43–69.
- Cogley, T., Sargent, T. J., 2005. Drift and volatilities: Monetary policies and outcomes in the post WWII U.S. *Review of Economic Dynamics* 8, 262–302.
- Coibion, O., Gorodnichenko, Y., 2012. What can survey forecasts tell us about informational rigidities? *Journal of Political Economy* 120, 116–159.
- Croushore, D., 2010. An evaluation of inflation forecasts from surveys using real-time data. *B.E. Journal of Macroeconomics* 10.
- Crump, R. K., Eusepi, S., Moench, E., 2014. Data insight: Which growth rate? It's a weighty subject. *Liberty Street Economics Blog*.
- Crump, R. K., Eusepi, S., Tambalotti, A., Topa, G., 2015. Subjective intertemporal substitution. Staff Report 734, Federal Reserve Bank of New York.
- Dai, Q., Philippon, T., 2006. Fiscal policy and the term structure of interest rates, working paper.

- Dai, Q., Singleton, K. J., 2000. Specification analysis of affine term structure models. *Journal of Finance* 55, 1943–1978.
- Darin, R., Hetzel, R. L., 1995. An empirical measure of the real rate of interest. *Federal Reserve Bank of Richmond Economic Quarterly* 81, 17–47.
- De Graeve, F., Emiris, M., Wouters, R., 2009. A structural decomposition of the US yield curve. *Journal of Monetary Economics* 56, 545–559.
- Del Negro, M., Eusepi, S., Giannoni, M., Sbordone, A., Tambalotti, A., Cocci, M., Hasegawa, R., Linder, M. H., 2013. The FRBNY DSGE model. Staff Report 647, Federal Reserve Bank of New York.
- Dewachter, H., Lyrio, M., 2008. Learning, macroeconomic dynamics and the term structure of interest rates. In: Campbell, J. Y. (ed.), *Asset Prices and Monetary Policy*, University of Chicago Press, Chicago, IL.
- Dewachter, H., Lyrio, M., 2011. A new-Keynesian model of the yield curve with learning dynamics: A Bayesian evaluation, working paper.
- Diebold, F. X., Li, C., 2006. Forecasting the term structure of government bond yields. *Journal of Econometrics* 130, 337–364.
- Diebold, F. X., Rudebusch, G. D., Aruoba, S. B., 2006. The macroeconomy and the yield curve: a dynamic latent factor approach. *Journal of Econometrics* 131, 309–338.
- Duffee, G., 2002. Term premia and interest rate forecasts in affine models. *Journal of Finance* 57, 405–443.
- Duffie, D., 2001. *Dynamic Asset Pricing Theory*. Princeton University Press.
- Duffie, D., Kan, R., 1996. A yield-factor model of interest rates. *Mathematical Finance* 6, 379–406.
- Edge, R. M., Laubach, T., Williams, J. C., 2007. Learning and shifts in long-run productivity growth. *Journal of Monetary Economics* 54, 2421–2438.
- Estrella, A., 2005. Why does the yield curve predict output and inflation? *Economic Journal* 115, 722–744.
- Estrella, A., Hardouvelis, G. A., 1991. The term structure as a predictor of real economic activity. *Journal of Finance* 46, 555–576.
- Estrella, A., Mishkin, F. S., 1998. Predicting U.S. recessions: Financial variables as leading indicators. *Review of Economics and Statistics* 80, 45–61.
- Fama, E. F., Bliss, R. R., 1987. The information in long-maturity forward rates. *American Economic Review* 4, 680–692.
- Faust, J., Wright, J. H., 2013. Forecasting inflation. *Handbook of Economic Forecasting* 2, 2–56.
- Favero, C. A., Kaminska, I., Söderström, U., 2005. The predictive power of the yield spread: further evidence and a structural interpretation. Discussion paper, CEPR.

- Frankel, J. A., Froot, K. A., 1987. Using survey data to test standard propositions regarding exchange rate expectations. *American Economic Review* 77, 133–153.
- Friedman, B. M., 1979. Interest rate expectations versus forward rates: Evidence from and expectations survey. *Journal of Finance* 34, 965–973.
- Friedman, B. M., 1980. Survey evidence on the ‘rationality’ of interest rate expectations. *Journal of Monetary Economics* 6, 453–465.
- Froot, K. A., 1989. New hope for the expectations hypothesis of the term structure of interest rates. *Journal of Finance* 44, 283–305.
- Fuhrer, J. C., 1996. Monetary policy shifts and long-term interest rates. *Quarterly Journal of Economics* 111, 1183–1209.
- Galí, J., 1999. Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? *American Economic Review* 89, 249–270.
- Gennaioli, N., Ma, Y., Shleifer, A., 2015. Expectations and investment. *NBER Macroeconomics Annual* 30.
- Gertler, M., Karadi, P., 2013. QE 1 vs. 2 vs. 3...: A framework for analyzing large-scale asset purchases as a monetary policy tool. *International Journal of Central Banking* 9, 5–53.
- Gertler, M., Karadi, P., 2015. Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics* 7, 44–76.
- Ghysels, E., Horan, C., Moench, E., 2014. Forecasting through the rear-view mirror: Data revisions and bond return predictability. *Staff Report 581*, Federal Reserve Bank of New York.
- Gilchrist, S., Zakrajšek, E., 2012. Credit spreads and business cycle fluctuations. *American Economic Review* 102, 1692–1720.
- Golay, E. C., Friedman, S., McMorrow, M., 2013. Understanding the New York Fed’s Survey of Primary Dealers. *Current Issues in Economics and Finance* 19, 1–8.
- Greenwood, R., Shleifer, A., 2014. Expectations of returns and expected returns. *Review of Financial Studies* 27, 714–746.
- Gürkaynak, R., Sack, B., Swanson, E. T., 2005a. Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *International Journal of Central Banking* 1, 55–93.
- Gürkaynak, R., Sack, B., Swanson, E. T., 2005b. The sensitivity of long-term interest rates to economic news: Evidence and implications for macroeconomic models. *American Economic Review* 95, 425–436.
- Gürkaynak, R., Wright, J. H., 2012. Macroeconomics and the term structure. *Journal of Economic Literature* 52, 331–367.
- Gurkaynak, R. S., Sack, B., Wright, J. H., 2007. The U.S. treasury yield curve: 1961 to the present. *Journal of Monetary Economics* 54, 2291–2304.

- Gurkaynak, R. S., Sack, B., Wright, J. H., 2010. The TIPS yield curve and inflation compensation. *American Economic Journal: Macroeconomics* 2, 70–92.
- Hamilton, J. D., 1996. This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics* 38, 215–20.
- Hamilton, J. D., 2003. What is an oil shock? *Journal of Econometrics* 113, 363–98.
- Hamilton, J. D., Kim, D. H., 2002. A reexamination of the predictability of economic activity using the yield spread. *Journal of Money, Credit, and Banking* 34, 340–360.
- Havrilesky, T., 1988. New evidence on expected long term real interest rates. *Journal of Forensic Economics* 1, 19–23.
- Hodrick, R. J., 1992. Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *Review of Financial Studies* 5, 357–386.
- Holland, A. S., 1984. Real interest rates: What accounts for their recent rise. *Federal Reserve Bank of St. Louis* 18, 18–29.
- Jo, S., Sekkel, R., 2016. Macroeconomic uncertainty through the lens of professional forecasters, staff working paper.
- Joslin, S., Le, A., Singleton, K. J., 2013. Why Gaussian macro-finance term structure models are (nearly) unconstrained factor-VARs. *Journal of Financial Economics* 109, 604 – 622.
- Joslin, S., Priebisch, M., Singleton, K. J., 2014. Risk premiums in dynamic term structure models with unspanned macro risks. *The Journal of Finance* 69, 1197–1233.
- Joslin, S., Singleton, K. J., Zhu, H., 2011. A new perspective on Gaussian dynamic term structure models. *Review of Financial Studies* 24, 926–970.
- Jurado, K., Ludvigson, S. C., Ng, S., 2015. Measuring uncertainty. *American Economic Review* 105, 1177–1216.
- Justiniano, A., Primiceri, G. E., Tambalotti, A., 2010. Investment shocks and business cycles. *Journal of Monetary Economics* 57, 132–145.
- Kilian, L., 2008. Exogenous oil supply shocks: How big are they and how much do they matter for the U.S. economy. *Review of Economics and Statistics* 90, 216–240.
- Kim, D. H., Orphanides, A., 2012. Term structure estimation with survey data on interest rate forecasts. *Journal of Financial and Quantitative Analysis* 47, 241–272.
- Kim, D. H., Wright, J. H., 2005. An arbitrage-free three-factor term structure model and the recent behavior of long-term yields and distant-horizon forward rates. *Finance and Economics Discussion Series* 2005-33, Board of Governors of the Federal Reserve System.
- Koijen, R. S. J., Schmeling, M., Vrugt, E. B., 2015. Survey expectations of returns and asset pricing puzzles, working paper.
- Kozicki, S., Tinsley, P. A., 2001. Shifting endpoints in the term structure of interest rates. *Journal of Monetary Economics* 47, 613–652.

- Kozicki, S., Tinsley, P. A., 2005. What do you expect? Imperfect policy credibility and tests of the expectations hypothesis. *Journal of Monetary Economics* 52, 421–447.
- Kozicki, S., Tinsley, P. A., 2012. Effective use of survey information in estimating the evolution of expected inflation. *Journal of Money, Credit and Banking* 44, 145–169.
- Kuttner, K. N., 2001. Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics* 47, 523–544.
- Laubach, T., 2009. New evidence on the interest rate effects of budget deficits and debt. *Journal of the European Economic Association* 7, 858–885.
- Laubach, T., Tetlow, R. J., Williams, J. C., 2007. Learning and the role of macroeconomic factors in the term structure of interest rates, working paper.
- Laubach, T., Williams, J. C., 2003. Measuring the natural rate of interest. *The Review of Economics and Statistics* 85, 1063–1070.
- Levin, A. T., Taylor, J. B., 2013. Falling behind the curve: A positive analysis of stop-start monetary policies and the great inflation. In: Bordo, M. D., Orphanides, A. (eds.), *The Great Inflation: The Great Inflation: The Rebirth of Modern Central Banking*, University of Chicago Press, Chicago, IL.
- Ludvigson, S. C., Ng, S., 2009. Macro factors in bond risk premia. *Review of Financial Studies* 22, 5027–5067.
- Mankiw, N. G., Reis, R., Wolfers, J., 2003. Disagreement about inflation expectations. In: *NBER Macroeconomics Annual 2003*, National Bureau of Economic Research, vol. 18, pp. 209–270.
- Manski, C. F., 2004. Measuring expectations. *Econometrica* 72, 1329–1376.
- Mertens, K., Ravn, M. O., 2012. Empirical evidence on the aggregate effects of anticipated and unanticipated US tax policy shocks. *American Economic Journal: Economic Policy* 2, 145–81.
- Mishkin, F. S., 1990. The information in the longer maturity term structure about future inflation. *The Quarterly Journal of Economics* 105, 815–828.
- Moench, E., 2008. Forecasting the yield curve in a data-rich environment: A no-arbitrage factor-augmented VAR approach. *Journal of Econometrics* 146, 26–43.
- Müller, U. K., 2014. HAC corrections for strongly autocorrelated time series. *Journal of Business and Economic Statistics* 32, 311–322.
- Mundell, R., 1963. Inflation and real interest. *Journal of Political Economy* 71(3), 280–283.
- Patton, A. J., Timmermann, A., 2010. Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics* 57, 803–820.
- Piazzesi, M., 2003. Affine term structure models. In: *Handbook of Financial Econometrics*, Elsevier, vol. 1, chap. 12, pp. 691–758.
- Piazzesi, M., Salomao, J., Schneider, M., 2015. Trend and cycle in bond premia, working paper.

- Piazzesi, M., Schneider, M., 2007. Equilibrium yield curves. In: Acemoglu, D., Rogoff, K., Woodford, M. (eds.), *NBER Macroeconomics Annual 2006, Volume 21*, MIT Press, Cambridge, MA.
- Prell, M. J., 1973. How well do the experts forecast interest rates? Federal Reserve Bank of Kansas City Monthly Review 58, 3–13.
- Ramey, V. A., 2011. Identifying government spending shocks: It’s all in the timing. Quarterly Journal of Economics 126, 1–50.
- Romer, C. D., Romer, D. H., 2004. A new measure of monetary shocks: Derivation and implications. American Economic Review 94, 1055–1084.
- Romer, C. D., Romer, D. H., 2010. The macroeconomic effects of tax changes: Estimates based on a new measure of fiscal shocks. American Economic Review 100, 763–801.
- Rosenberg, J. V., Maurer, S., 2008. Signal or noise? implications of the term premium for recession forecasting. Economic Policy Review 14, 1–11.
- Rudebusch, G. D., Sack, B. P., Swanson, E. T., 2007. Macroeconomic implications of changes in the term premium. Federal Reserve Bank of St. Louis Review 89, 241–69.
- Rudebusch, G. D., Swanson, E. T., 2008. Examining the bond premium puzzle with a DSGE model. Journal of Monetary Economics 55, 111–126.
- Rudebusch, G. D., Swanson, E. T., 2012. The bond premium in a DSGE model with long-run real and nominal risks. American Economic Journal: Macroeconomics 4, 105–143.
- Rudebusch, G. D., Wu, T., 2008. A macro-finance model of the term structure, monetary policy and the economy. Economic Journal 118, 906–926.
- Schrumpf, A., Wang, Q., 2010. A reappraisal of the leading indicator properties of the yield curve under structural instability. International Journal of Forecasting 26, 836 – 857.
- Singleton, K. J., 2006. Empirical Dynamic Asset Pricing. Princeton University Press.
- Stock, J. H., Watson, M. W., 1989. New indexes of coincident and leading economic indicators. In: *NBER Macroeconomics Annual 1989*, National Bureau of Economic Research, vol. 4, pp. 351–409.
- Stock, J. H., Watson, M. W., 2007. Why has U.S. inflation become harder to forecast? Journal of Money, Credit and Banking 39, 3–33.
- Tobin, J., 1965. Money and economic growth. Econometrica pp. 671–684.
- Valkanov, R., 2003. Long-horizon regressions: theoretical results and applications. Journal of Financial Economics 68, 201–232.
- van Binsbergen, J. H., Fernández-Villaverde, J., Koijen, R. S., Rubio-Ramírez, J., 2012. The term structure of interest rates in a DSGE model with recursive preferences. Journal of Monetary Economics 59, 634–648.
- van Dijk, D., Koopman, S. J., van der Wel, M., Wright, J. H., 2014. Forecasting interest rates with shifting endpoints. Journal of Applied Econometrics 29, 693–712.

- Woodford, M., 2003. Interest and prices: foundations of a theory of monetary policy. Princeton University Press.
- Wright, J. H., 2011. Term premia and inflation uncertainty: Empirical evidence from an international panel dataset. *American Economic Review* 101, 1514–34.

Table 1: **Summary of Surveys**

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), Livingston Survey (Liv.), Survey of Primary Dealers, 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. For ongoing surveys, the reported frequency of questions pertaining to longer-term forecasts refer to the current scheduled frequency. Forecasts for output growth (RGDP) are based on real GNP growth prior to 1992 and real GDP growth after. Entries of the form Q0-Q6 imply that horizons Q1, Q2, . . . , Q6 are available; all other notation is defined in Section 2.

	BCFF	BCEI	CE	DMP	GN	Liv.	SPD	SPF
Survey Sample (full)								
<i>Frequency</i>	<i>Monthly</i>	<i>Monthly</i>	<i>Monthly</i>	<i>Irregular</i>	<i>Quarterly</i>	<i>Biannually</i>	<i>8 per year</i>	<i>Quarterly</i>
RGDP:	1984–present	1978–present	1989–present	n/a	n/a	1971–present	2011–present	1968–present
CPI:	1984–present	1980–present	1989–present	1978-1987	n/a	1946–present	2011–present	1981–present
TBILL:	1982–present	1982–present	1989–present	n/a	1969-1986	1992–present	n/a	1981–present
Survey Sample (LT)								
<i>Frequency</i>	<i>Biannually</i>	<i>Biannually</i>	<i>Quarterly</i>	<i>n/a</i>	<i>n/a</i>	<i>n/a</i>	<i>8 per year</i>	<i>Quarterly</i>
RGDP:	1984–present	1979–present	1989–present	n/a	n/a	1990–present	2012–present	1992–present
CPI:	1984–present	1984–present	1989–present	1978-1987	n/a	1990–present	2011–present	1991–present
TBILL:	1983–present	1983–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	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	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	n/a	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	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	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	n/a	n/a	n/a	n/a	n/a	Y3, Y0-9

Table 2: **Estimated Parameters**

This table provides the estimated parameters described in Section 3. The bottom panel gives the variance of the observation errors for each variable and horizon class. “VST” denotes *very short term* forecasts, “ST” denotes *short term* forecasts, “MT” denotes *medium term* forecasts, and “LT” denotes *long term* forecasts.

Φ	Σ^ν	Σ^η
$\begin{bmatrix} 0.7986 & -0.3245 & 0.0047 \\ 0.0057 & 0.8660 & 0.0163 \\ 0.0323 & -0.4792 & 1.0424 \end{bmatrix}$	$\begin{bmatrix} 0.7898 & 0.0294 & 0.0838 \\ 0.0294 & 0.0165 & 0.0534 \\ 0.0838 & 0.0534 & 0.2159 \end{bmatrix}$	$\begin{bmatrix} 0.0299 & -0.0087 \\ -0.0087 & 0.0222 \end{bmatrix}$
Real Output Growth	CPI Inflation	3-month T-Bill
VST : $\begin{bmatrix} 0.2670 \end{bmatrix}$	$\begin{bmatrix} 0.0625 \end{bmatrix}$	$\begin{bmatrix} 0.0943 \end{bmatrix}$
ST : $\begin{bmatrix} 0.0634 \end{bmatrix}$	$\begin{bmatrix} 0.0237 \end{bmatrix}$	$\begin{bmatrix} 0.0290 \end{bmatrix}$
MT : $\begin{bmatrix} 0.1043 \end{bmatrix}$	$\begin{bmatrix} 0.0219 \end{bmatrix}$	$\begin{bmatrix} 0.0942 \end{bmatrix}$
LT : $\begin{bmatrix} 0.0476 \end{bmatrix}$	$\begin{bmatrix} 0.0807 \end{bmatrix}$	$\begin{bmatrix} 0.1562 \end{bmatrix}$

Table 3: **Variance Decompositions for Yield Components: 198303-201412**

This Table presents variance decompositions for one-year forward rates ranging from one though ten-years out. For each maturity, the numbers shown represent the ratio of the covariance of the respective forward with its individual components (average expected real short rate, average expected inflation, and term premium) divided by the variance of the forward. The top panel provides variance decompositions for forward rates in levels, and the bottom panel for the first difference of the forward rates. The sample period is March 1983–December 2014.

	1	2	3	4	5	6	7	8	9
Levels									
Avg Exp Real Rate	0.45	0.32	0.22	0.15	0.11	0.07	0.06	0.04	0.04
Avg Exp Inflation	0.31	0.32	0.33	0.34	0.35	0.36	0.37	0.38	0.39
Fwd Term Premium	0.24	0.36	0.45	0.51	0.55	0.56	0.57	0.57	0.57
Differences									
Avg Exp Real Rate	0.20	0.10	0.05	0.03	0.03	0.02	0.02	0.02	0.01
Avg Exp Inflation	0.07	0.05	0.04	0.04	0.04	0.04	0.05	0.05	0.06
Fwd Term Premium	0.73	0.85	0.91	0.93	0.93	0.93	0.93	0.93	0.93

Table 4: **Variance Decompositions for Yield Components: 198303-200712**

This Table presents variance decompositions for one-year forward rates ranging from one though ten-years out. For each maturity, the numbers shown represent the ratio of the covariance of the respective forward with its individual components (average expected real short rate, average expected inflation, and term premium) divided by the variance of the forward. The top panel provides variance decompositions for forward rates in levels, and the bottom panel for the first difference of the forward rates. The sample period is March 1983–December 2007.

	1	2	3	4	5	6	7	8	9
Levels									
Avg Exp Real Rate	0.31	0.19	0.11	0.07	0.04	0.02	0.01	0.00	-0.00
Avg Exp Inflation	0.39	0.39	0.40	0.41	0.42	0.43	0.44	0.45	0.46
Fwd Term Premium	0.30	0.42	0.49	0.53	0.55	0.55	0.55	0.55	0.55
Differences									
Avg Exp Real Rate	0.20	0.10	0.05	0.02	0.01	-0.00	-0.01	-0.01	-0.02
Avg Exp Inflation	0.07	0.06	0.05	0.06	0.06	0.06	0.07	0.07	0.07
Fwd Term Premium	0.73	0.85	0.90	0.92	0.93	0.94	0.94	0.95	0.95

Table 5: **Predictive Regressions for RGDP Growth**

This Table presents results for predictive regressions from equation (5.3). h denotes the forecast horizon in quarters. $TS10Y$ is the 10-year three-month term spread, $TP10Y$ the term premium and $RNTS10Y$ the expected path of future nominal short rates (“risk-neutral term spread”) component of the spread. $RRNTS10Y$ denotes the expected path of future real short rates and $INFTS10Y$ the expected path of future inflation. For each regressor, coefficients are reported in the first column and t -statistics based on Newey-West standard errors with 12 lags in the second. The top panel provides results for the 1983-2014 and the bottom for the 1983-2007 sample.

h	TS10Y		TP10Y		RNTS10Y		RRNTS10Y		INFTS10Y		R2adj
1983-2014											
1	0.08	(0.37)									-0.01
			0.70***	(3.53)	-0.06	(-0.29)					0.09
			0.98***	(3.10)			0.65	(1.65)	-6.26	(-1.69)	0.15
2	0.17	(0.86)									-0.00
			0.69***	(3.49)	0.05	(0.21)					0.07
			0.91***	(3.10)			0.61*	(1.77)	-4.82	(-1.46)	0.11
3	0.25	(1.16)									0.01
			0.70***	(3.43)	0.14	(0.58)					0.06
			0.88***	(3.26)			0.63*	(1.88)	-4.10	(-1.36)	0.08
4	0.35	(1.46)									0.02
			0.78***	(2.82)	0.24	(0.97)					0.07
			0.96***	(3.00)			0.71**	(1.99)	-3.76	(-1.38)	0.09
6	0.52*	(1.70)									0.06
			0.83**	(2.51)	0.44	(1.47)					0.08
			0.89**	(2.49)			0.59	(1.39)	-0.87	(-0.41)	0.08
8	0.53	(1.53)									0.06
			0.81*	(1.95)	0.45	(1.44)					0.08
			0.77*	(1.75)			0.33	(0.84)	1.43	(0.64)	0.07
12	0.12	(0.42)									-0.01
			0.52	(1.15)	0.02	(0.11)					0.03
			0.55	(1.14)			0.16	(0.36)	-1.11	(-0.43)	0.02
1983-2008											
1	0.34**	(2.02)									0.02
			0.68***	(3.13)	0.17	(0.96)					0.06
			0.85***	(2.66)			1.11**	(2.21)	-6.72	(-2.14)	0.11
2	0.34*	(1.73)									0.02
			0.55**	(2.43)	0.23	(1.08)					0.03
			0.69**	(2.27)			0.99**	(2.21)	-5.27	(-1.65)	0.06
3	0.38*	(1.76)									0.04
			0.51**	(2.38)	0.32	(1.31)					0.03
			0.64**	(2.43)			0.98**	(2.25)	-4.51	(-1.47)	0.05
4	0.34	(1.44)									0.03
			0.47**	(2.16)	0.29	(1.06)					0.03
			0.56**	(2.50)			0.79**	(2.27)	-3.41	(-1.14)	0.03
6	0.38	(1.56)									0.04
			0.48**	(2.28)	0.34	(1.23)					0.03
			0.48**	(2.39)			0.34	(0.87)	0.29	(0.09)	0.02
8	0.26	(1.36)									0.01
			0.29*	(1.66)	0.25	(1.07)					-0.00
			0.25	(1.10)			0.04	(0.10)	1.76	(0.47)	-0.01
12	-0.11	(-0.47)									-0.01
			-0.00	(-0.01)	-0.13	(-0.67)					-0.02
			-0.12	(-0.32)			-0.60	(-1.22)	3.29	(1.23)	-0.01

Figure 1: **Examples of Fitted Values**

These figures show model-implied forecasts (grey) against observed survey data. Q3 forecasts for CPI are used so as to include the Q3-4 Livingston Survey forecast. “Long-run” denotes assorted longer-run forecasts out to a maximum of 11 years.

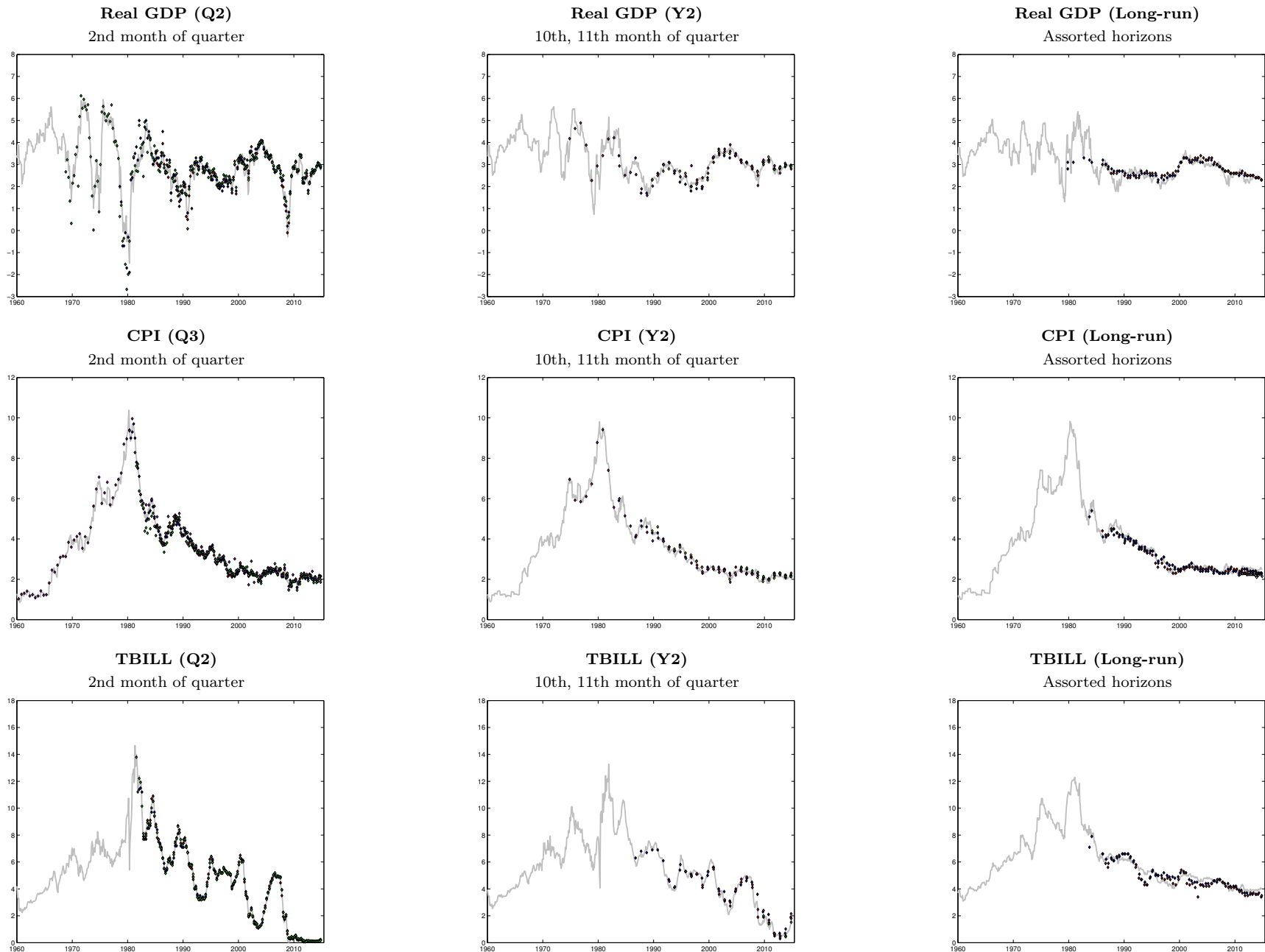


Figure 2: **Nominal and Real Expected Path of Short-Term Interest Rates**

These figures show the evolution of the secondary market 3-month Treasury bill available from the H.15 release of the Federal Reserve Board, underlying inflation as measured by π_t discussed in Section 3, and the ex-ante real short-term interest rate, measured as the difference between the secondary market 3-month Treasury bill rate and one-month ahead expected inflation $\mathbb{E}_t[\pi_{t+1}]$, as discussed in Section 3. The grey lines represent the term-structure of forecasts for the corresponding series at that point in time out ten years.

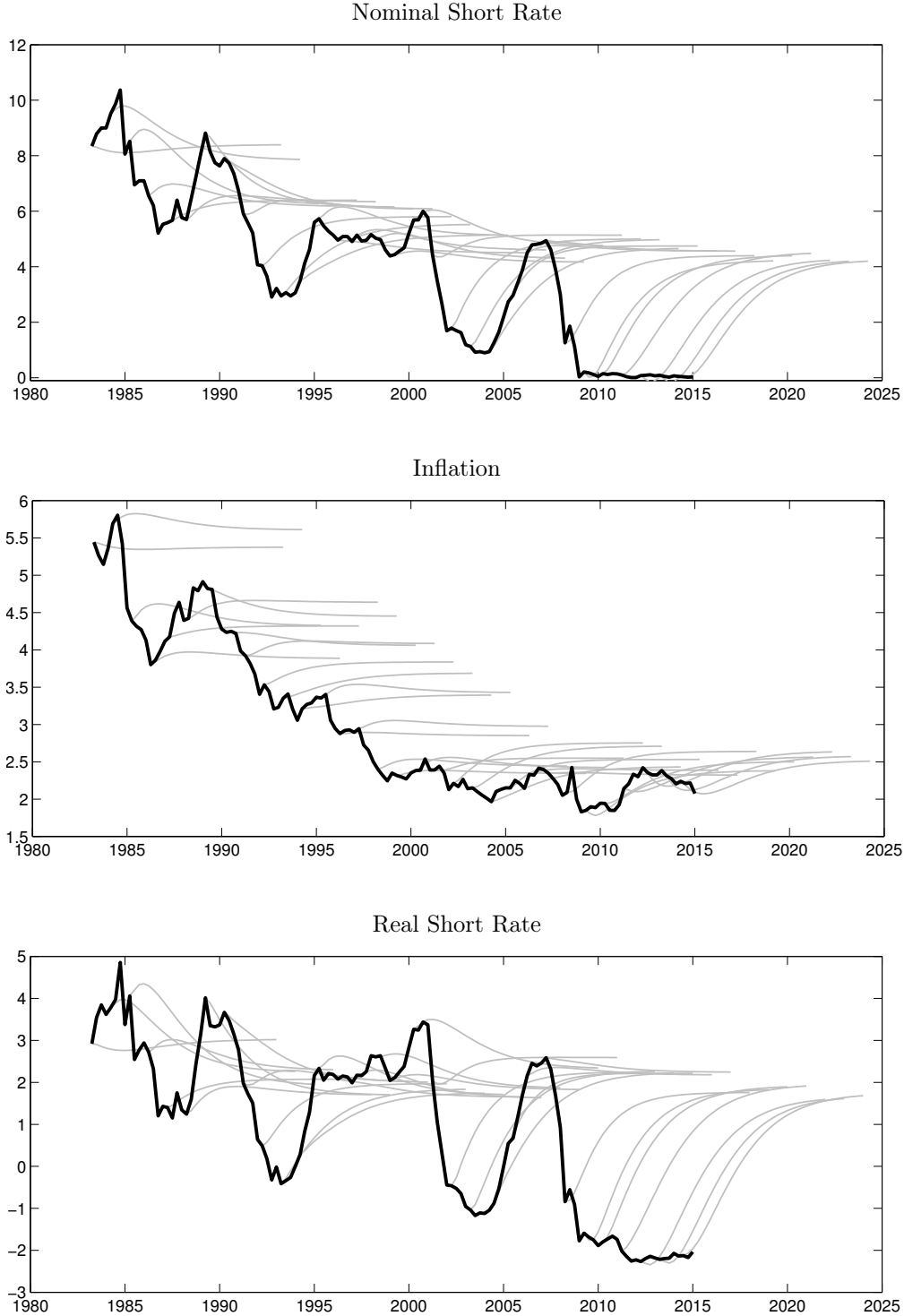


Figure 3: **Expected Real Rates and Expected Inflation**

These figures show the evolution of the ex-ante real short-term interest rate and expected inflation. Expected inflation is measured as the one-month ahead forecast, $\mathbb{E}_t[\pi_{t+1}]$, as discussed in Section 3 and the real short-term interest rate is the difference between the secondary market 3-month Treasury bill rate from the H.15 release of the Federal Reserve Board and expected inflation. The right column shows the corresponding scatterplot to the time-series plot in the left column.

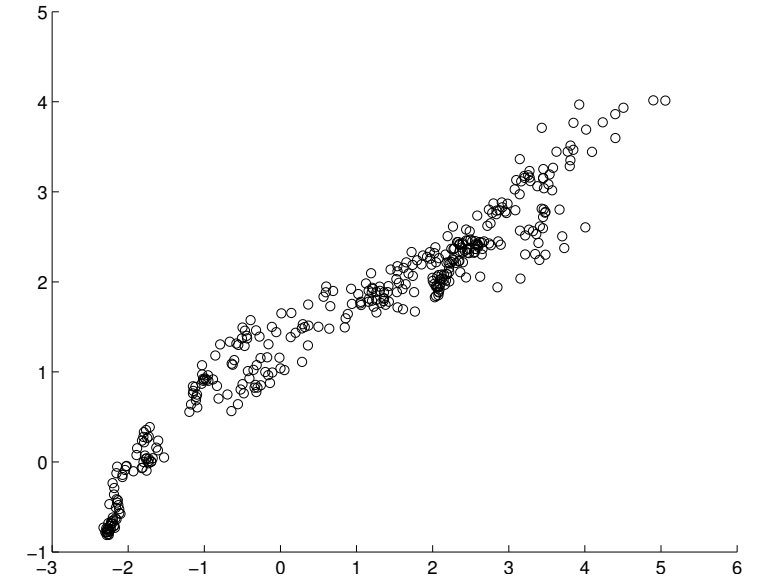
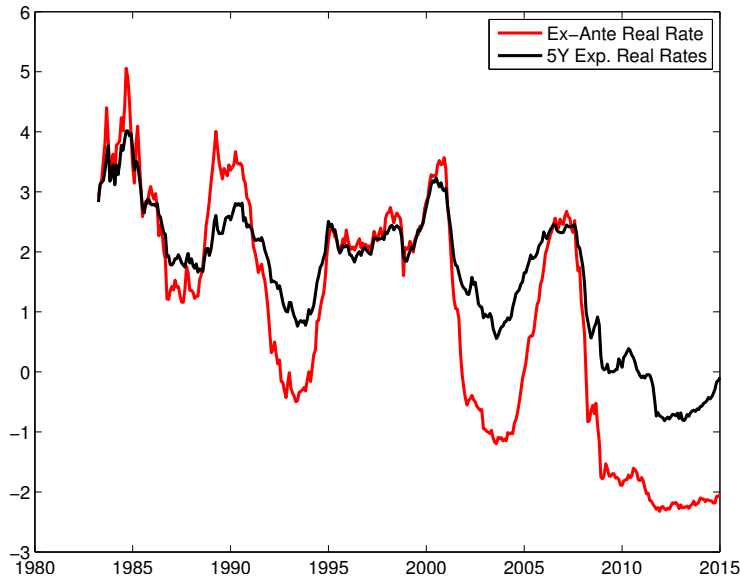
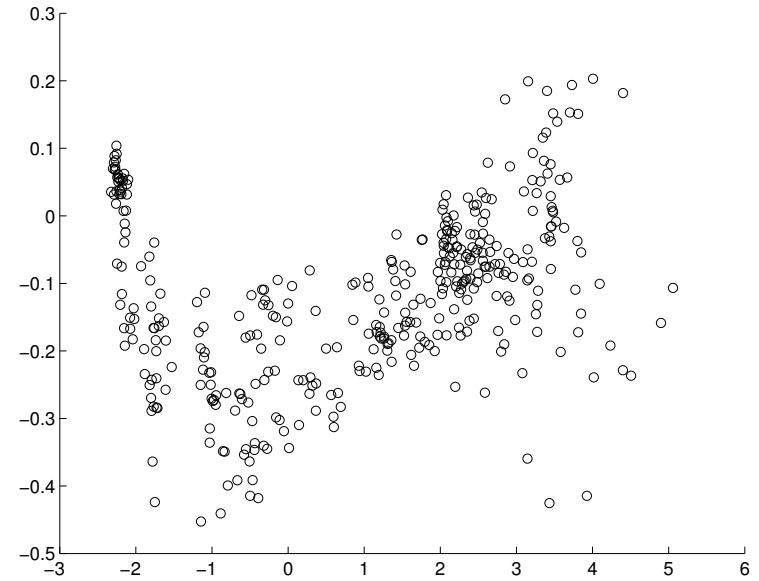
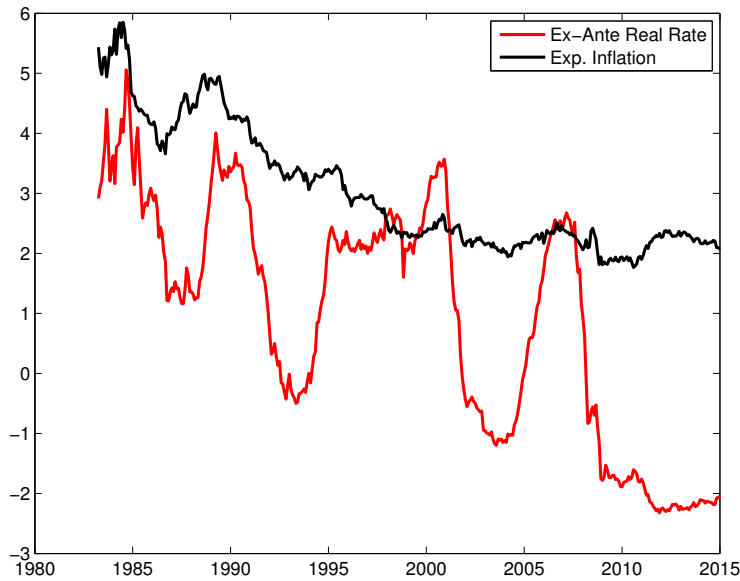


Figure 4: **Forward Rate Decompositions**

These figures show the decomposition of forward yields into the expected path of forward short-term nominal interest rates and the forward term premium as discussed in Section 4. Treasury forward yields are based on the zero coupon bond yields from the [Gurkaynak et al. \(2007\)](#) dataset available on the Board of Governors of the Federal Reserve's research data page.

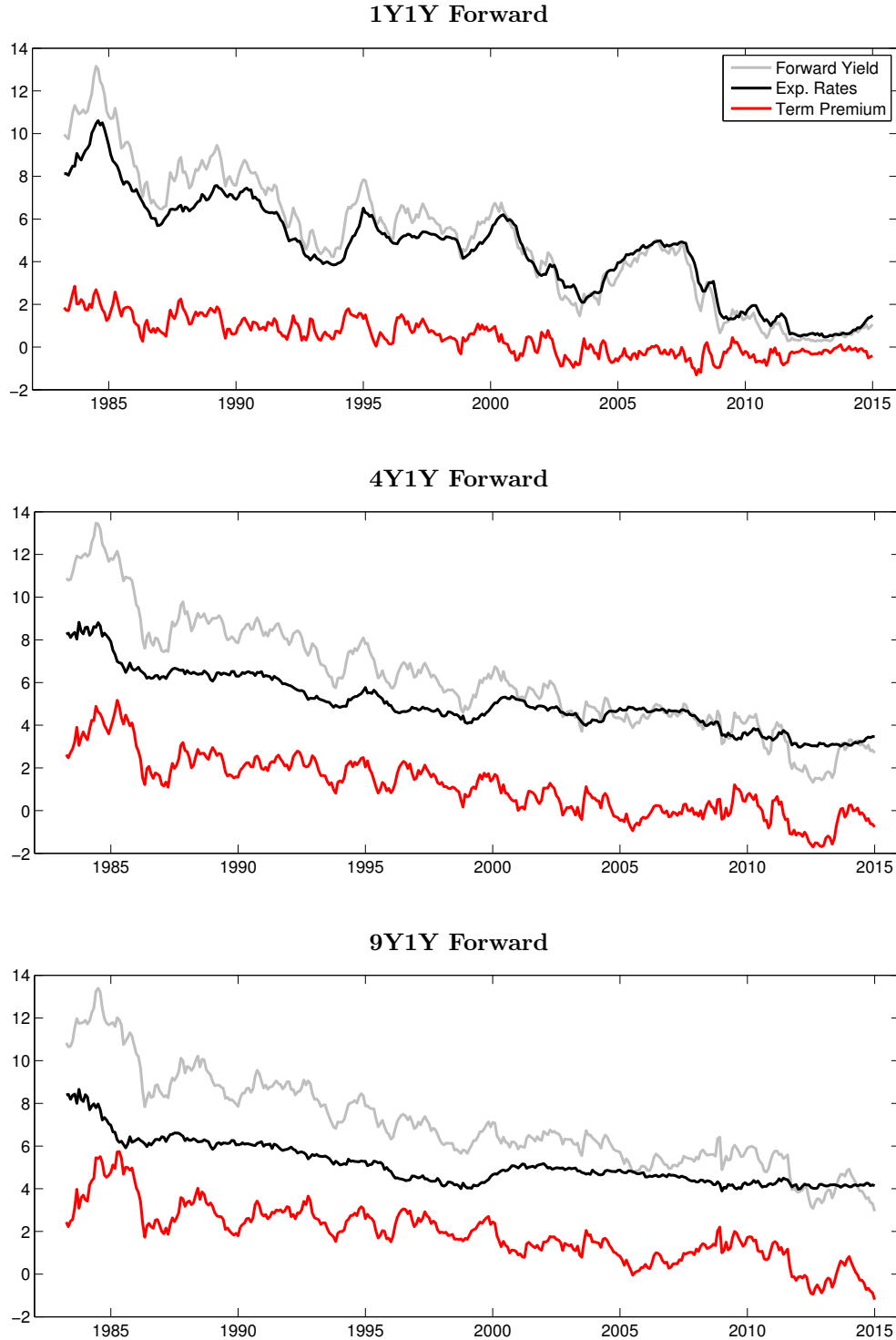


Figure 5: **Expected Rate Decompositions**

These figures show the decomposition of Treasury (forward) yields into the expected path of short-term (forward) real interest rates, expected (forward) inflation and the (forward) nominal term premium as discussed in Section 4. Treasury (forward) yields are (based on) the zero coupon bond yields from the [Gurkaynak et al. \(2007\)](#) dataset available on the Board of Governors of the Federal Reserve's research data page.

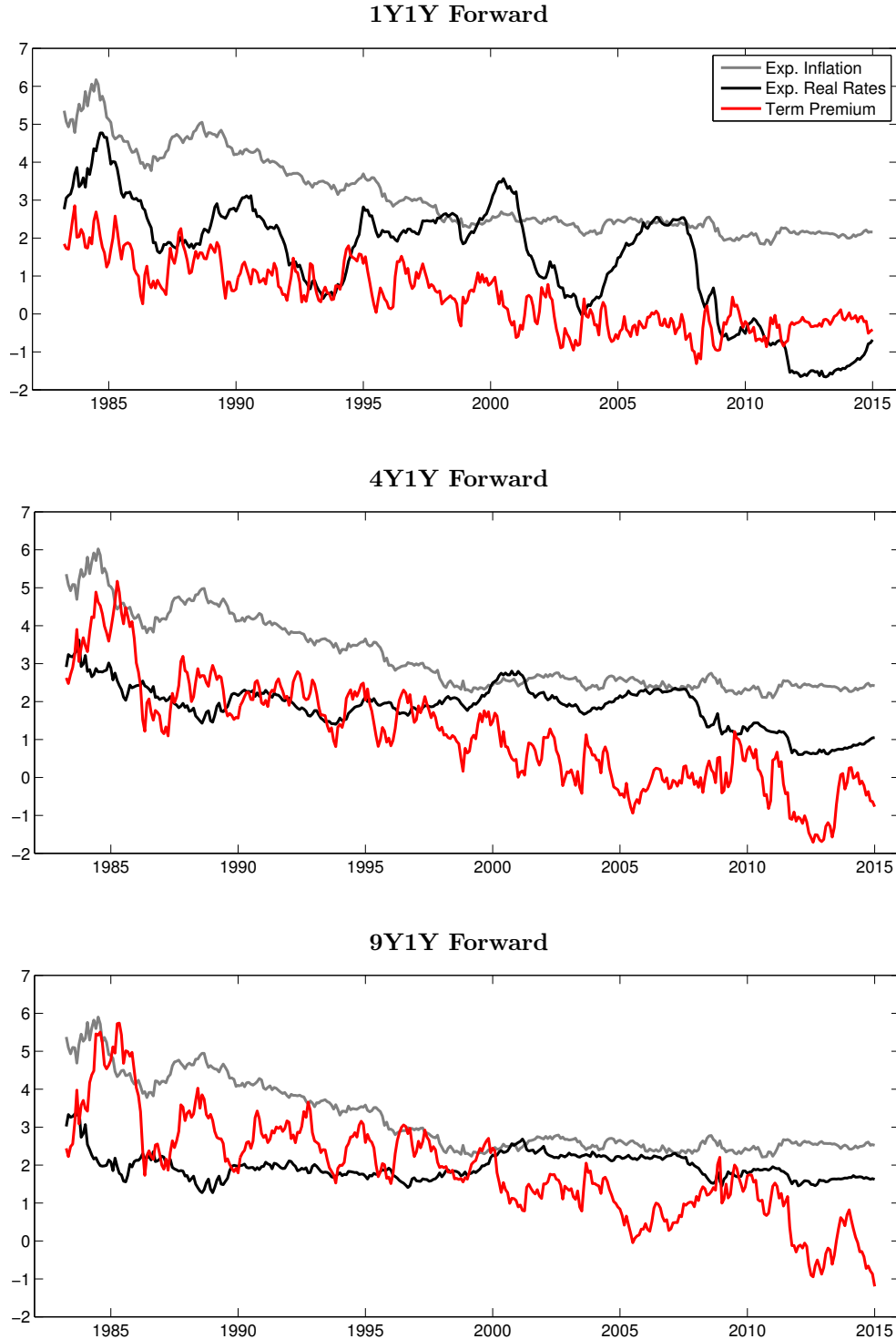


Figure 6: Co-Movement of Expected Rates and Term Premiums

These figures show the decomposition of forward yields into their constituent components. The left column shows four-quarter changes in the expected path of forward short-term nominal interest rates and the forward term premium as discussed in Section 4. The right column shows the nominal and real forward term premiums. Nominal and real Treasury forward yields are based on the zero coupon bond yields from the [Gurkaynak et al. \(2007\)](#) and [Gurkaynak et al. \(2010\)](#) datasets available on the Board of Governors of the Federal Reserve's research data page.

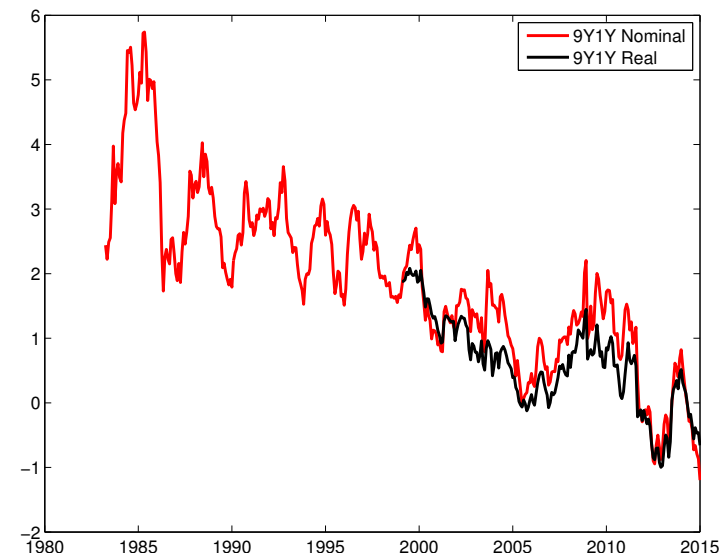
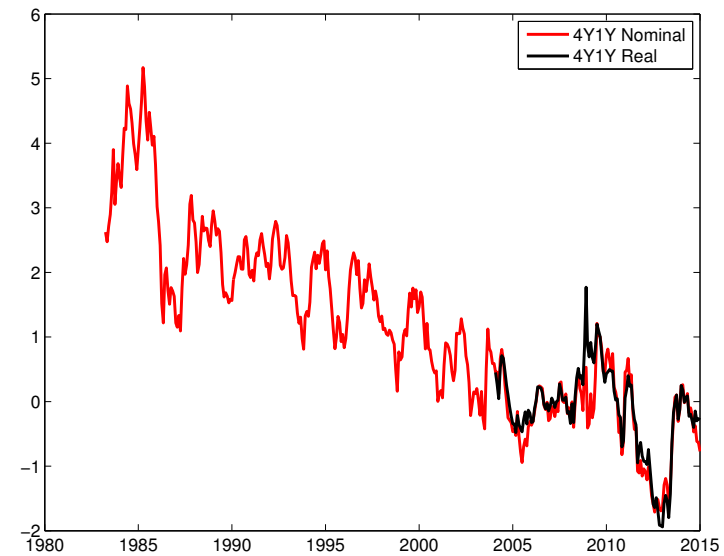
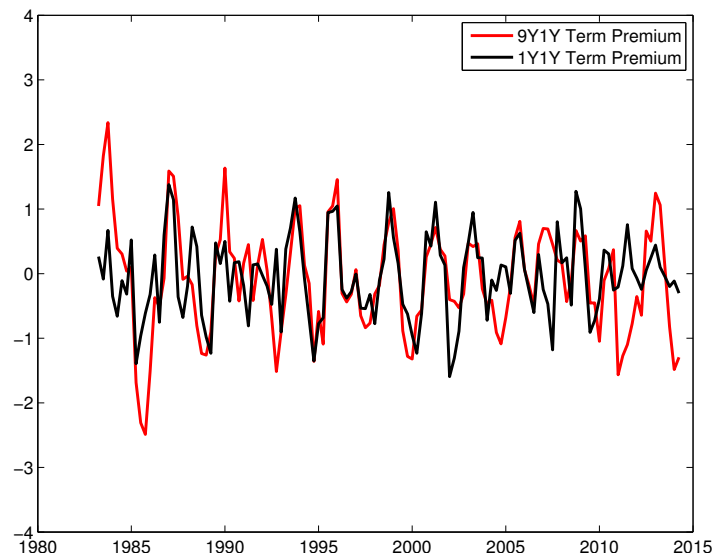
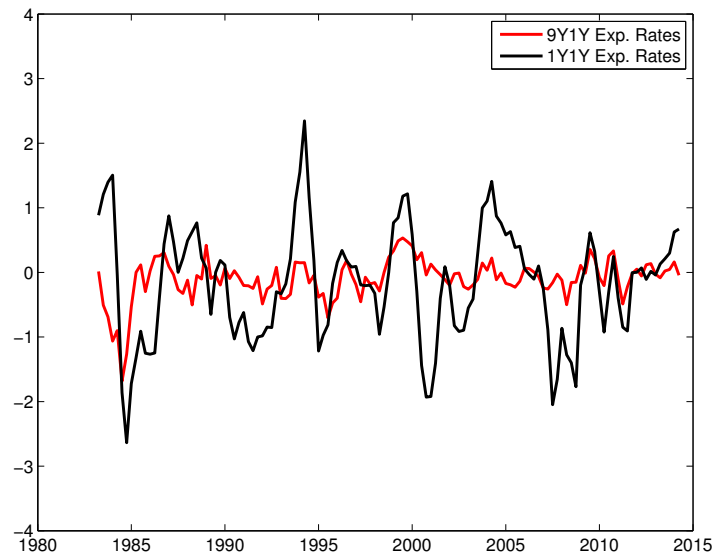


Figure 7: **Expected Path of Short-Term Interest Rates**

These figures show the decomposition of forward yields into the expected path of forward short-term nominal interest rates and the forward term premium as discussed in Section 4 along with the corresponding measures based on the VAR specification discussed in Section 4.2. Treasury forward yields are based on the zero coupon bond yields from the Gurkaynak et al. (2007) dataset available on the Board of Governors of the Federal Reserve's research data page.

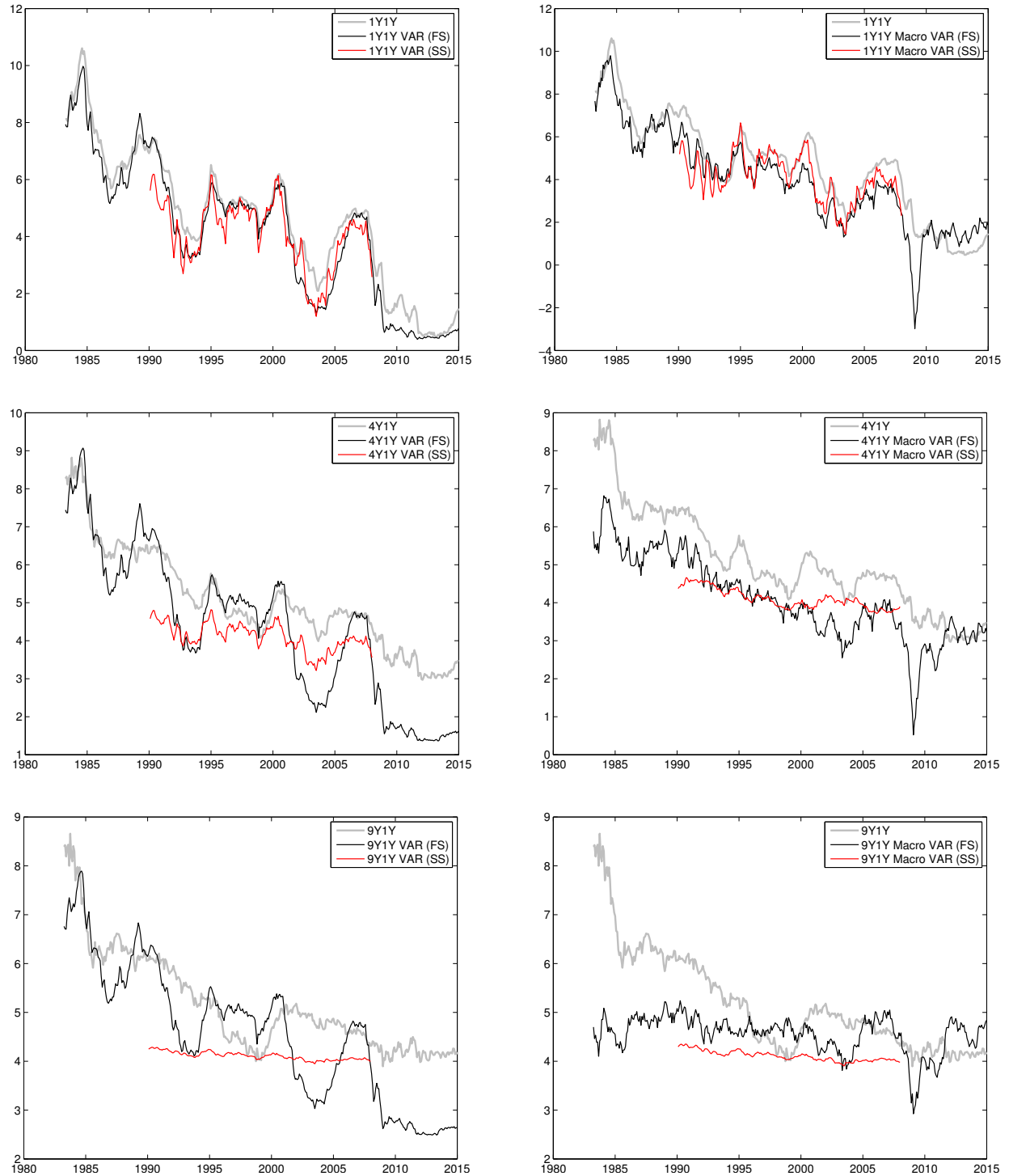


Figure 8: **Term Premiums**

These figures show the decomposition of forward yields into the expected path of forward short-term nominal interest rates and the forward term premium as discussed in Section 4 along with the corresponding measures based on a VAR specification which augments the VAR discussed in Section 4.2 with two additional series: (i) the 3-month moving average of the Chicago Fed National Activity Index obtained from the Federal Reserve Bank of Chicago's economic data page; (ii) year-over-year core CPI inflation obtained from the Bureau of Labor Statistics. Treasury forward yields are based on the zero coupon bond yields from the [Gurkaynak et al. \(2007\)](#) dataset available on the Board of Governors of the Federal Reserve's research data page.

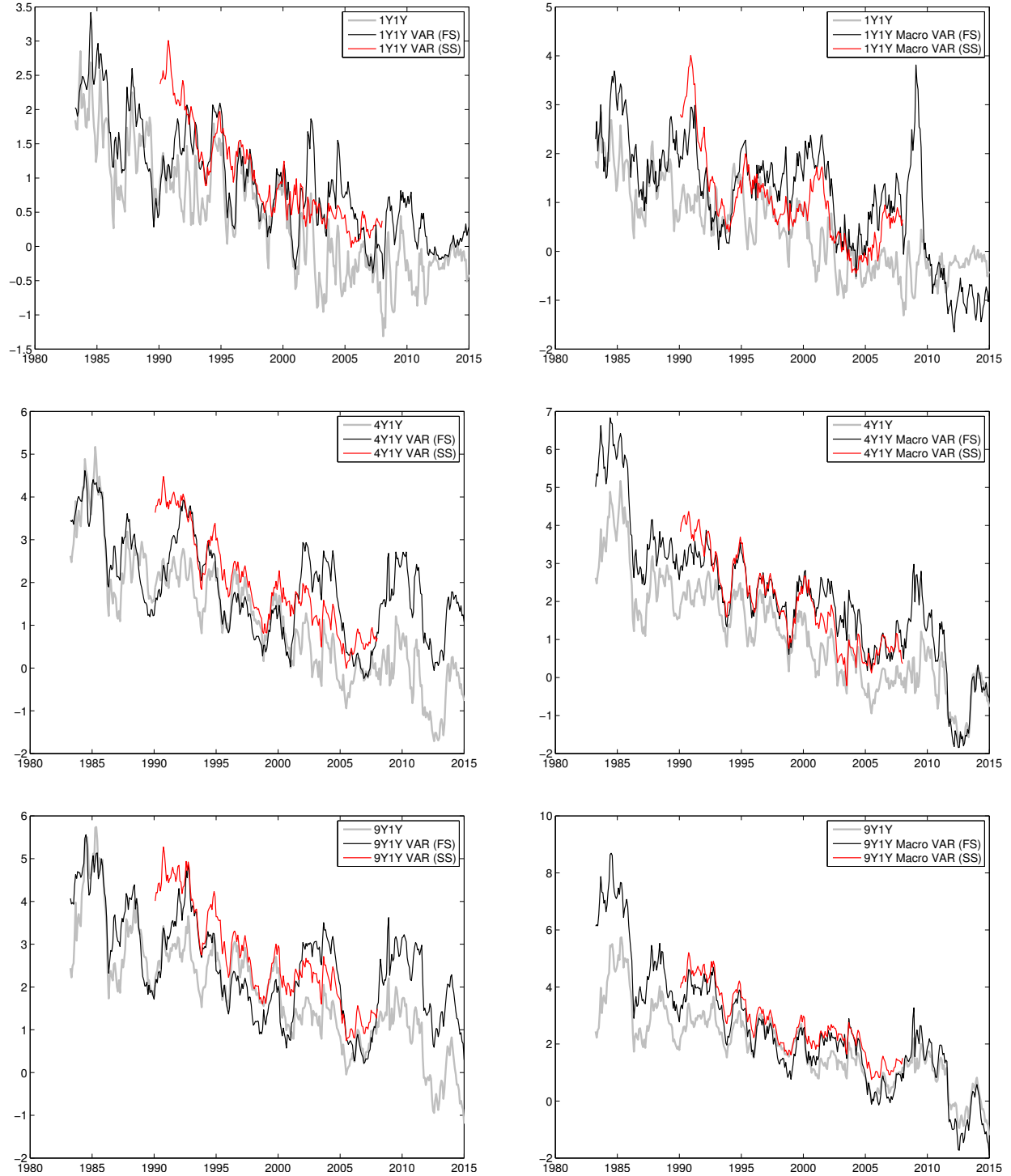


Figure 9: Correlation of Expected Rates and Term Premiums

These figures show scatterplots of the monthly change in expected future short rates and the change in the forward term premium for selected maturities. The sample period is July 1990–December 2014.

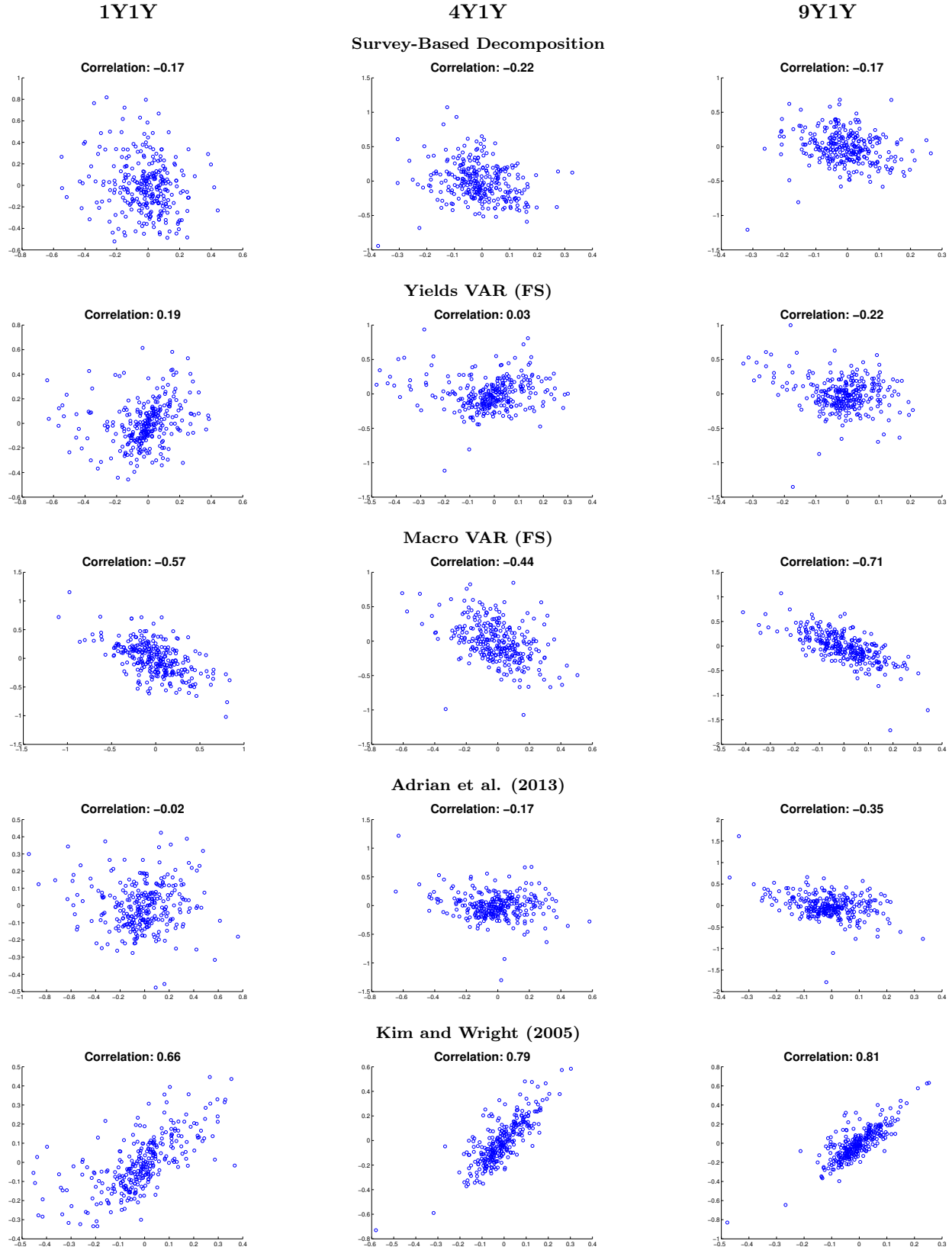


Figure 10: **Impulse Response of Yield Decompositions: Policy Shocks**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

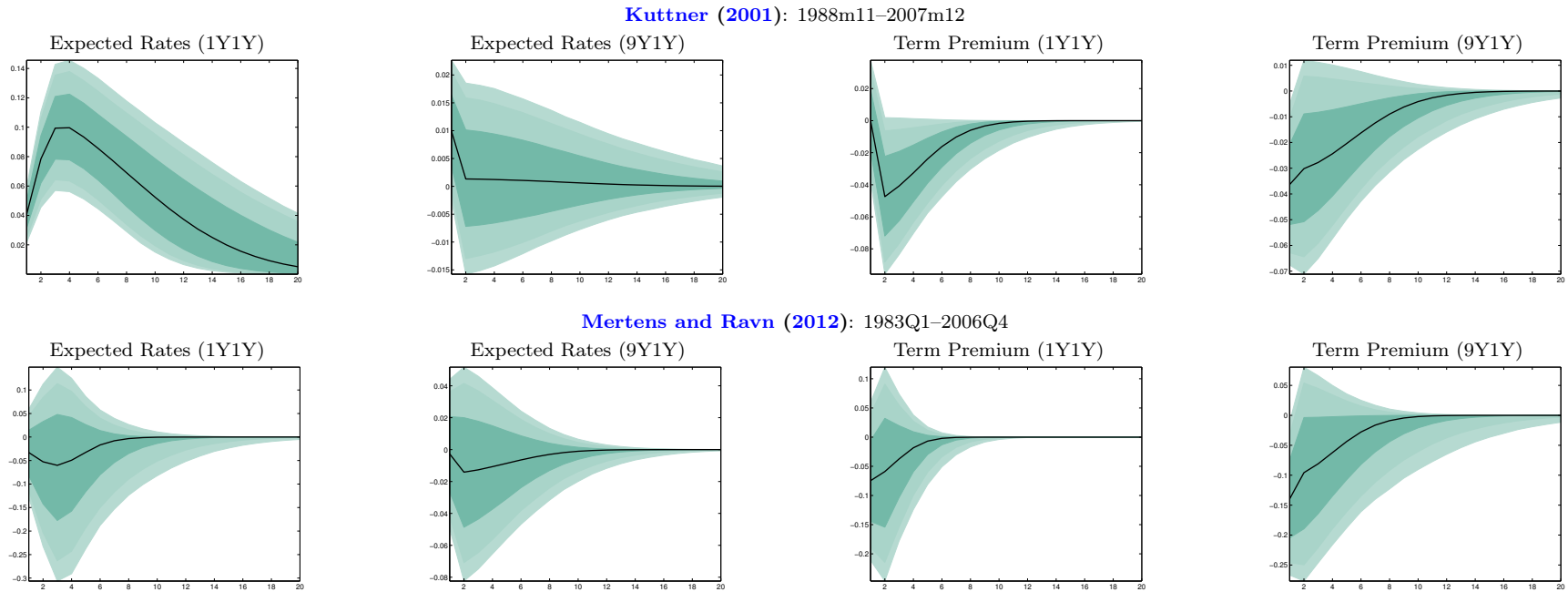


Figure 11: Impulse Response of Yield Decompositions: Demand Shocks

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

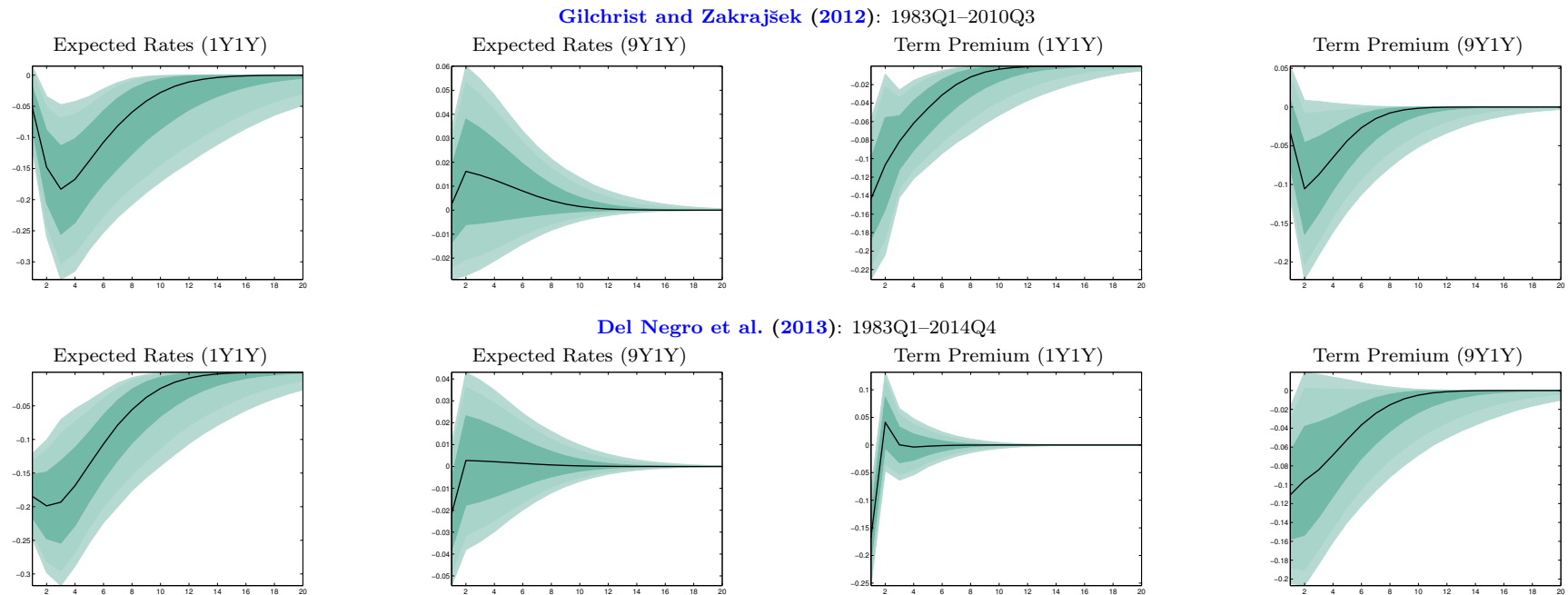


Figure 12: Impulse Response of Yield Decompositions: Demand Shocks

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

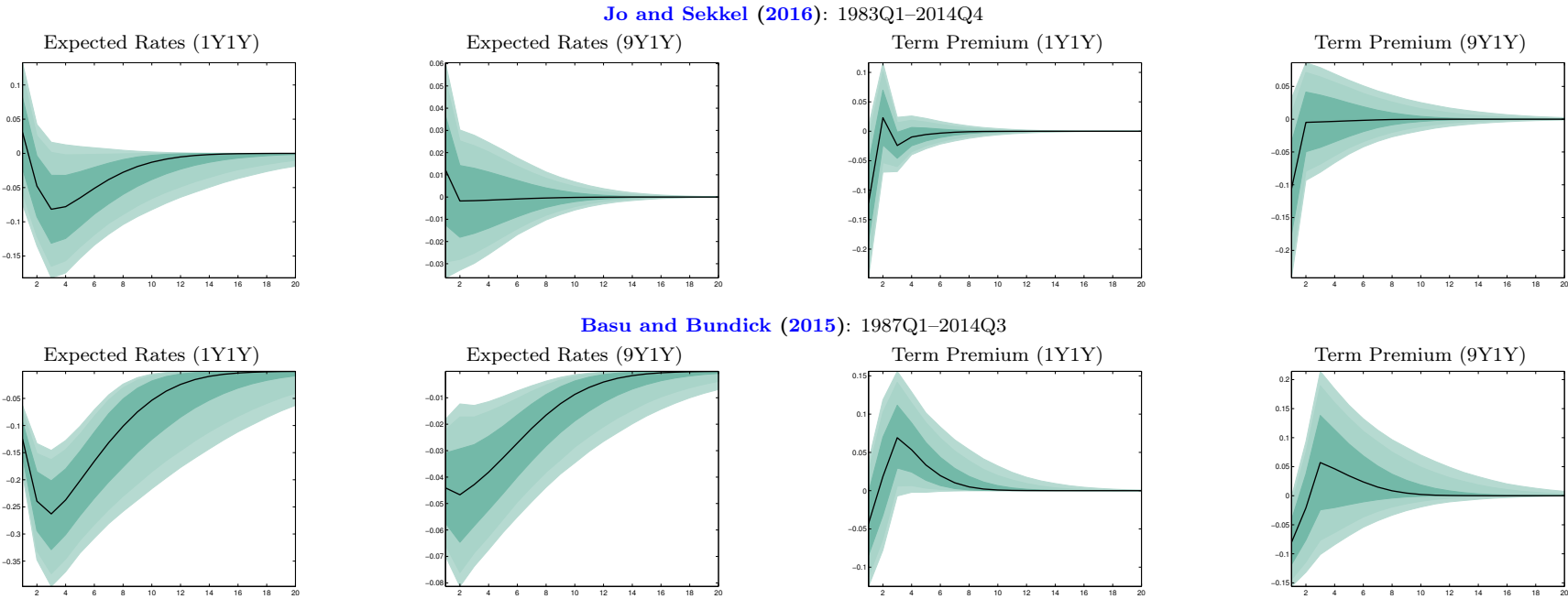
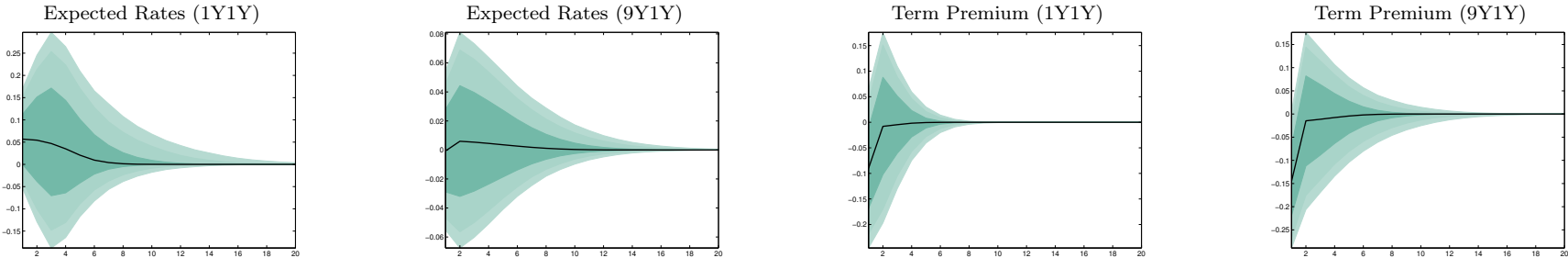


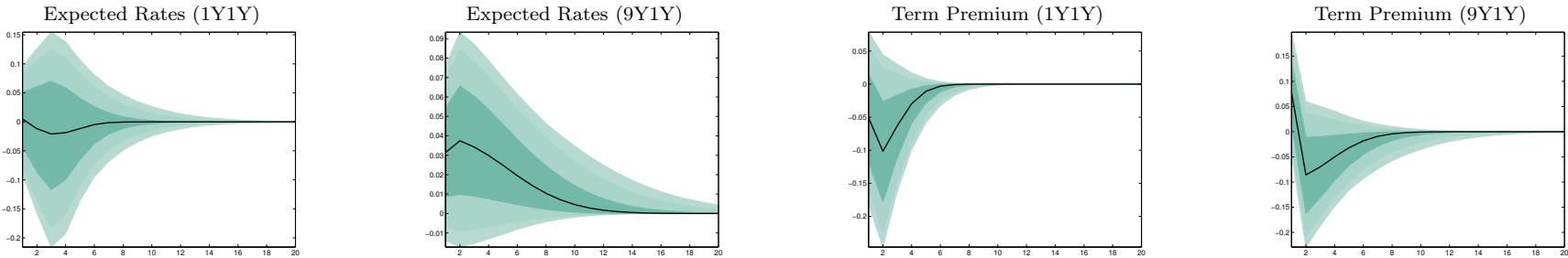
Figure 13: Impulse Response of Yield Decompositions: Supply Shocks

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

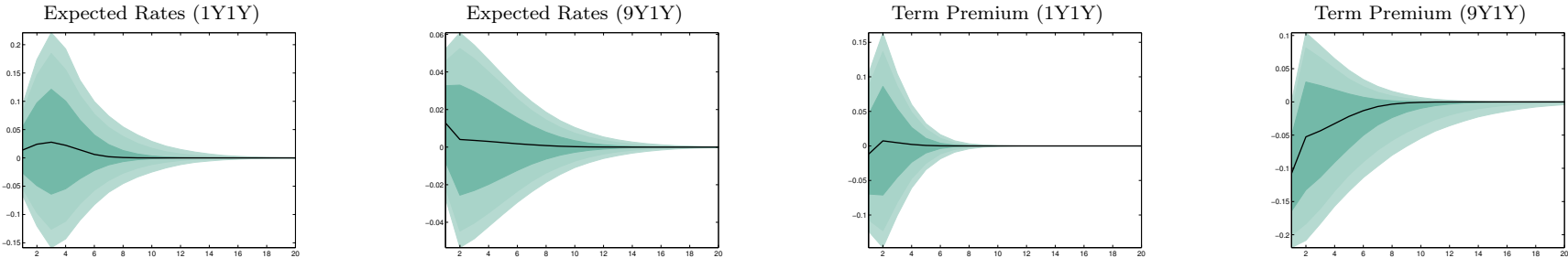
Kilian (2008): 1983Q1–2004Q3



Hamilton (2003): 1983Q1–2007Q4



Barsky and Sims (2011): 1983Q1–2007Q3



Supplementary Appendix for “Term Structure of Expectations and Bond Yields”

Richard K. Crump, Stefano Eusepi & Emanuel Moench

Figure 14: **Decomposition of Forward Rates**

These figures show the decomposition of forward yields into the expected path of forward short-term nominal interest rates and the forward term premium as discussed in Section 4 along with the corresponding measures based on the methods of [Adrian et al. \(2013\)](#) (ACM) and [Kim and Wright \(2005\)](#) (KW). The ACM and KW forward yield components are based on data obtained from the Federal Reserve Bank of New York's data & indicators page and the Board of Governors of the Federal Reserve's research data page, respectively. Treasury forward yields are based on the zero coupon bond yields from the [Gurkaynak et al. \(2007\)](#) dataset available on the Board of Governors of the Federal Reserve's research data page.

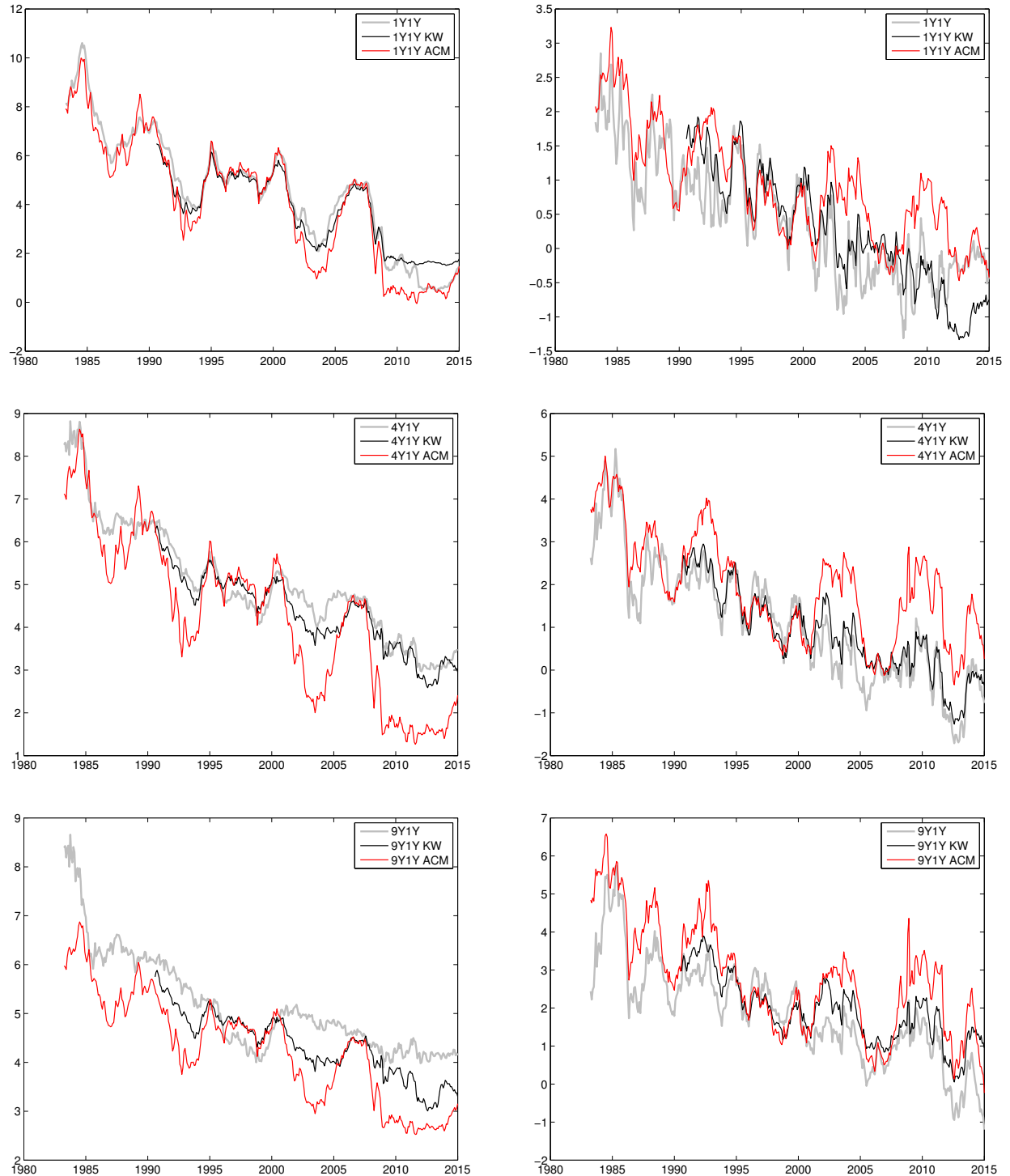


Table 6: Predictive Regressions for RGDI Growth

This Table presents results for predictive regressions from equation (5.3) where Δg_{t+h} represents the rate of growth of real gross domestic income (GDI) from period $t+h-1$ to period $t+h$, and ζ_{t+h}^g is an innovation. h denotes the forecast horizon in quarters. $TS10Y$ is the 10-year three-month term spread, $TP10Y$ the term premium and $RNTS10Y$ the expected path of future nominal short rates (“risk-neutral term spread”) component of the spread. $RRNTS10Y$ denotes the expected path of future real short rates and $INFTS10Y$ the expected path of future inflation. For each regressor, coefficients are reported in the first column and t -statistics based on Newey-West standard errors with 12 lags in the second. The top panel provides results for the 1983-2014 and the bottom for the 1983-2007 sample.

h	TS10Y		TP10Y		RNTS10Y		RRNTS10Y		INFTS10Y		R2adj
1983-2014											
1	0.13	(0.53)									-0.01
			0.68**	(2.35)	0.00	(0.01)					0.06
			0.89**	(2.21)			0.55	(1.21)	-4.73	(-1.14)	0.08
2	0.29	(1.19)									0.01
			0.76***	(2.63)	0.18	(0.69)					0.05
			0.97**	(2.51)			0.70	(1.65)	-4.42	(-1.16)	0.08
3	0.44*	(1.76)									0.03
			0.86***	(2.96)	0.34	(1.29)					0.06
			1.04***	(2.87)			0.83**	(2.02)	-3.89	(-1.11)	0.08
4	0.50*	(1.80)									0.04
			0.87**	(2.56)	0.41	(1.48)					0.07
			1.08***	(2.83)			0.96**	(2.24)	-4.32	(-1.37)	0.09
6	0.66*	(1.84)									0.08
			0.91**	(2.19)	0.59*	(1.74)					0.09
			1.00**	(2.22)			0.85*	(1.65)	-1.56	(-0.72)	0.09
8	0.71**	(1.99)									0.09
			0.99**	(2.22)	0.63**	(1.97)					0.11
			0.98**	(1.96)			0.58	(1.19)	1.04	(0.47)	0.10
12	0.29	(1.16)									0.01
			0.78*	(1.82)	0.16	(1.06)					0.06
			0.78	(1.65)			0.16	(0.36)	0.15	(0.05)	0.05
1983-2008											
1	0.39	(1.40)									0.02
			0.71**	(2.24)	0.24	(0.80)					0.04
			0.77**	(2.06)			0.60	(1.12)	-2.40	(-0.65)	0.04
2	0.47	(1.62)									0.04
			0.68**	(2.20)	0.36	(1.16)					0.04
			0.80**	(2.16)			0.96*	(1.80)	-4.01	(-0.92)	0.05
3	0.54*	(1.89)									0.05
			0.67**	(2.06)	0.48	(1.56)					0.05
			0.81**	(2.16)			1.21**	(1.97)	-4.88	(-1.01)	0.06
4	0.49*	(1.69)									0.04
			0.58*	(1.77)	0.45	(1.51)					0.03
			0.73**	(2.21)			1.22**	(2.40)	-5.18	(-1.28)	0.05
6	0.52*	(1.79)									0.05
			0.60	(1.65)	0.48*	(1.68)					0.04
			0.66*	(1.87)			0.81*	(1.91)	-1.88	(-0.66)	0.04
8	0.46**	(2.06)									0.04
			0.58*	(1.72)	0.42*	(1.79)					0.03
			0.59	(1.46)			0.47	(0.86)	0.04	(0.01)	0.02
12	0.12	(0.44)									-0.01
			0.51	(1.29)	0.02	(0.10)					0.01
			0.39	(0.91)			-0.49	(-1.05)	3.71	(1.47)	0.02

Table 7: Predictive Regressions for RPCE Growth

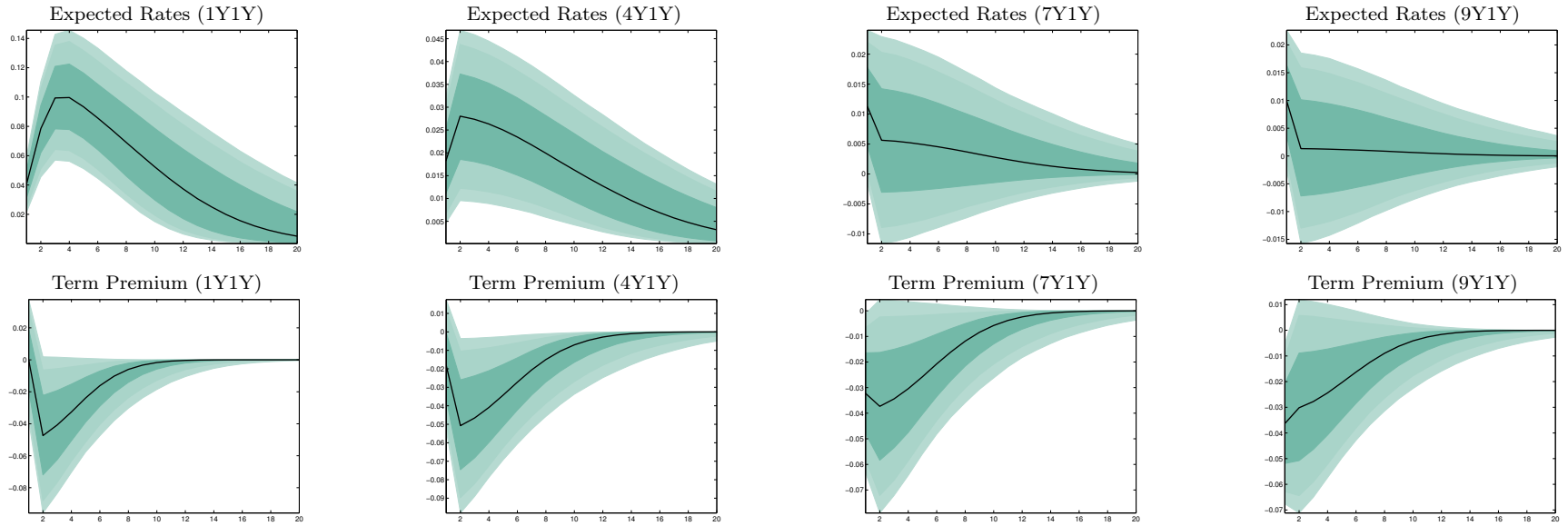
This Table presents results for predictive regressions from equation (5.3) where Δg_{t+h} represents the rate of growth of real personal consumption expenditures (PCE) from period $t + h - 1$ to period $t + h$, and ζ_{t+h}^g is an innovation. h denotes the forecast horizon in quarters. $TS10Y$ is the 10-year three-month term spread, $TP10Y$ the term premium and $RNTS10Y$ the expected path of future nominal short rates (“risk-neutral term spread”) component of the spread. $RRNTS10Y$ denotes the expected path of future real short rates and $INFTS10Y$ the expected path of future inflation. For each regressor, coefficients are reported in the first column and t -statistics based on Newey-West standard errors with 12 lags in the second. The top panel provides results for the 1983-2014 and the bottom for the 1983-2007 sample.

h	TS10Y		TP10Y		RNTS10Y		RRNTS10Y		INFTS10Y		R2adj
1983-2014											
1	-0.04	(-0.19)									-0.01
			0.43**	(2.51)	-0.15	(-0.62)					0.07
			0.48*	(1.74)			-0.03	(-0.08)	-1.26	(-0.39)	0.07
2	0.02	(0.07)									-0.01
			0.53***	(2.99)	-0.11	(-0.42)					0.09
			0.65***	(2.65)			0.21	(0.68)	-2.84	(-1.07)	0.10
3	0.24	(0.96)									0.01
			0.69***	(3.17)	0.12	(0.49)					0.09
			0.72**	(2.38)			0.21	(0.56)	-0.59	(-0.21)	0.08
4	0.29	(1.10)									0.02
			0.76***	(2.86)	0.18	(0.65)					0.10
			0.82**	(2.51)			0.34	(0.92)	-1.25	(-0.52)	0.10
6	0.44	(1.38)									0.05
			0.82**	(2.44)	0.34	(1.10)					0.10
			0.82**	(2.15)			0.35	(0.81)	0.28	(0.13)	0.09
8	0.35	(1.00)									0.03
			0.67	(1.64)	0.26	(0.81)					0.06
			0.62	(1.36)			0.12	(0.27)	1.45	(0.66)	0.06
12	0.01	(0.03)									-0.01
			0.48	(1.13)	-0.11	(-0.51)					0.07
			0.57	(1.27)			0.29	(0.72)	-3.31	(-1.64)	0.08
1983-2008											
1	0.20	(1.04)									0.00
			0.35*	(1.66)	0.13	(0.58)					0.00
			0.33	(1.34)			0.03	(0.07)	0.85	(0.27)	-0.01
2	0.21	(1.08)									0.01
			0.44**	(2.36)	0.11	(0.43)					0.02
			0.50**	(2.32)			0.45	(1.40)	-2.43	(-1.26)	0.02
3	0.37	(1.57)									0.04
			0.50**	(2.37)	0.31	(1.20)					0.04
			0.43**	(2.14)			-0.05	(-0.16)	2.94	(1.59)	0.04
4	0.31	(1.24)									0.02
			0.48**	(2.26)	0.23	(0.82)					0.03
			0.46**	(2.04)			0.09	(0.27)	1.27	(0.50)	0.02
6	0.34	(1.32)									0.03
			0.47**	(2.01)	0.29	(0.98)					0.03
			0.43*	(1.72)			0.05	(0.11)	2.04	(0.59)	0.02
8	0.10	(0.49)									-0.01
			0.19	(0.87)	0.08	(0.30)					-0.02
			0.14	(0.50)			-0.19	(-0.44)	2.03	(0.53)	-0.02
12	-0.29	(-1.72)									0.02
			-0.10	(-0.38)	-0.33	(-2.18)					0.02
			-0.08	(-0.26)			-0.24	(-0.82)	-1.02	(-0.57)	0.01

Figure 15: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Kuttner (2001): 1988m11–2007m12



Gürkaynak et al. (2005b): Target Shock, 1990m2–2004m12

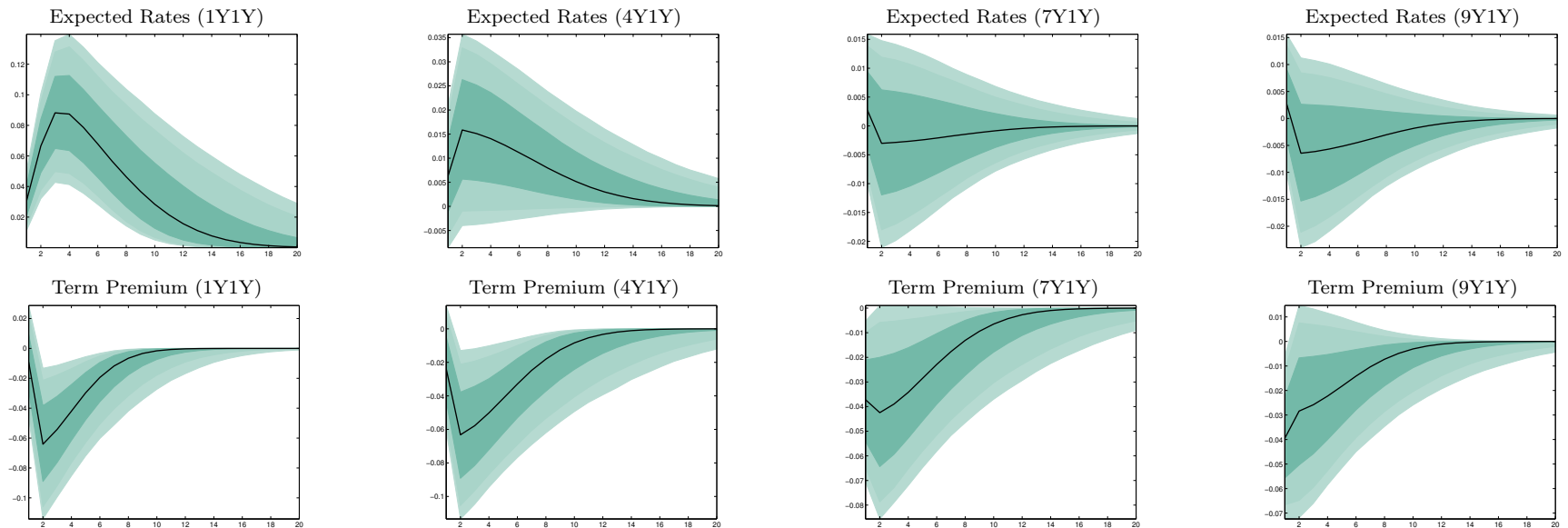
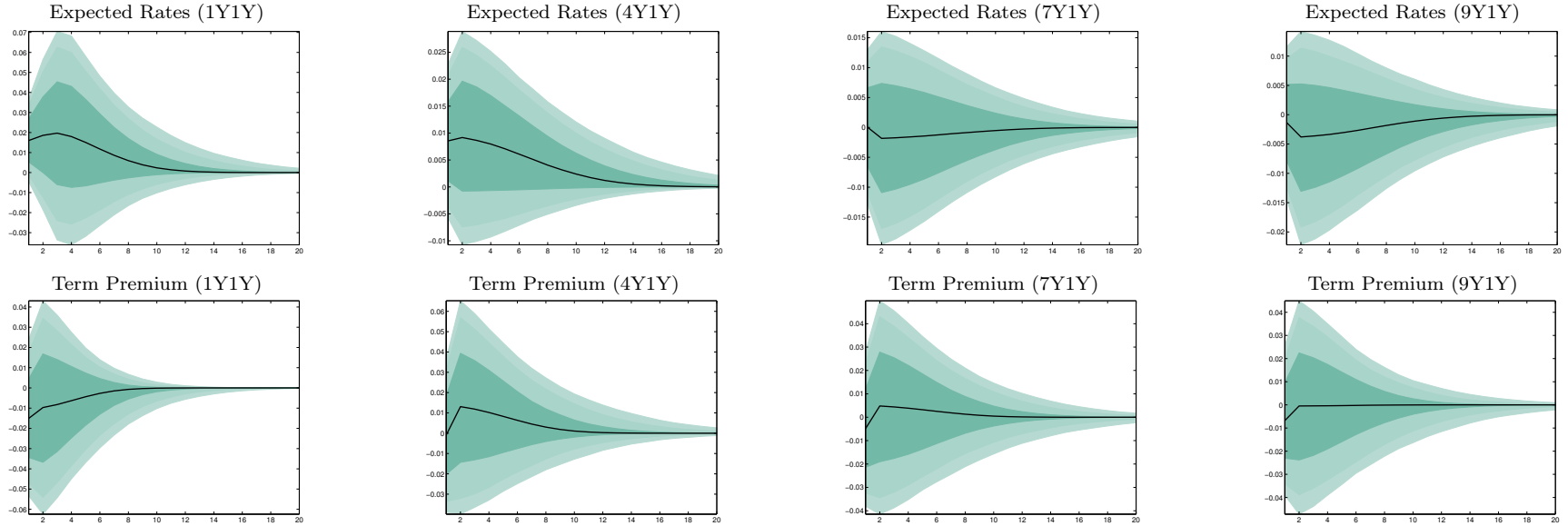


Figure 16: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Gürkaynak et al. (2005b): Path Shock, 1990m2–2004m12



Romer and Romer (2010): 1983Q1–2007Q4

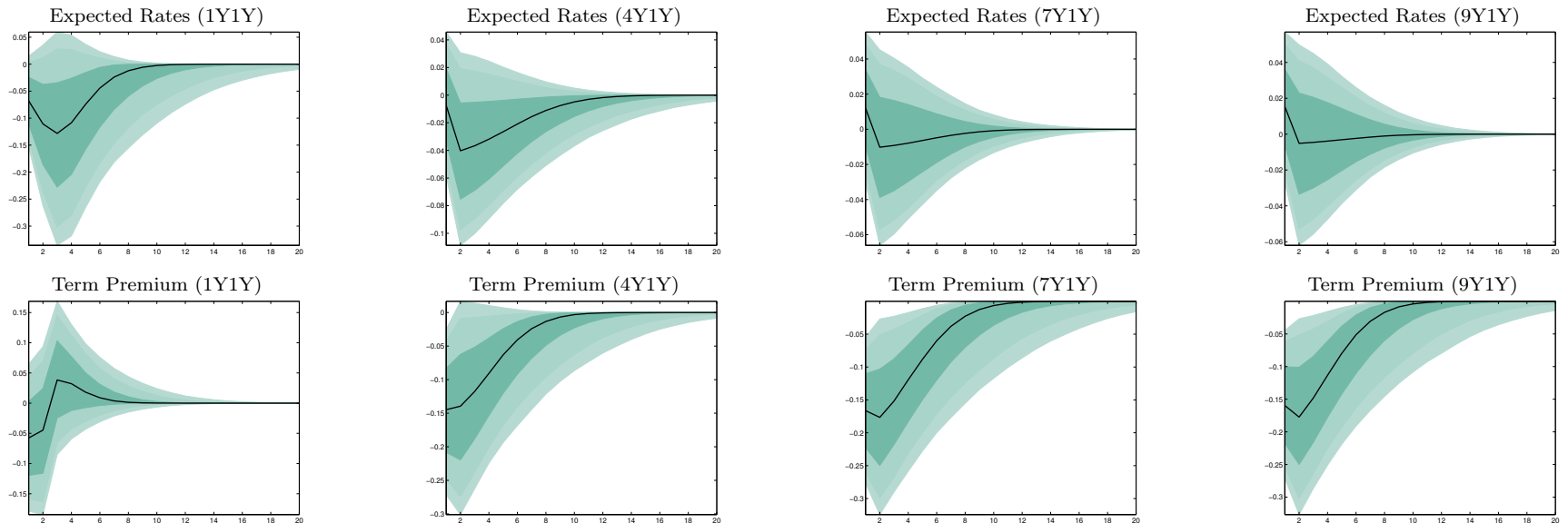
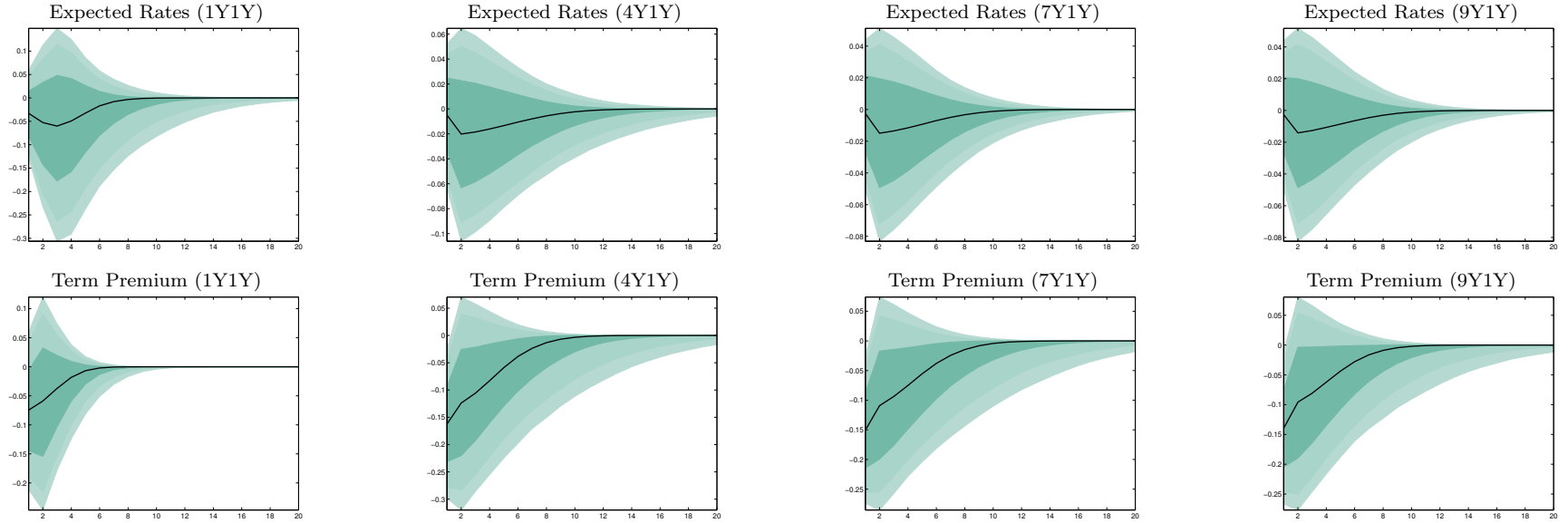


Figure 17: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Mertens and Ravn (2012): 1983Q1–2006Q4



Ramey (2011): 1983Q1–2010Q4

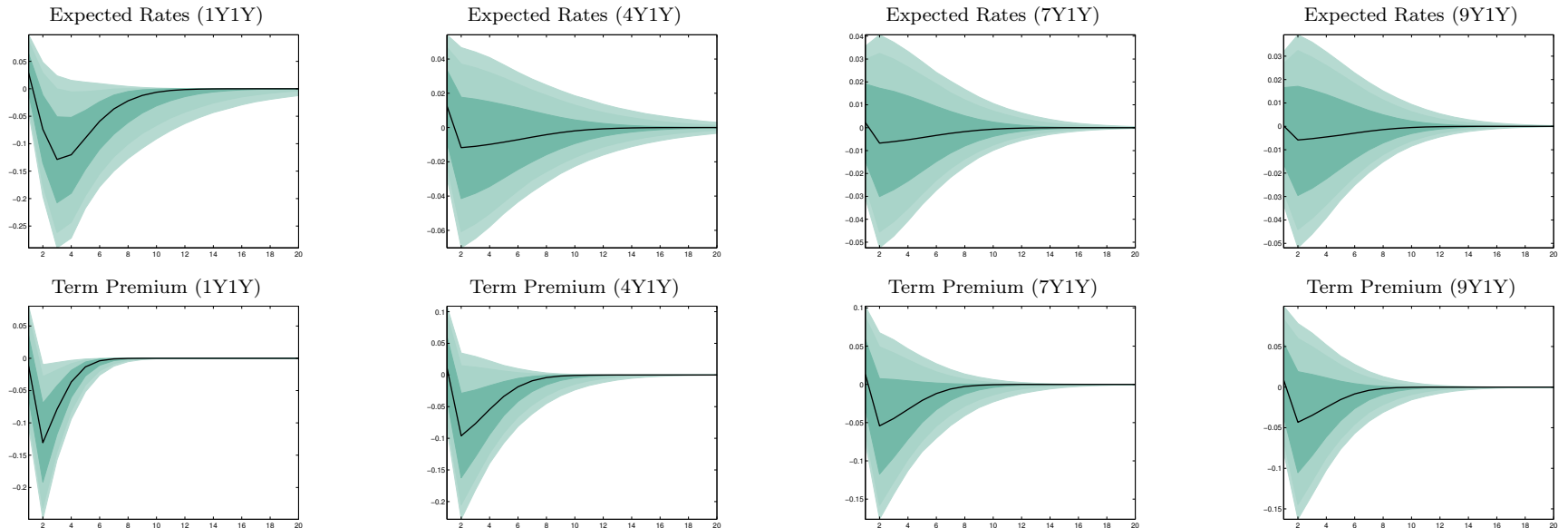
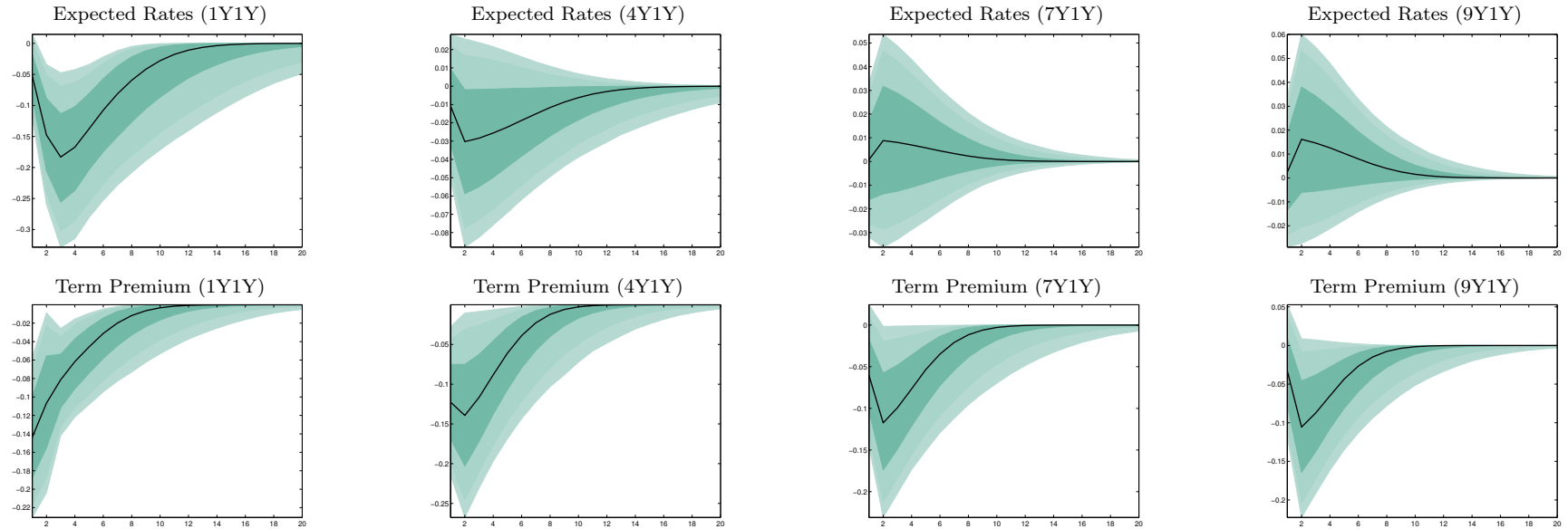


Figure 18: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Gilchrist and Zakrajšek (2012): 1983Q1–2010Q3



Del Negro et al. (2013): 1983Q1–2014Q4

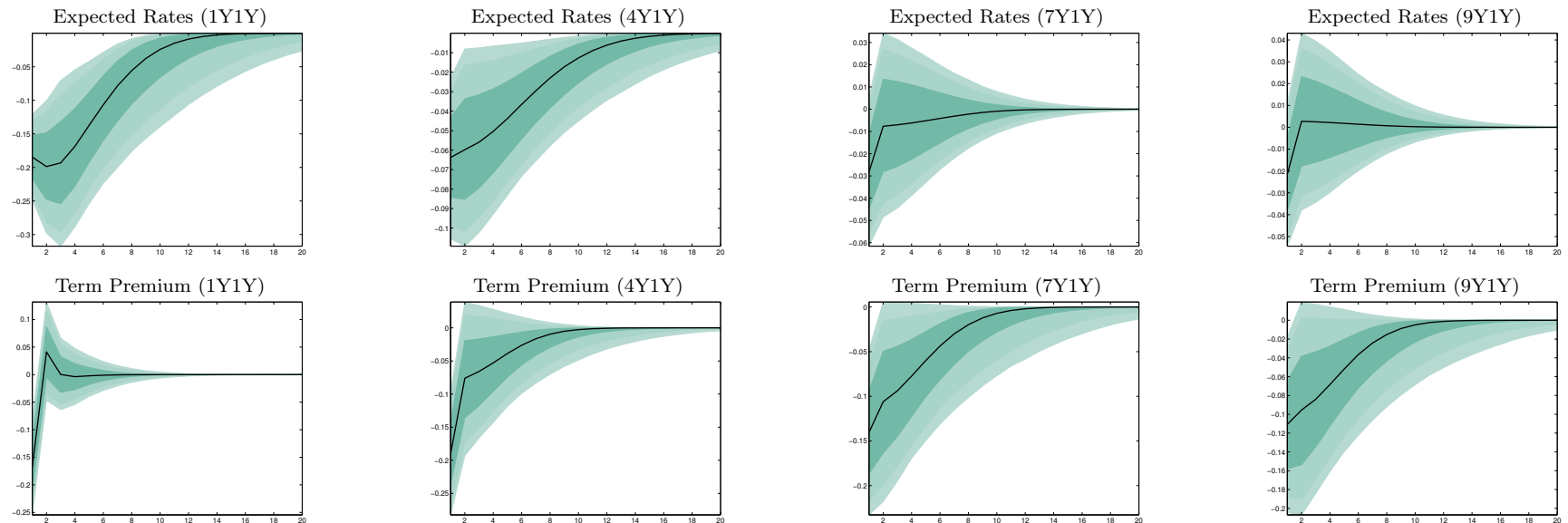
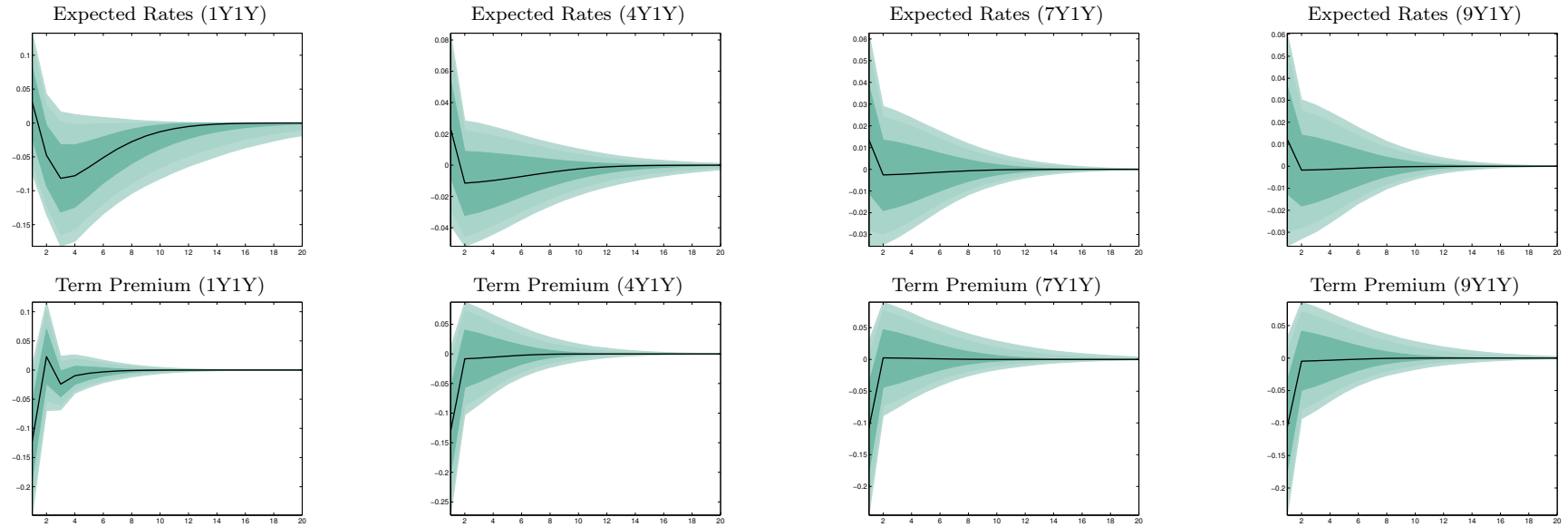


Figure 19: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Jo and Sekkel (2016) : 1983Q1–2014Q4



Basu and Bundick (2015): 1987Q1–2014Q3

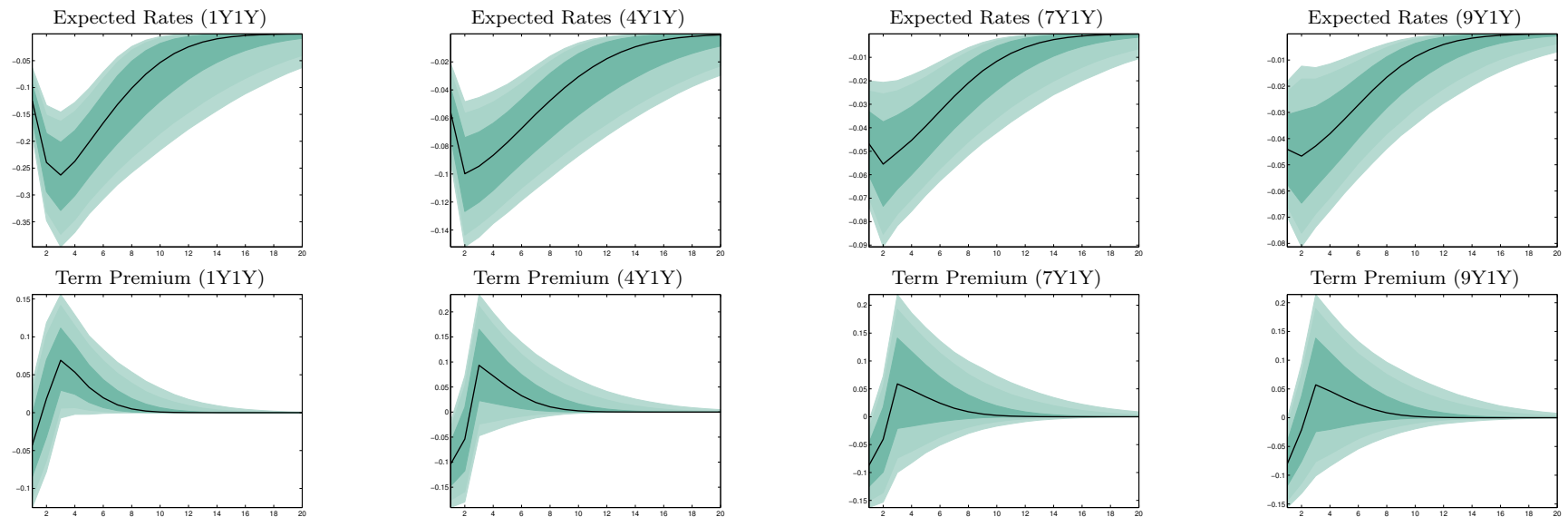
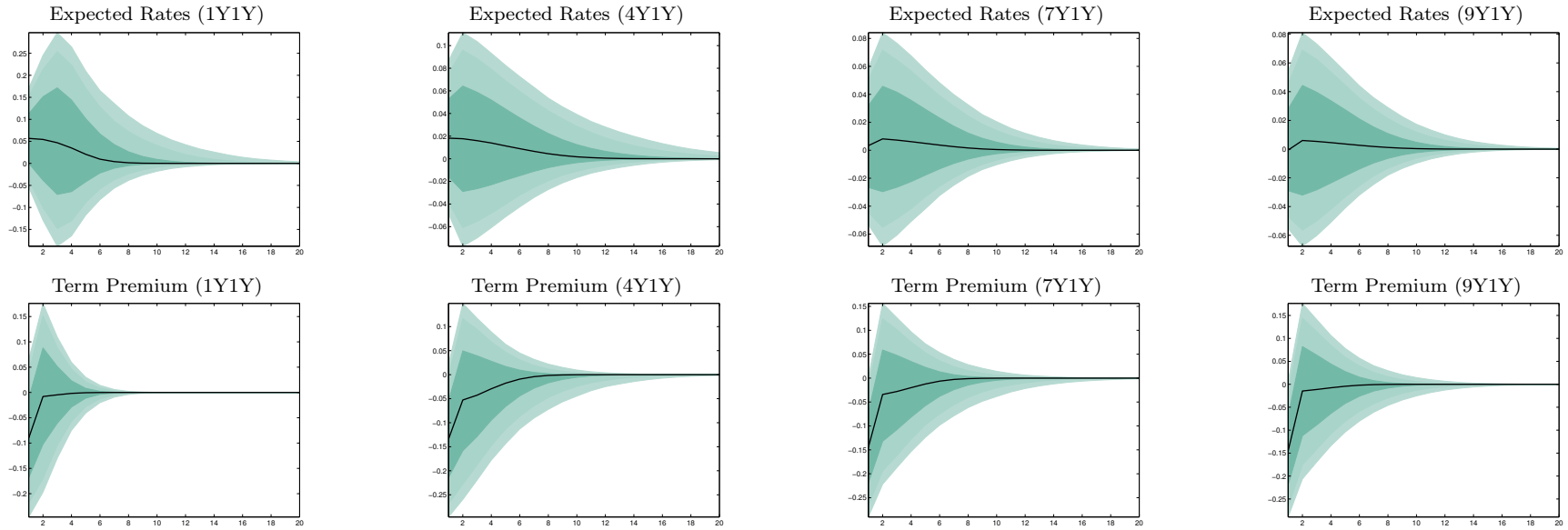


Figure 20: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Kilian (2008): 1983Q1–2004Q3



Hamilton (2003): 1983Q1–2007Q4

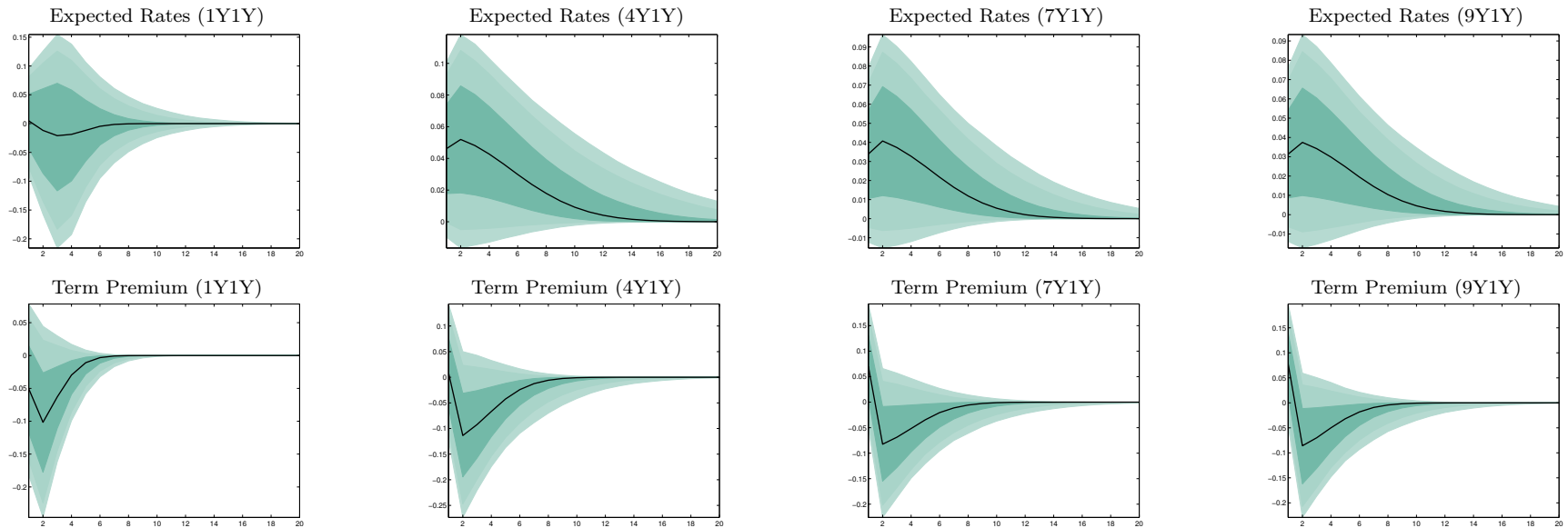
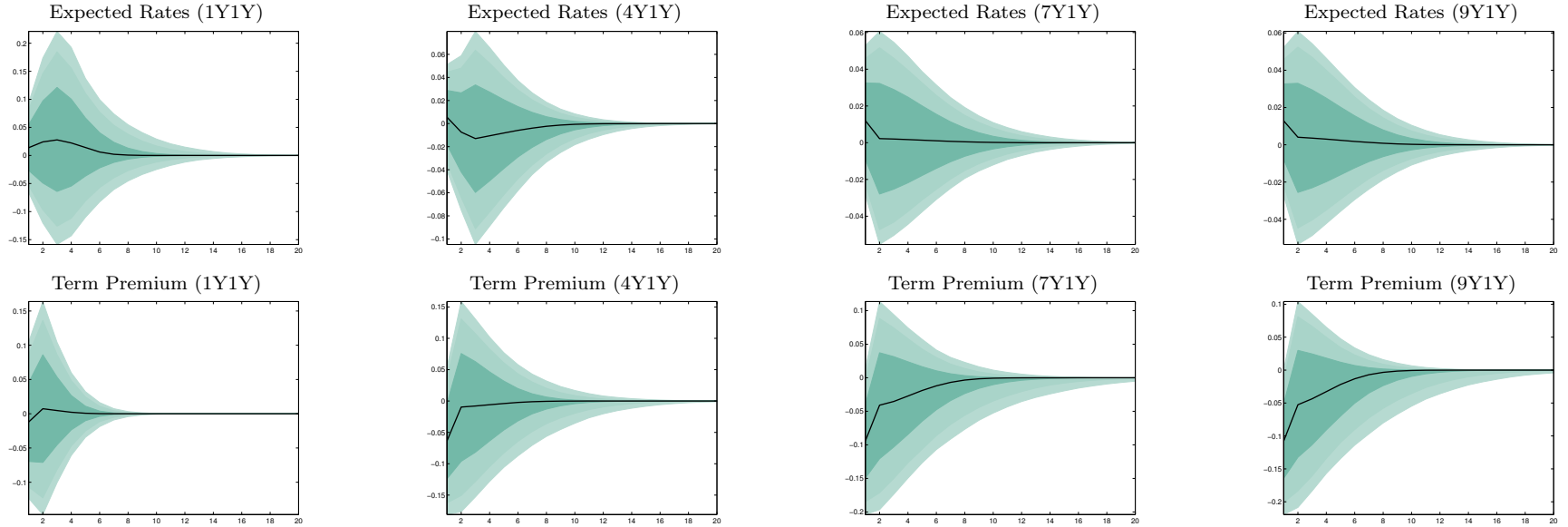


Figure 21: **Impulse Response of Yield Decompositions**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Barsky and Sims (2011): 1983Q1–2007Q3



Gali (1999): 1983Q1–2007Q3

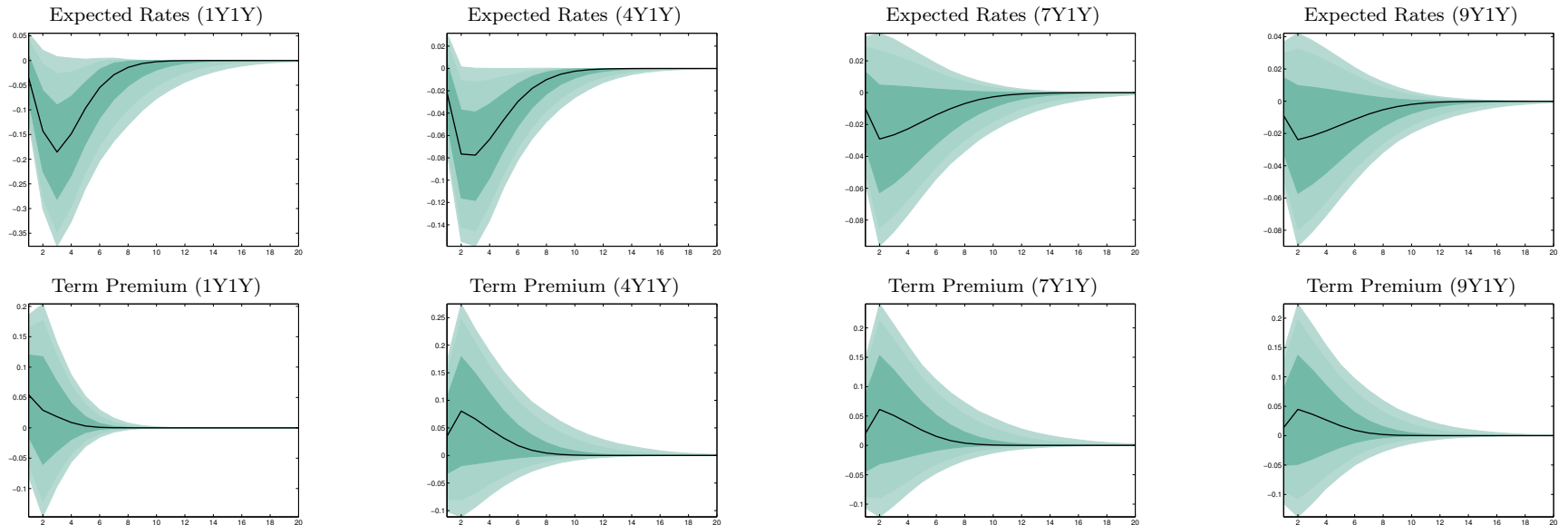
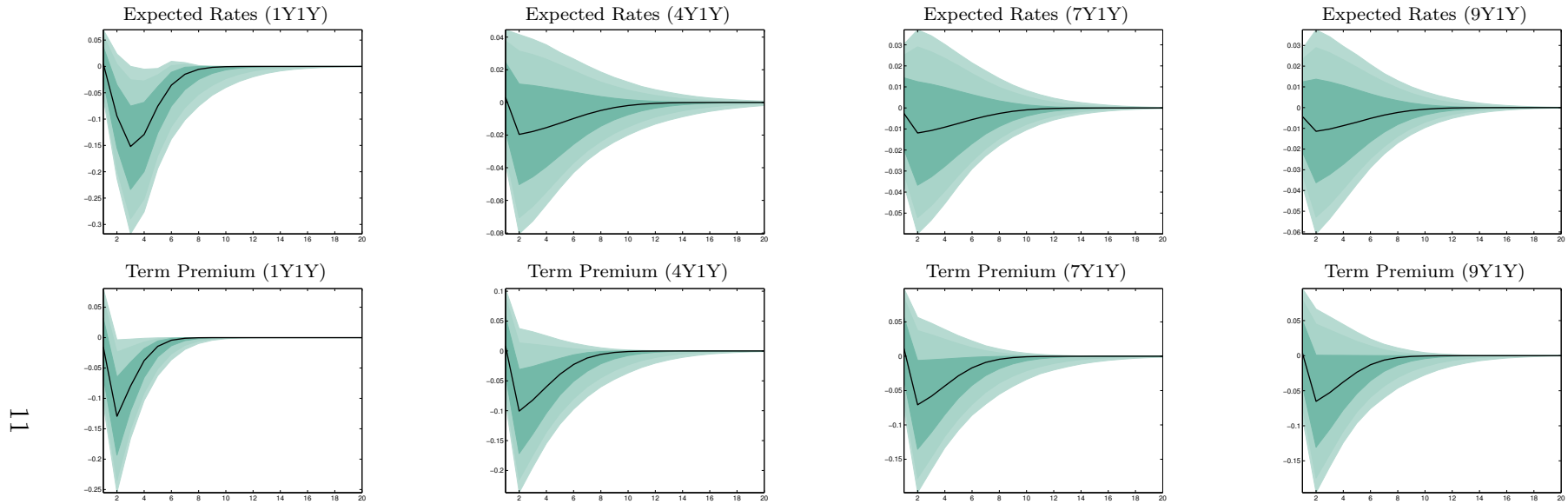


Figure 22: **Impulse Response of Yield Decompositions (Pre-Crisis)**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Ramey (2011): 1983Q1–2007Q4



Gilchrist and Zakrajšek (2012): 1983Q3–2007Q4

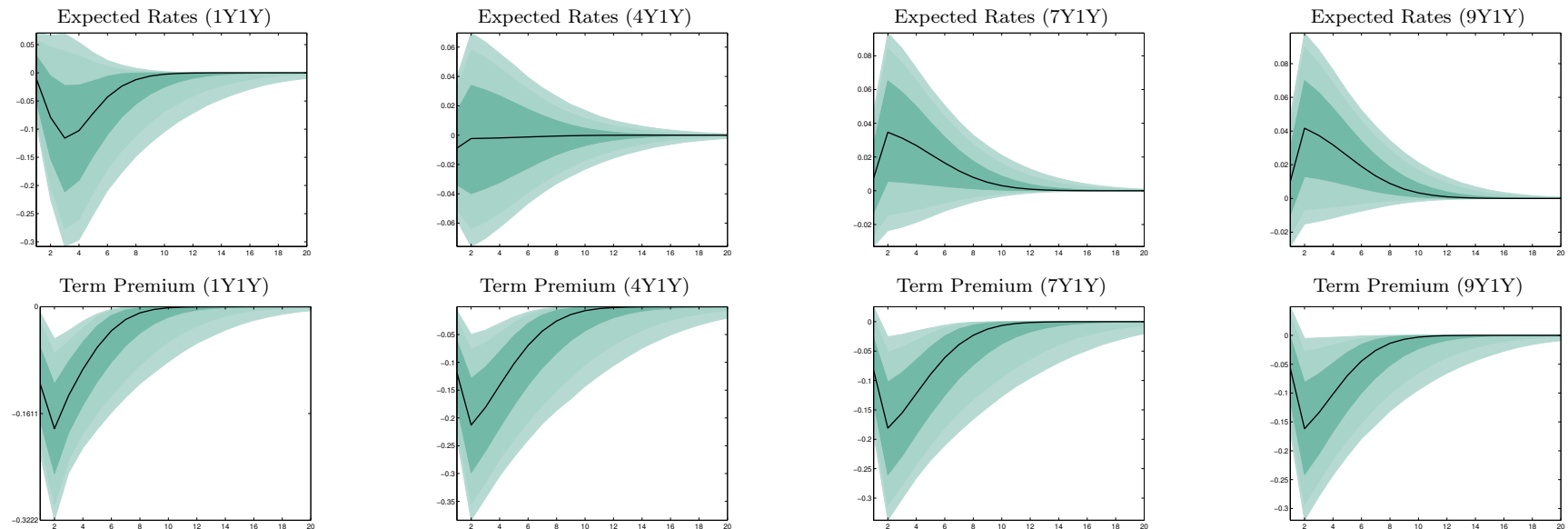
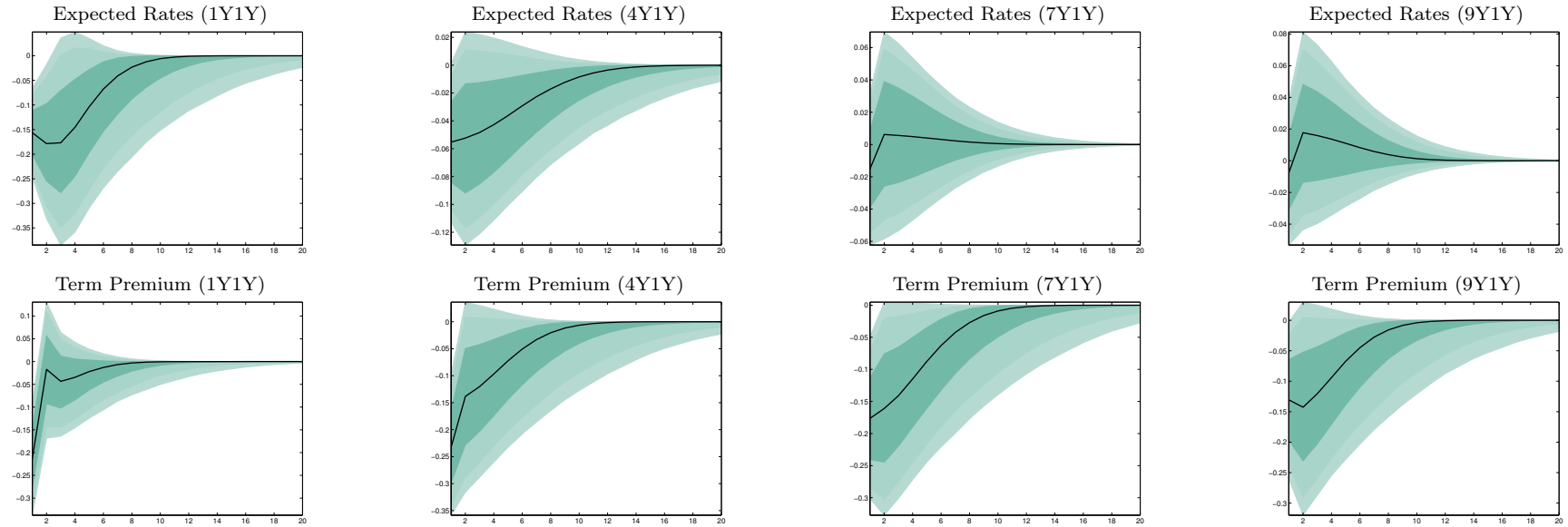


Figure 23: Impulse Response of Yield Decompositions (Pre-Crisis)

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Del Negro et al. (2013): 1983Q1–2007Q4



Jo and Sekkel (2016): 1983Q1–2007Q4

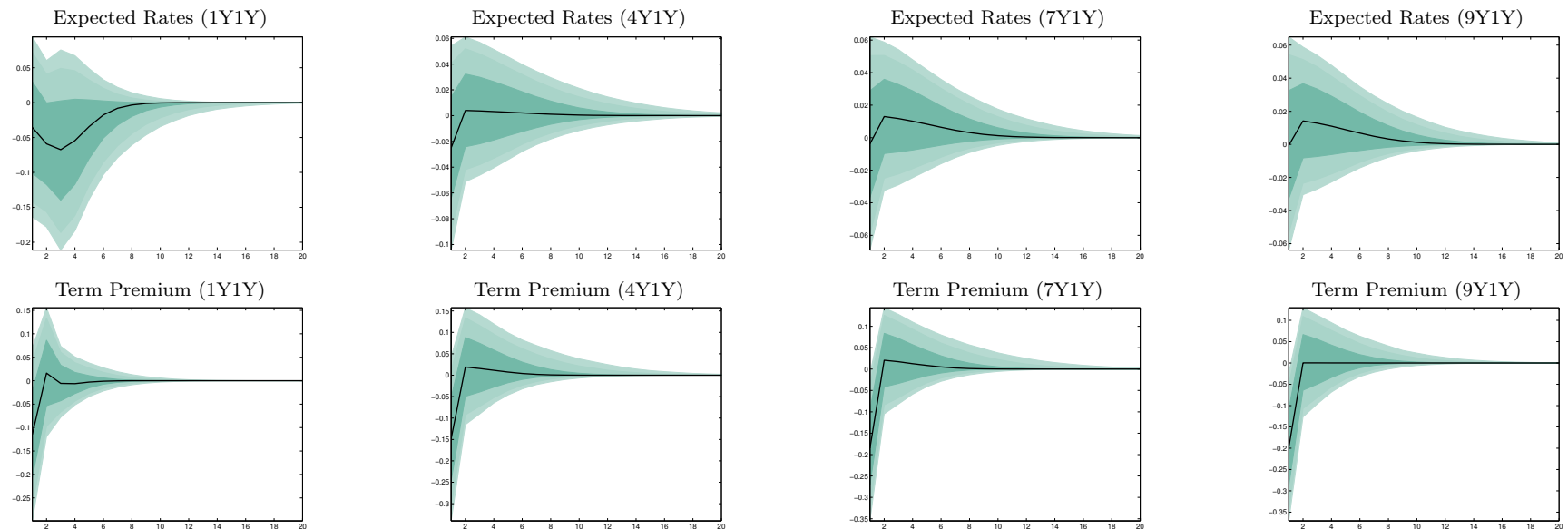


Figure 24: **Impulse Response of Yield Decompositions (Pre-Crisis)**

These figures show impulse response functions based on equation (5.3) corresponding to individual macroeconomic shocks. The black line represents the median response across simulations whereas the green shaded regions represent 68%, 90%, and 95% nominal coverage rates. All results are based on 10,000 simulations.

Basu and Bundick (2015): 1987Q1–2007Q4

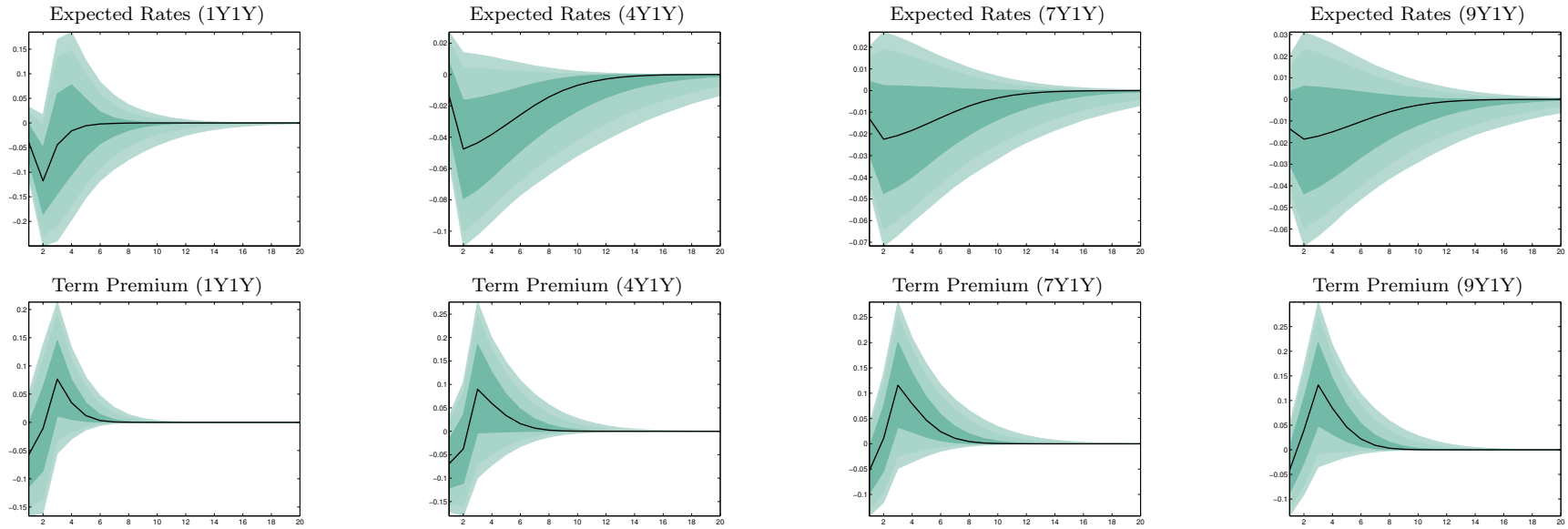


Table 8: **Changes in Yield Decompositions and Policy Shocks**

This table displays results from regressions of the change in the yield decomposition variable on the candidate policy shock. The shock series from [Kuttner \(2001\)](#) and [Gürkaynak et al. \(2005a\)](#) have a sample period of 1988m11-2007m12 and 1990m2-2004m12, respectively. OLS standard errors are shown in parantheses. *** ** and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include a constant term.

	$\Delta 1Y1Y$ Exp Rates	$\Delta 4Y1Y$ Exp Rates	$\Delta 7Y1Y$ Exp Rates	$\Delta 9Y1Y$ Exp Rates
Kuttner (2001)	0.624*** (0.118)	0.219*** (0.077)	0.129* (0.069)	0.115* (0.070)
Observations	230	230	230	230
Adjusted R^2	0.106	0.030	0.011	0.007
GSS (2005) Target	0.006*** (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Observations	179	179	179	179
Adjusted R^2	0.065	0.004	-0.003	-0.003
GSS (2005) Path	0.003** (0.001)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)
Observations	179	179	179	179
Adjusted R^2	0.027	0.002	-0.006	-0.006
	$\Delta 1Y1Y$ Term Prem	$\Delta 4Y1Y$ Term Prem	$\Delta 7Y1Y$ Term Prem	$\Delta 9Y1Y$ Term Prem
Kuttner (2001)	-0.020 (0.210)	-0.151 (0.198)	-0.289* (0.173)	-0.332* (0.172)
Observations	230	230	230	230
Adjusted R^2	-0.004	-0.002	0.008	0.012
GSS (2005) Target	-0.002 (0.003)	-0.004 (0.003)	-0.005** (0.002)	-0.006** (0.002)
Observations	179	179	179	179
Adjusted R^2	-0.002	0.005	0.024	0.026
GSS (2005) Path	-0.002 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Observations	179	179	179	179
Adjusted R^2	0.001	-0.005	-0.004	-0.003

Table 9: **Changes in Yield Decompositions and Policy Shocks (cont'd)**

This table displays results from regressions of the change in the yield decomposition variable on the candidate policy shock. The shock series from [Mertens and Ravn \(2012\)](#), [Romer and Romer \(2010\)](#) and [Ramey \(2011\)](#) are restricted to a sample period of 1983Q1-2006Q4, 1983Q1-2007Q4 and 1983Q1-2010Q4, respectively. OLS standard errors are shown in parantheses. *** ** and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include a constant term.

	$\Delta 1Y1Y$ Exp Rates	$\Delta 4Y1Y$ Exp Rates	$\Delta 7Y1Y$ Exp Rates	$\Delta 9Y1Y$ Exp Rates
Mertens-Ravn (2012)	-0.058 (0.126)	-0.034 (0.072)	-0.025 (0.060)	-0.023 (0.059)
Observations	96	96	96	96
Adjusted R^2	-0.008	-0.008	-0.009	-0.009
Romer-Romer (2010)	-0.207 (0.184)	0.038 (0.104)	0.112 (0.087)	0.125 (0.085)
Observations	100	100	100	100
Adjusted R^2	0.003	-0.009	0.007	0.011
Ramey (2011)	2.455 (3.259)	1.622 (1.763)	0.829 (1.459)	0.657 (1.440)
Observations	112	112	112	112
Adjusted R^2	-0.004	-0.001	-0.006	-0.007
	$\Delta 1Y1Y$ Term Prem	$\Delta 4Y1Y$ Term Prem	$\Delta 7Y1Y$ Term Prem	$\Delta 9Y1Y$ Term Prem
Mertens-Ravn (2012)	-0.280* (0.165)	-0.448*** (0.162)	-0.408*** (0.152)	-0.381** (0.156)
Observations	96	96	96	96
Adjusted R^2	0.020	0.065	0.062	0.050
Romer-Romer (2010)	-0.124 (0.244)	-0.597** (0.238)	-0.722*** (0.217)	-0.733*** (0.222)
Observations	100	100	100	100
Adjusted R^2	-0.008	0.051	0.092	0.091
Ramey (2011)	1.152 (4.204)	2.431 (4.219)	2.255 (3.826)	1.787 (3.877)
Observations	112	112	112	112
Adjusted R^2	-0.008	-0.006	-0.006	-0.007

Table 10: **Changes in Yield Decompositions and Demand Shocks**

This table displays results from regressions of the change in the yield decomposition variable on the candidate demand shock. The shock series from [Gilchrist and Zakrajšek \(2012\)](#), [Del Negro et al. \(2013\)](#) and [Jo and Sekkel \(2016\)](#) are restricted to a sample period of 1983Q1-2010Q3, 1983Q1-2014Q4 and 1983Q1-2014Q4, respectively. OLS standard errors are shown in parantheses. *** ** and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include a constant term.

	$\Delta 1Y1Y$ Exp Rates	$\Delta 4Y1Y$ Exp Rates	$\Delta 7Y1Y$ Exp Rates	$\Delta 9Y1Y$ Exp Rates
Gilchrist-Zakrajšek (2012)	-0.069* (0.040)	-0.013 (0.022)	0.001 (0.018)	0.003 (0.018)
Observations	111	111	111	111
Adjusted R^2	0.018	-0.006	-0.009	-0.009
spread	-6.696*** (1.302)	-1.929** (0.775)	-0.498 (0.650)	-0.245 (0.641)
Observations	128	128	128	128
Adjusted R^2	0.167	0.039	-0.003	-0.007
Jo-Sekkel (2015)	-0.630 (0.456)	0.005 (0.255)	0.101 (0.209)	0.112 (0.205)
Observations	128	128	128	128
Adjusted R^2	0.007	-0.008	-0.006	-0.006
	$\Delta 1Y1Y$ Term Prem	$\Delta 4Y1Y$ Term Prem	$\Delta 7Y1Y$ Term Prem	$\Delta 9Y1Y$ Term Prem
Gilchrist-Zakrajšek (2012)	-0.138*** (0.051)	-0.135*** (0.050)	-0.070 (0.047)	-0.040 (0.048)
Observations	111	111	111	111
Adjusted R^2	0.056	0.053	0.011	-0.003
spread	-3.340* (1.783)	-6.156*** (1.786)	-5.149*** (1.690)	-4.331** (1.722)
Observations	128	128	128	128
Adjusted R^2	0.019	0.079	0.061	0.040
Jo-Sekkel (2015)	0.040 (0.579)	-0.138 (0.598)	-0.014 (0.561)	-0.069 (0.565)
Observations	128	128	128	128
Adjusted R^2	-0.008	-0.008	-0.008	-0.008

Table 11: **Changes in Yield Decompositions and Demand Shocks**

This table displays results from regressions of the change in the yield decomposition variable on the candidate demand shock. The shock series from Kilian (2008), Hamilton (2003), Barsky and Sims (2011) and Gali (1999) are restricted to a sample period of 1983Q1-2004Q3, 1983Q1-2007Q4, 1983Q1-2007Q3 and 1983Q1-2007Q3, respectively. OLS standard errors are shown in parantheses. *** ** and * denote significance at the 1%, 5%, and 10% levels, respectively. All regressions include a constant term.

	$\Delta 1Y1Y$ Exp Rates	$\Delta 4Y1Y$ Exp Rates	$\Delta 7Y1Y$ Exp Rates	$\Delta 9Y1Y$ Exp Rates
KilianOil	0.034 (0.055)	0.016 (0.031)	0.003 (0.026)	0.000 (0.026)
Observations	87	87	87	87
Adjusted R^2	-0.007	-0.009	-0.012	-0.012
OilShocks	2.221 (1.881)	2.272** (1.039)	1.889** (0.871)	1.796** (0.861)
Observations	100	100	100	100
Adjusted R^2	0.004	0.037	0.036	0.033
NewsShocks	0.003 (0.045)	0.006 (0.026)	0.010 (0.021)	0.010 (0.021)
Observations	99	99	99	99
Adjusted R^2	-0.010	-0.010	-0.008	-0.008
TechShocks	-0.059 (0.054)	-0.020 (0.030)	-0.011 (0.026)	-0.010 (0.025)
Observations	99	99	99	99
Adjusted R^2	0.002	-0.006	-0.008	-0.009
	$\Delta 1Y1Y$ Term Prem	$\Delta 4Y1Y$ Term Prem	$\Delta 7Y1Y$ Term Prem	$\Delta 9Y1Y$ Term Prem
KilianOil	-0.086 (0.072)	-0.114 (0.072)	-0.116* (0.067)	-0.114* (0.068)
Observations	87	87	87	87
Adjusted R^2	0.005	0.018	0.023	0.021
OilShocks	-1.364 (2.499)	0.108 (2.508)	1.894 (2.331)	2.065 (2.380)
Observations	100	100	100	100
Adjusted R^2	-0.007	-0.010	-0.003	-0.003
NewsShocks	-0.026 (0.060)	-0.083 (0.060)	-0.113** (0.055)	-0.128** (0.056)
Observations	99	99	99	99
Adjusted R^2	-0.008	0.009	0.031	0.041
TechShocks	0.069 (0.071)	0.033 (0.072)	0.020 (0.067)	0.013 (0.069)
Observations	99	99	99	99
Adjusted R^2	-0.001	-0.008	-0.009	-0.010

Figure 25: **Fitted Survey Data**
Series 1–20

These figures show the survey data (red and blue) and the model-implied fitted survey data (green). BCFF designates the Blue Chip Financial Forecasts survey; BCEI, the Blue Chip Economic Indicators survey; CE designates the Consensus Economics survey; DMP designates the Decision Maker's Poll; Liv designates the Livingston Survey; SPD designates the Survey of Primary Dealers; and SPF designates the Survey of Professional Forecasters.

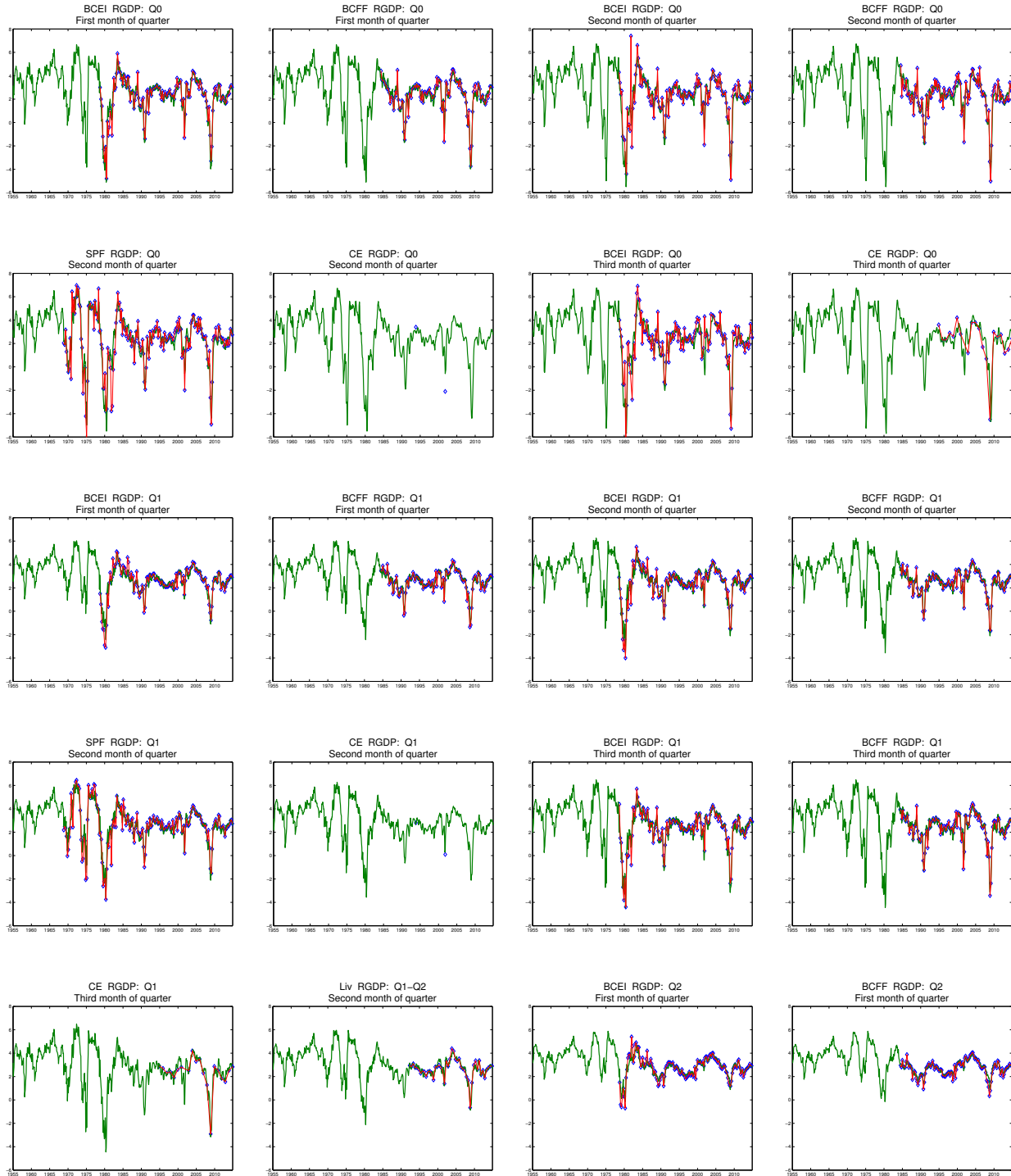


Figure 26: **Fitted Survey Data**
Series 21–40

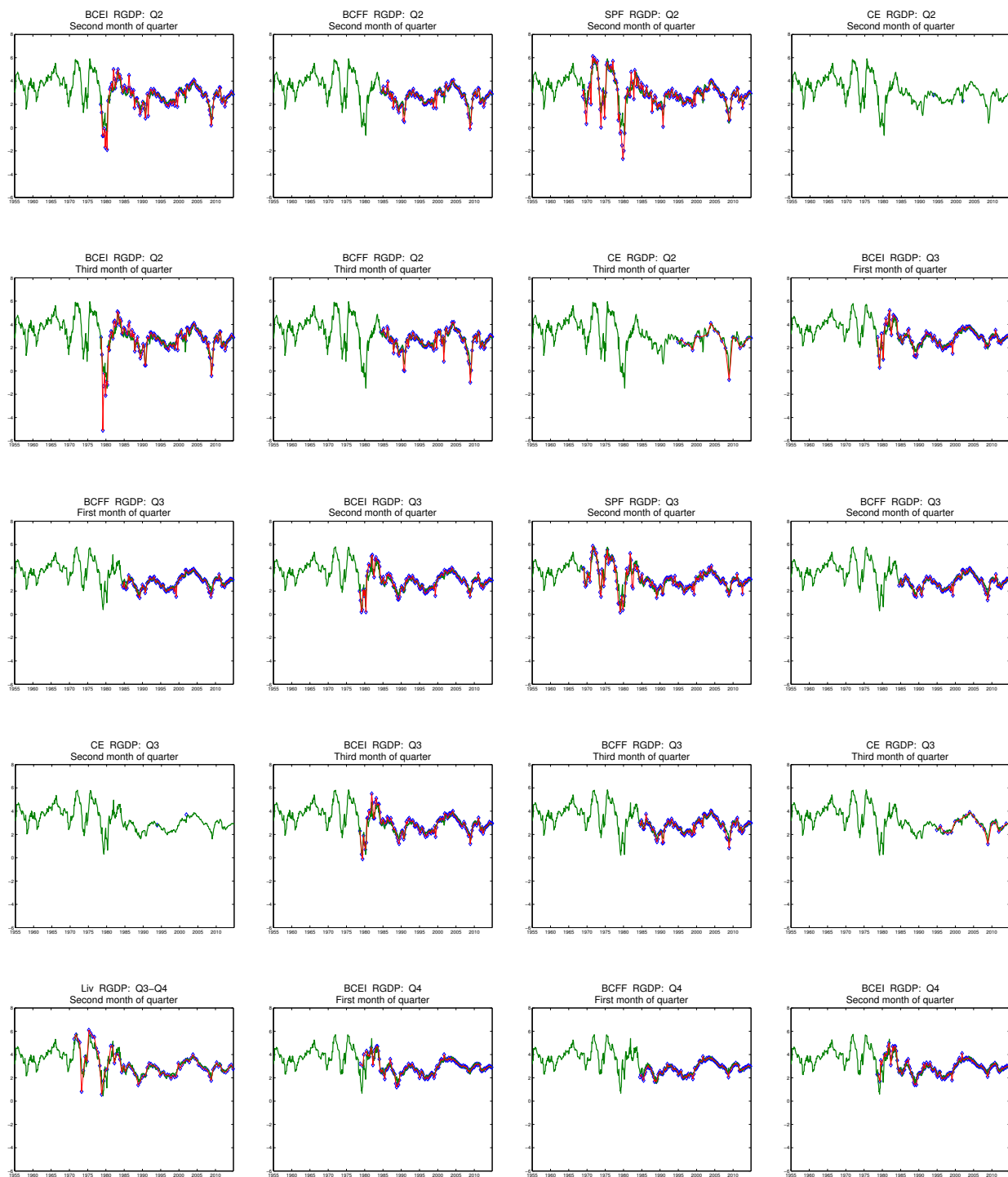


Figure 27: Fitted Survey Data
Series 41–60

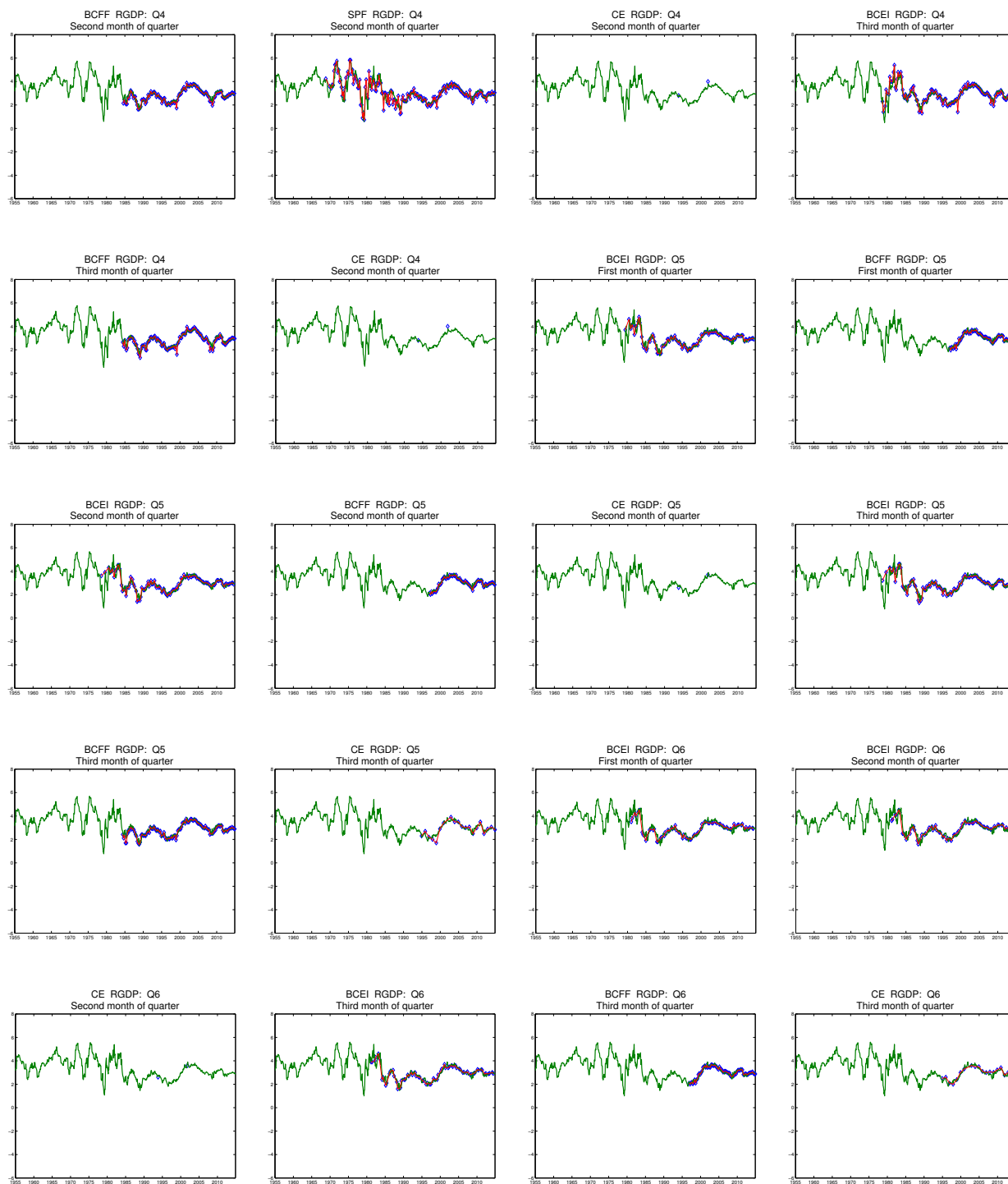


Figure 28: **Fitted Survey Data**
Series 61–80

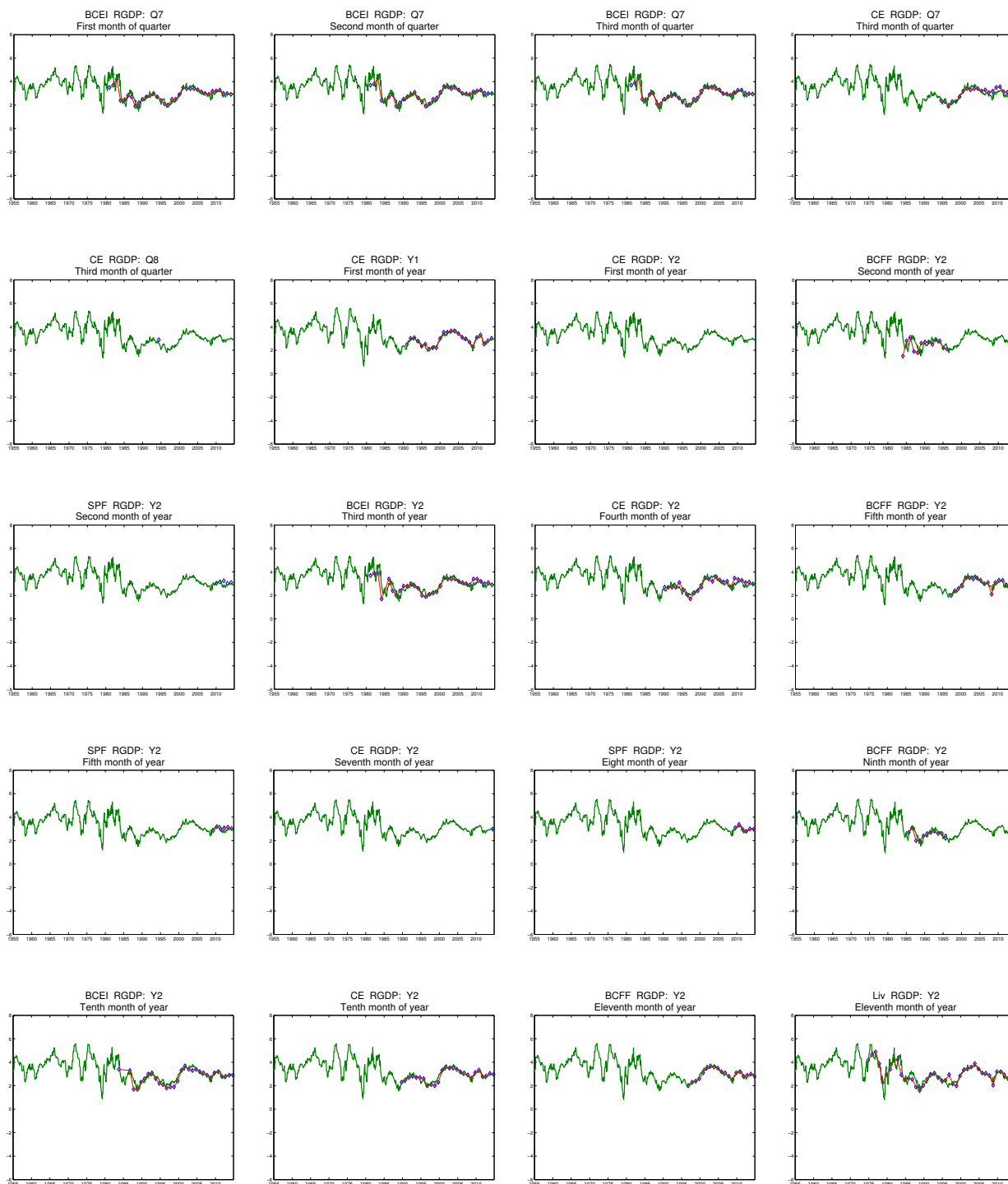


Figure 29: Fitted Survey Data
Series 81–100

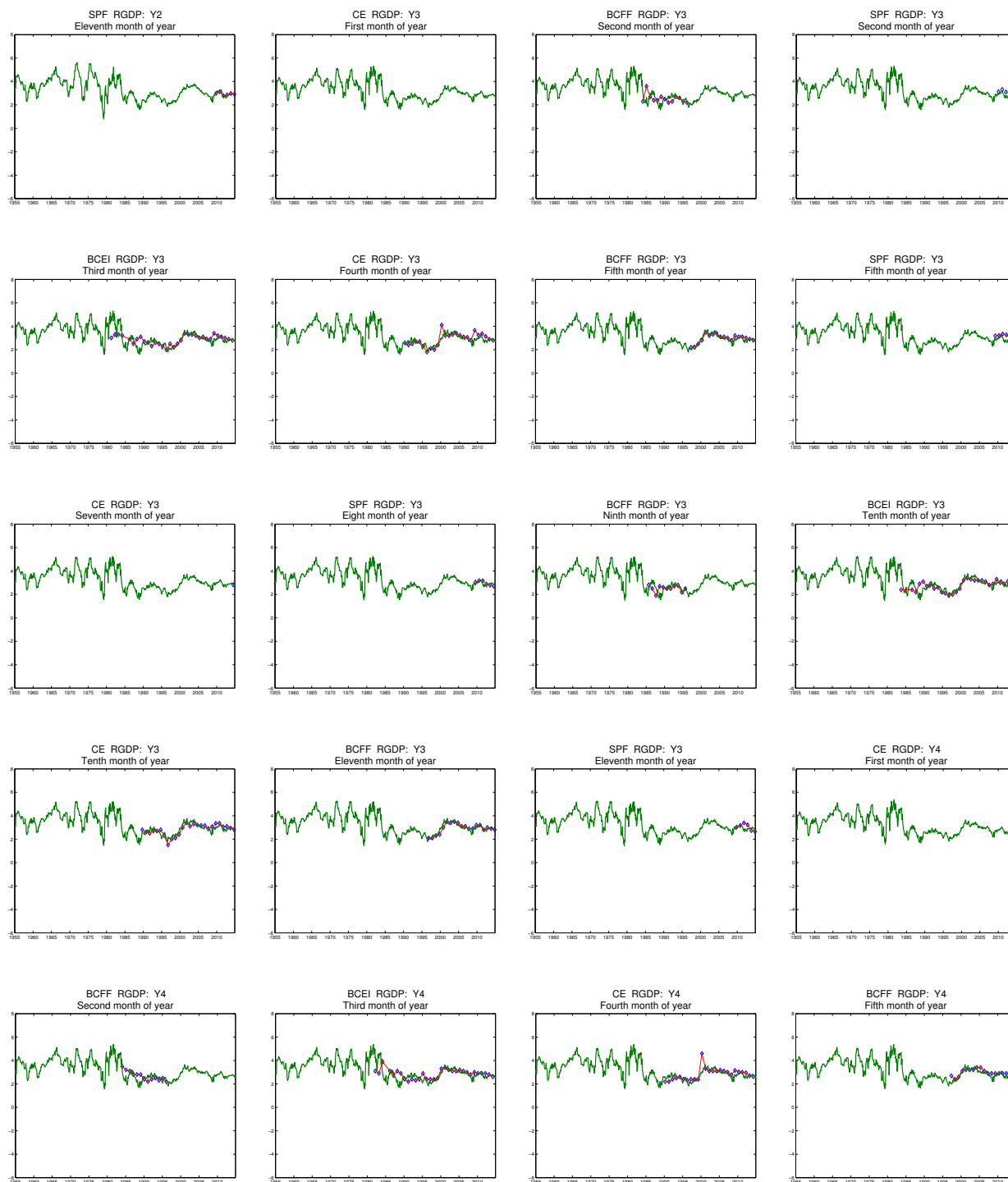


Figure 30: **Fitted Survey Data**
Series 101–120

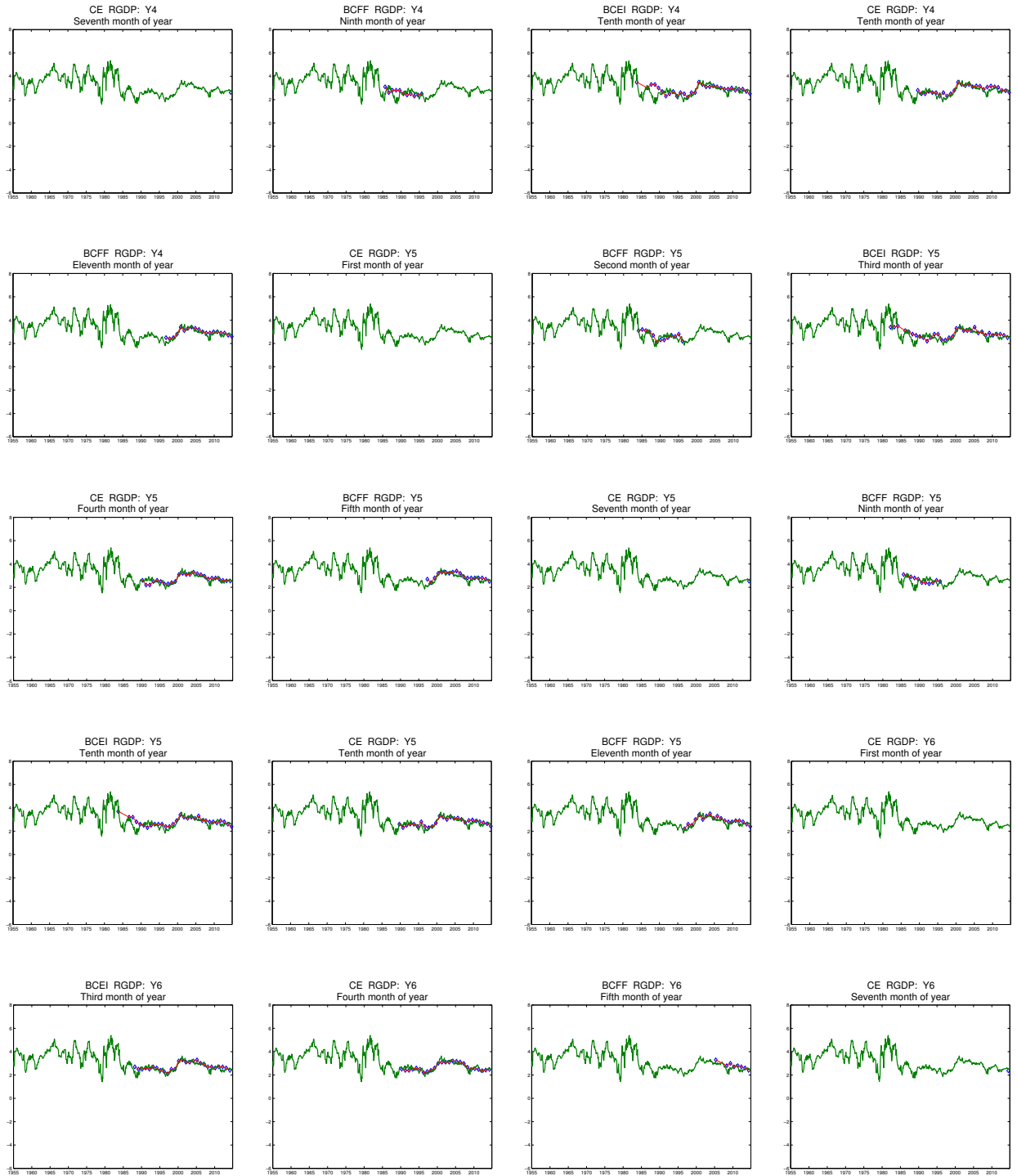


Figure 31: Fitted Survey Data
Series 121–140

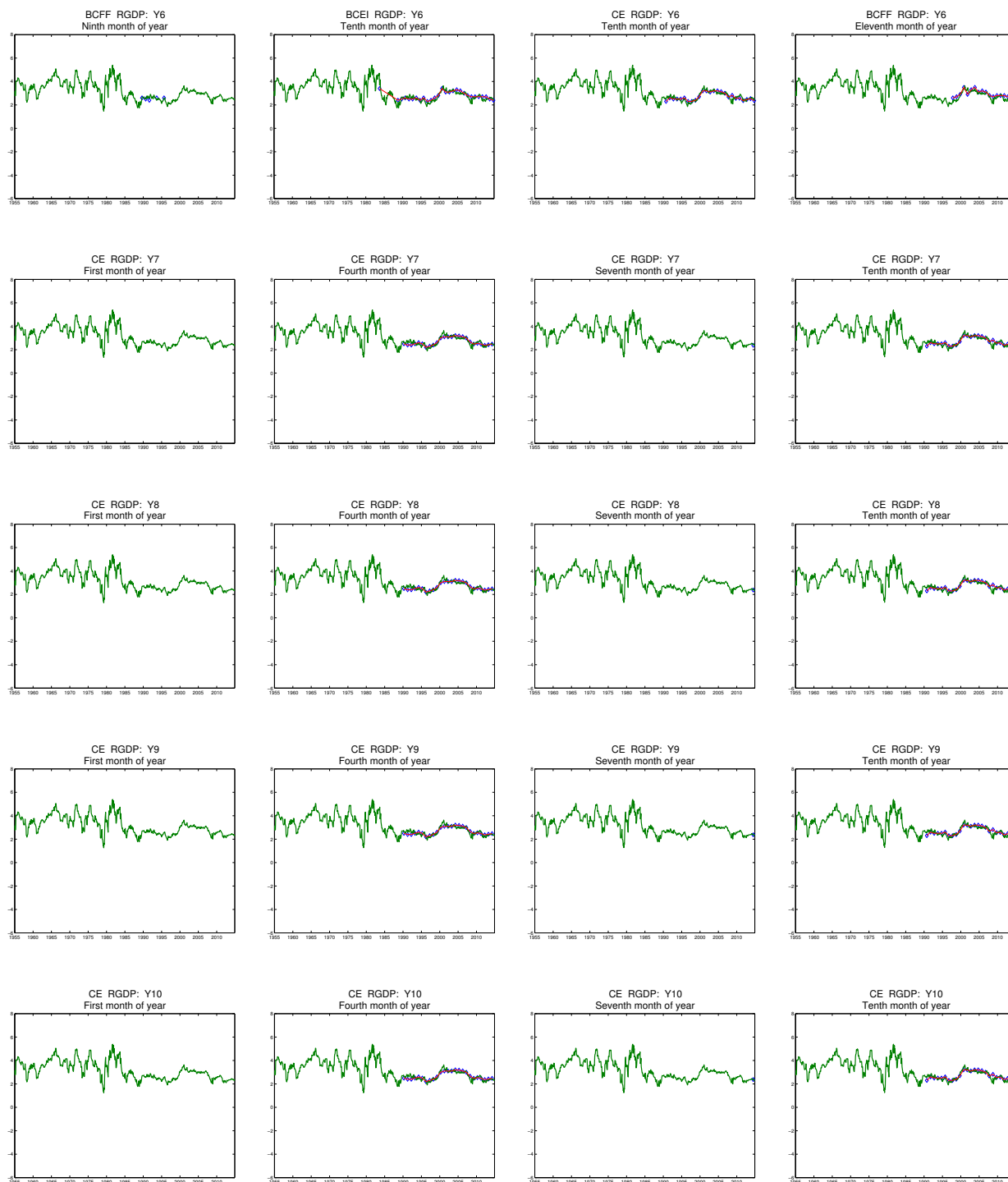


Figure 32: Fitted Survey Data
Series 141–160

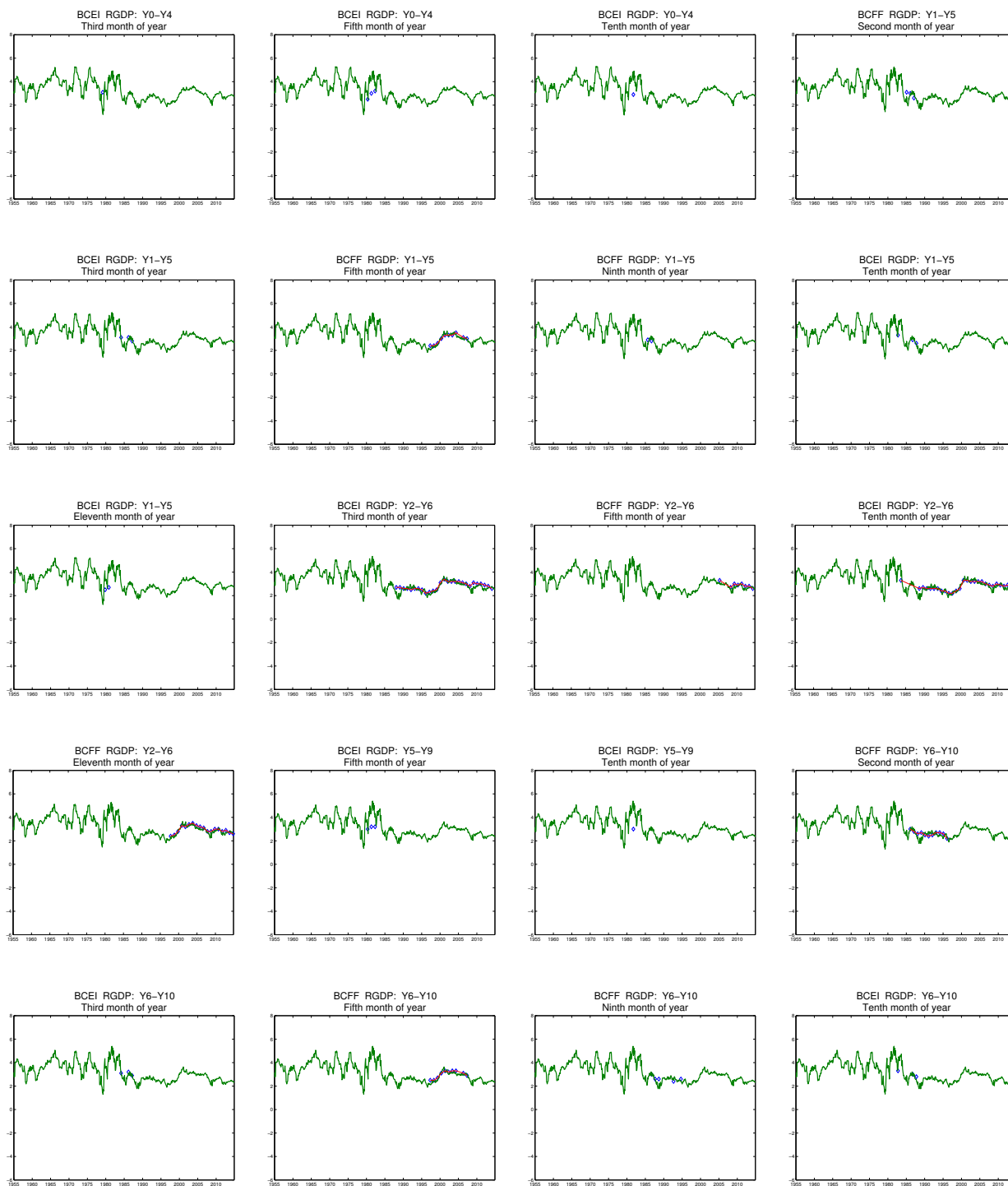


Figure 33: Fitted Survey Data
Series 161–180

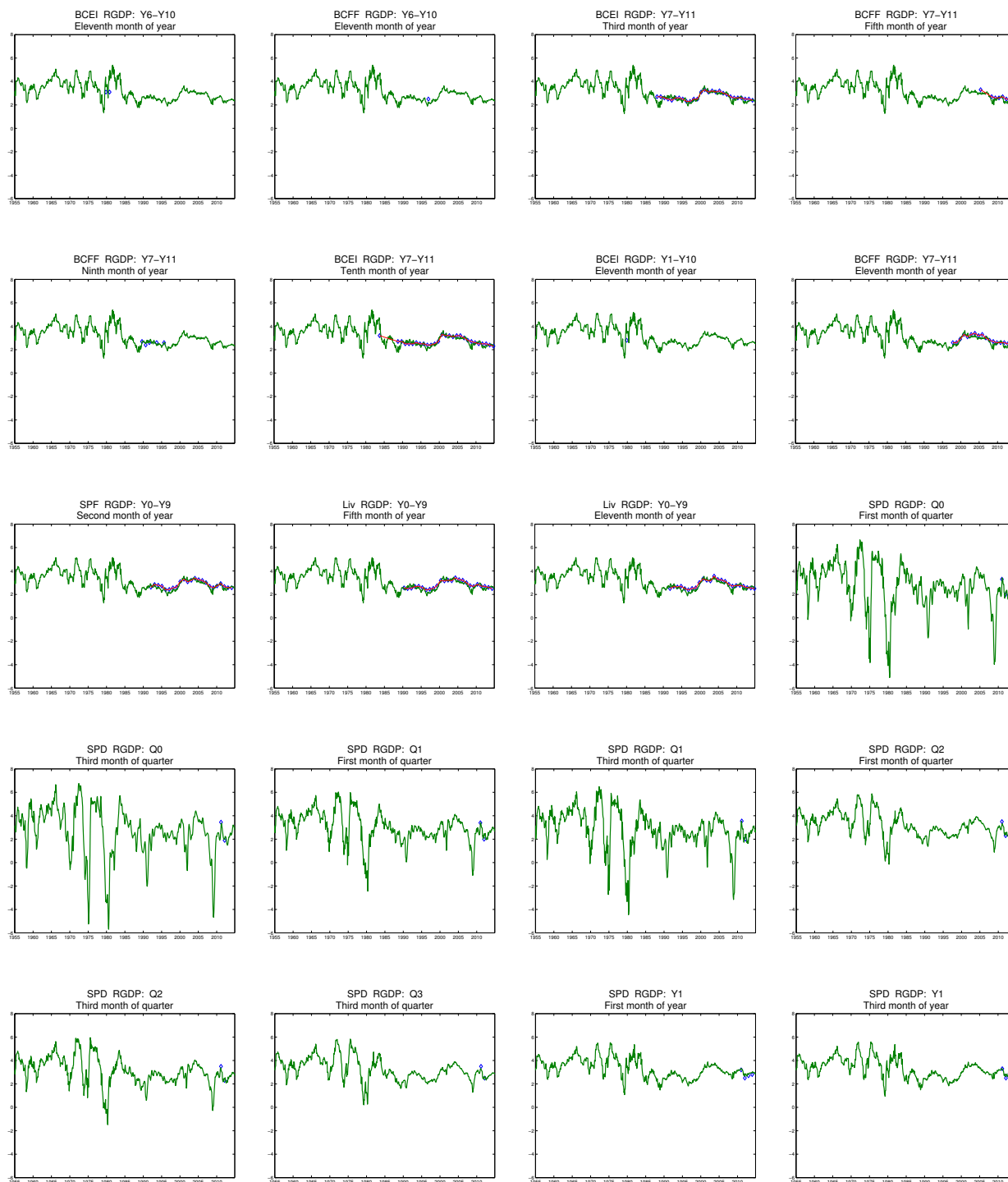


Figure 34: **Fitted Survey Data**
Series 181–200

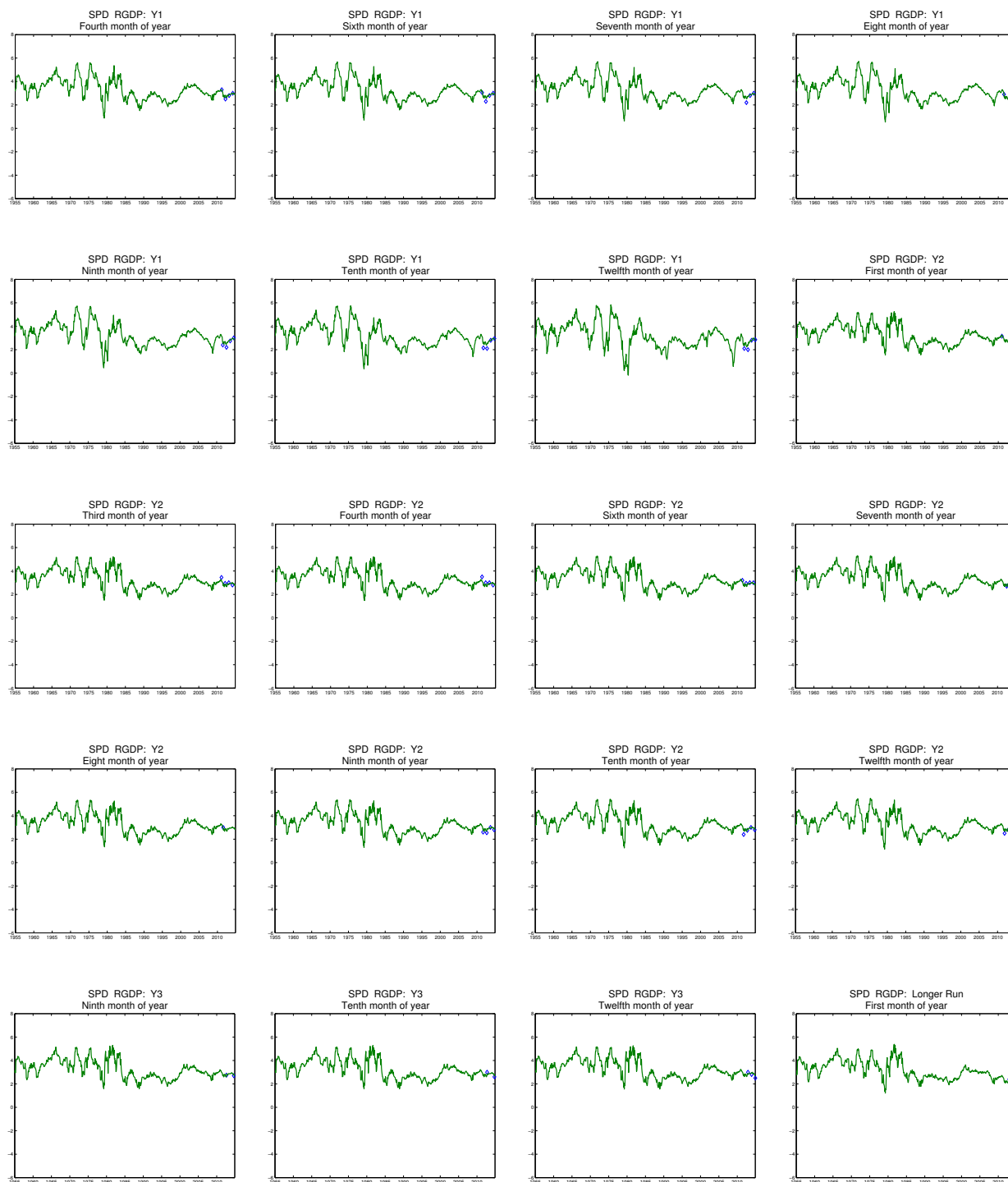


Figure 35: Fitted Survey Data
Series 201–220

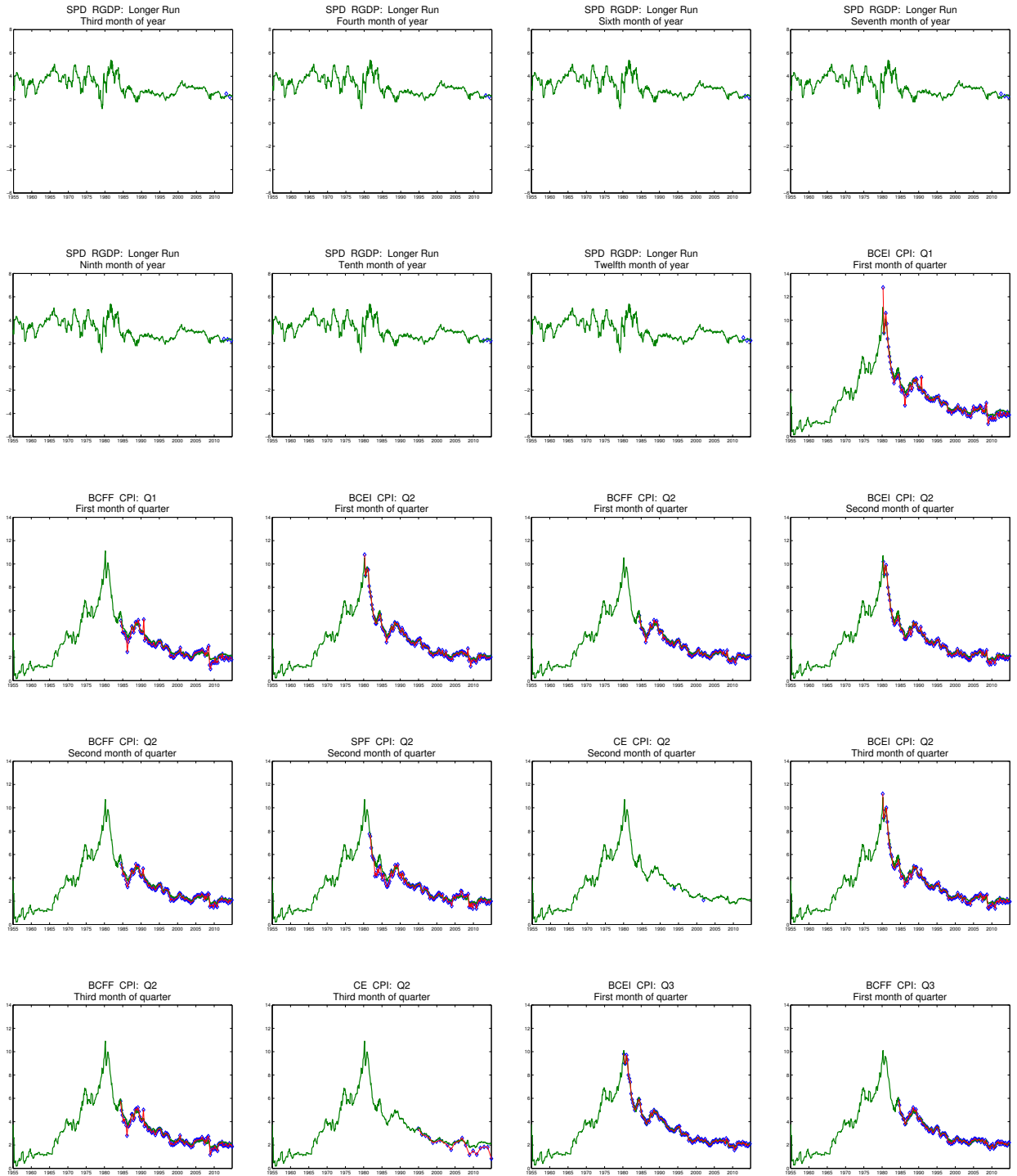


Figure 36: Fitted Survey Data
Series 221–240

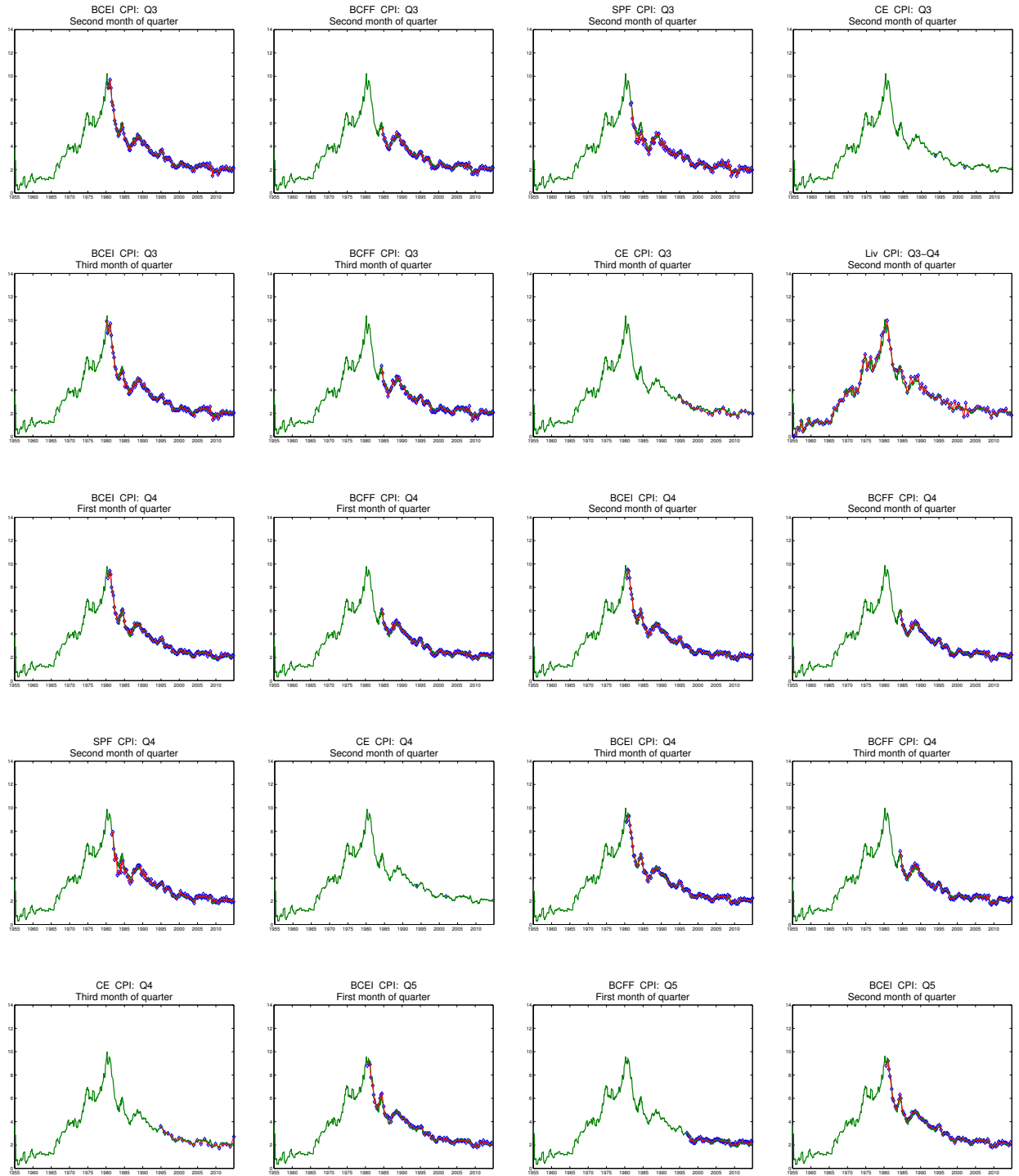


Figure 37: Fitted Survey Data
Series 241–260

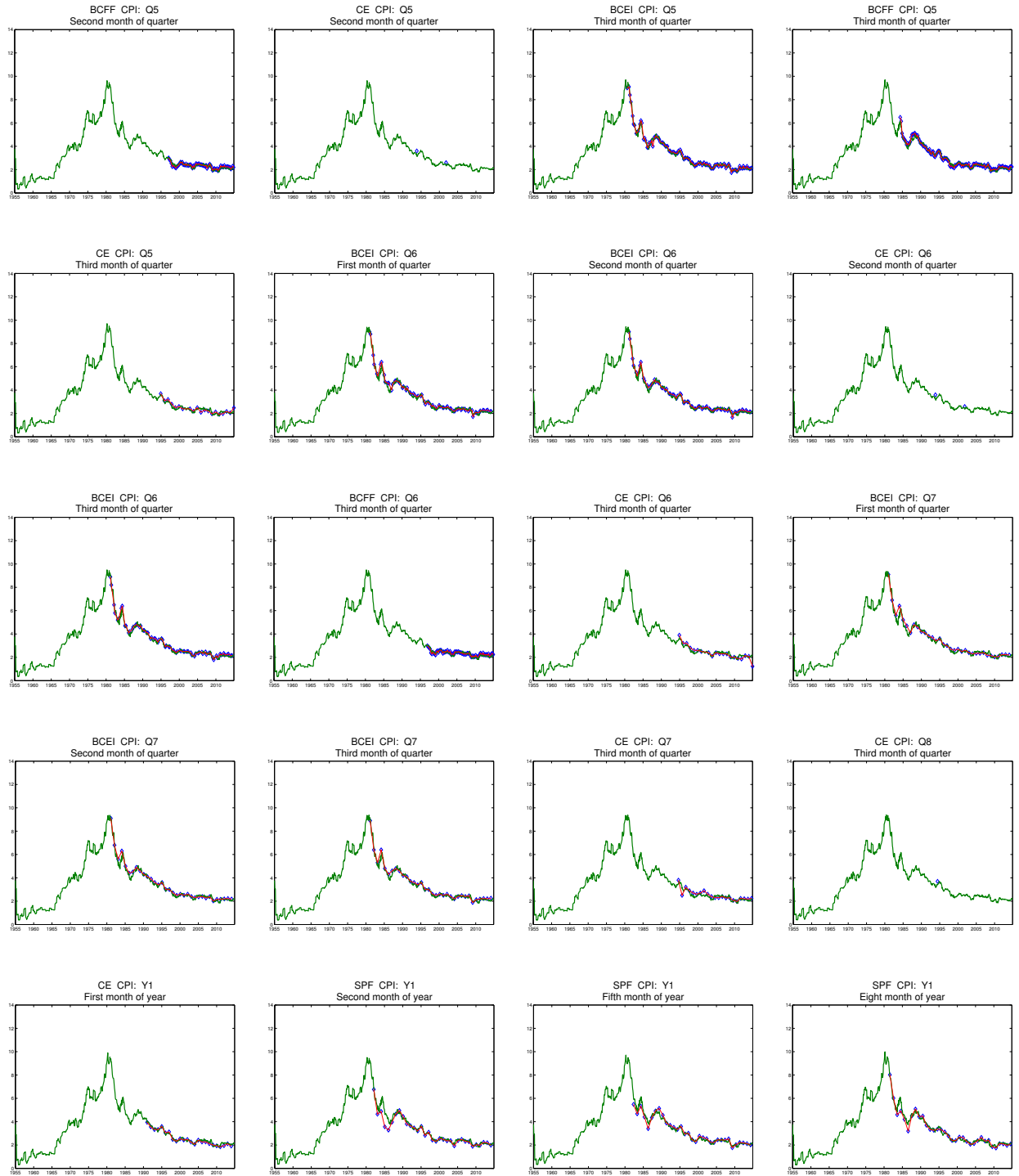


Figure 38: **Fitted Survey Data**
Series 261–280

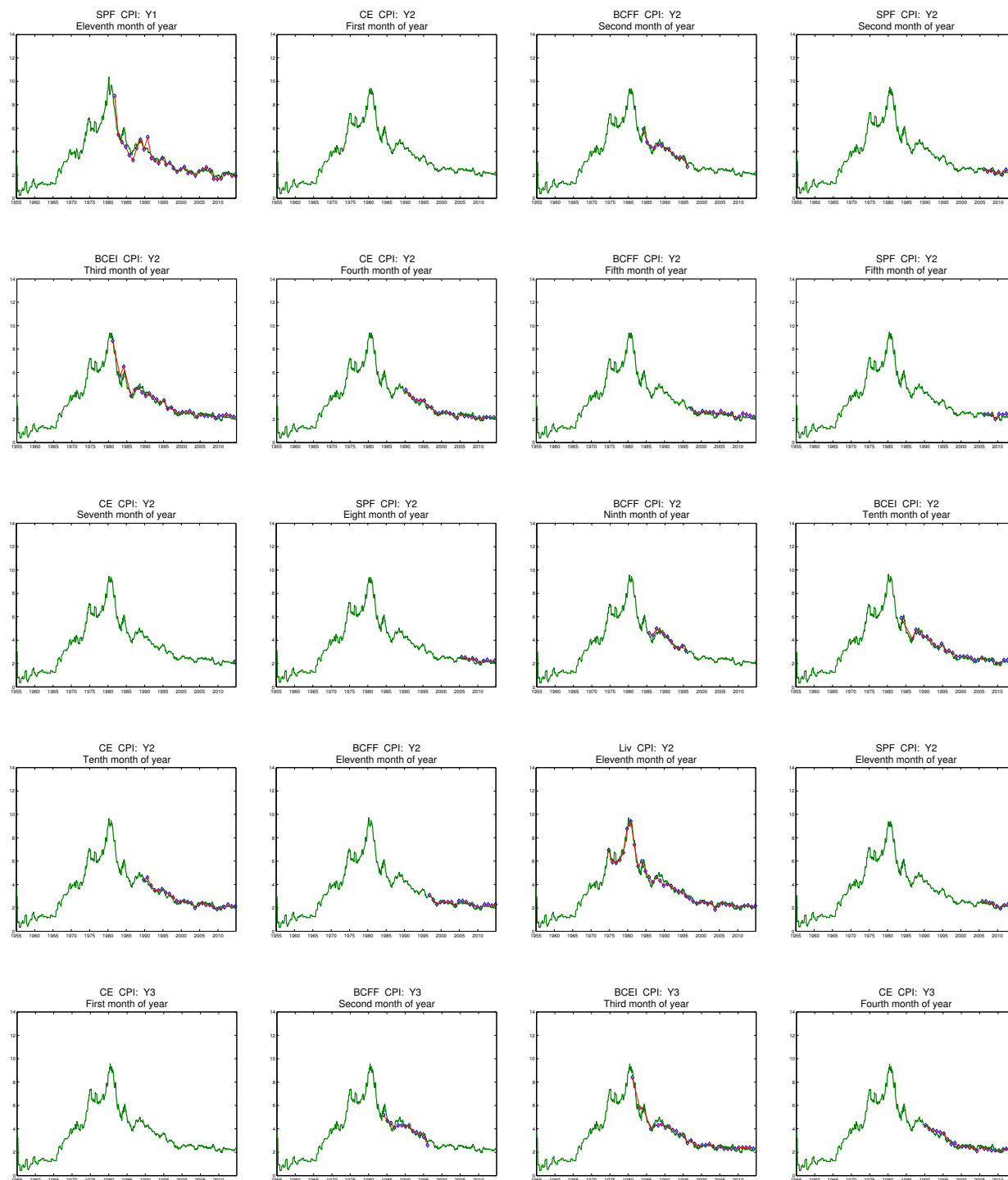


Figure 39: Fitted Survey Data
Series 281–300

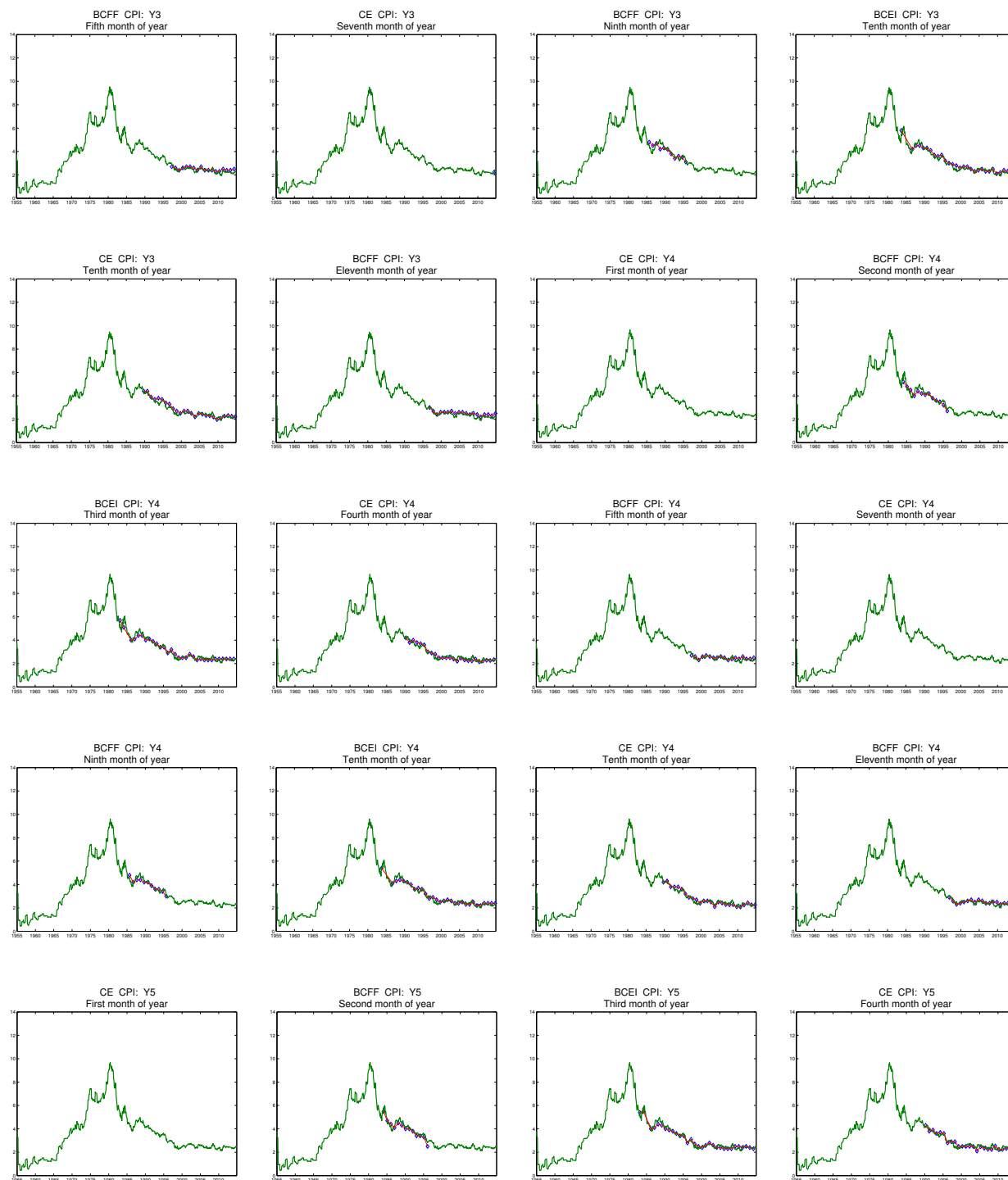


Figure 40: Fitted Survey Data
Series 301–320

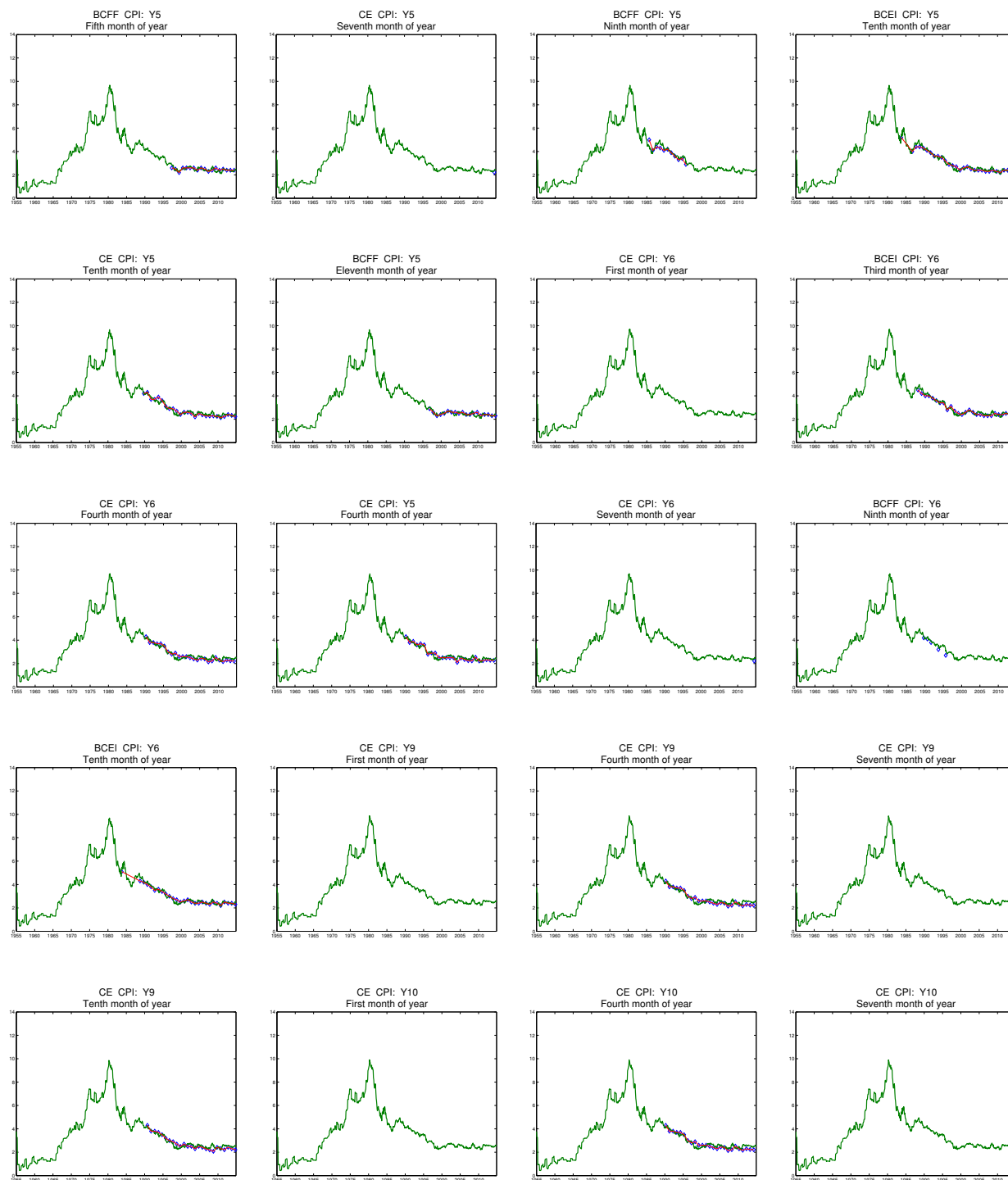


Figure 41: Fitted Survey Data
Series 321–340

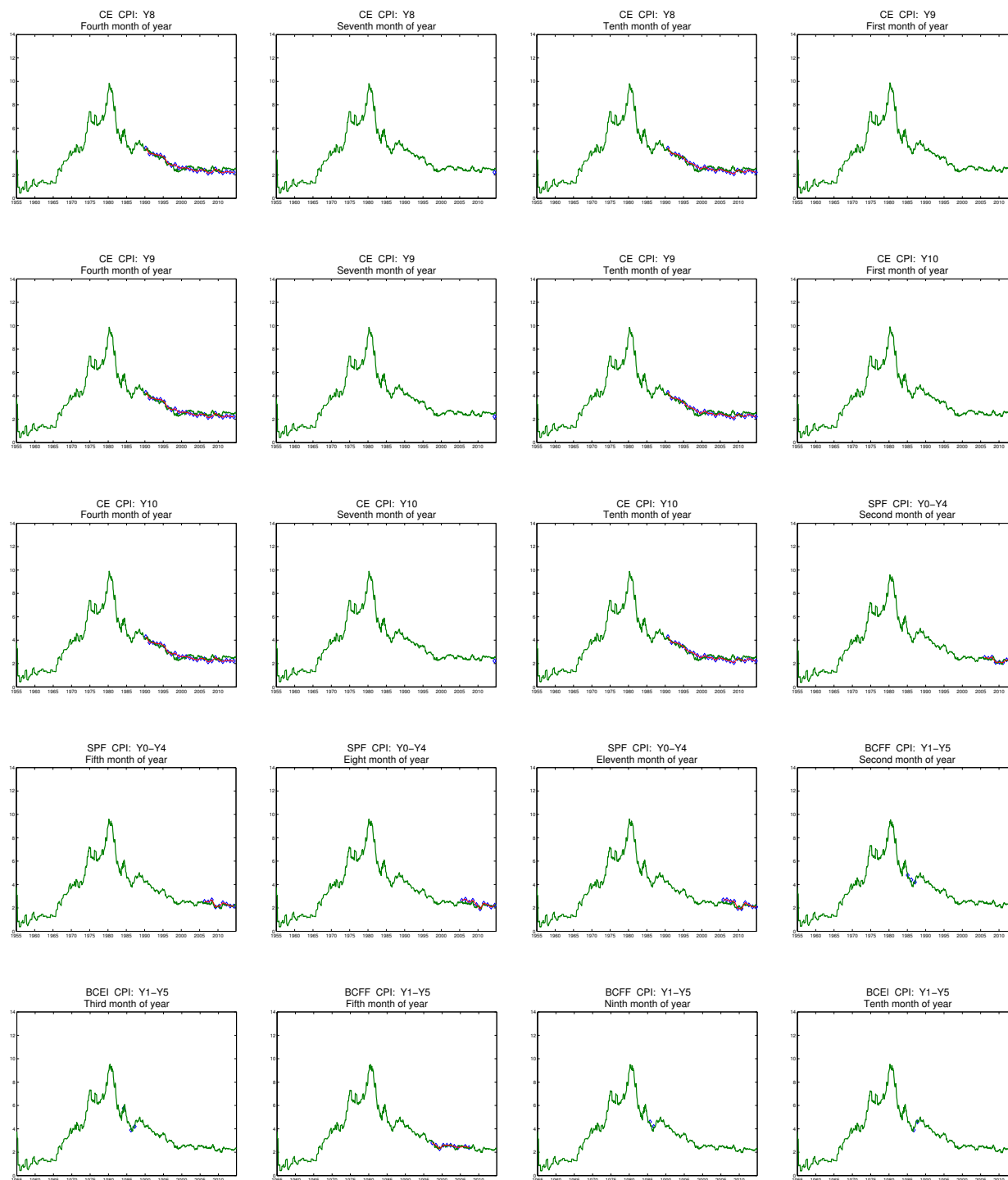


Figure 42: Fitted Survey Data
Series 341–360

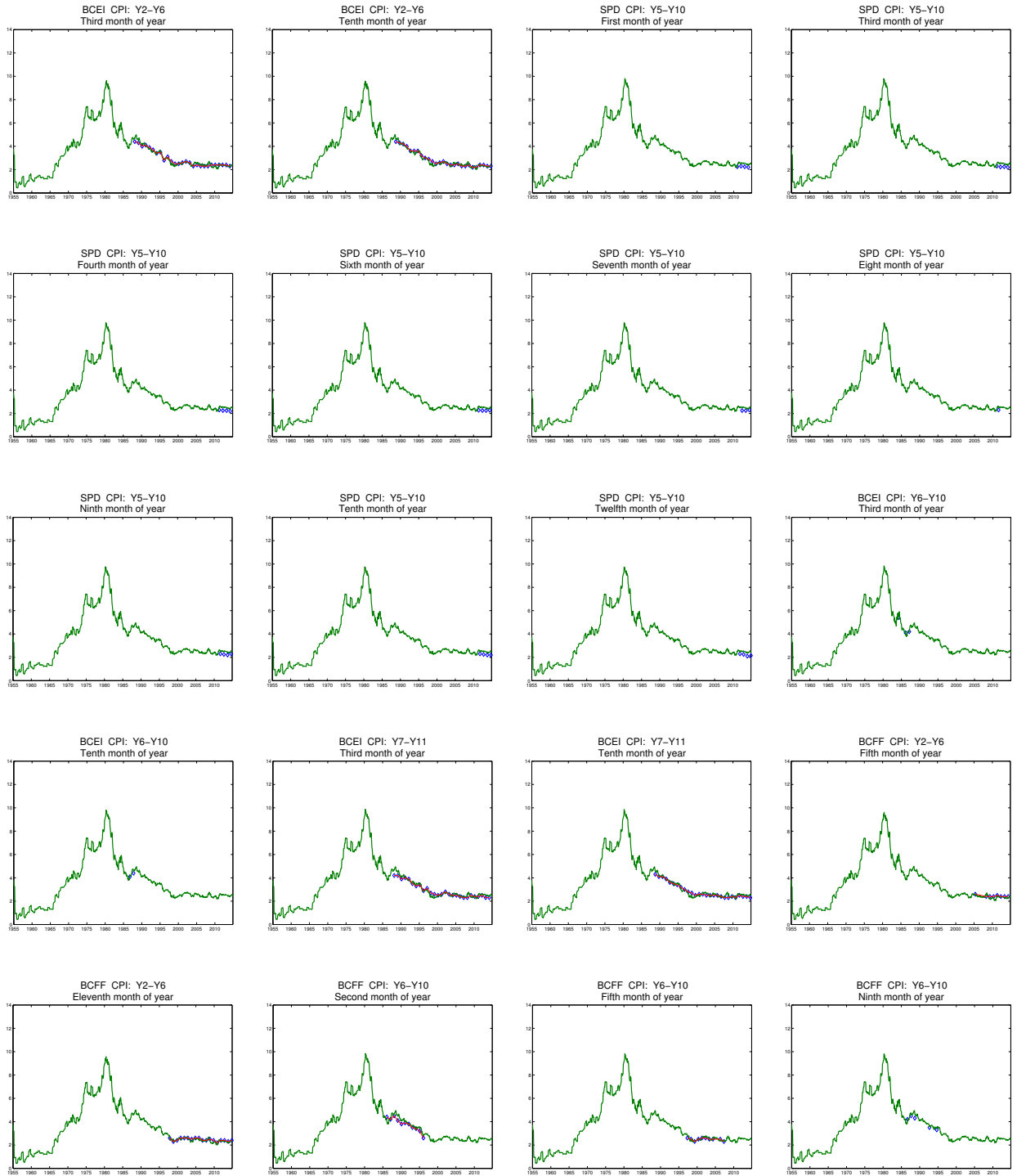


Figure 43: Fitted Survey Data
Series 361–380

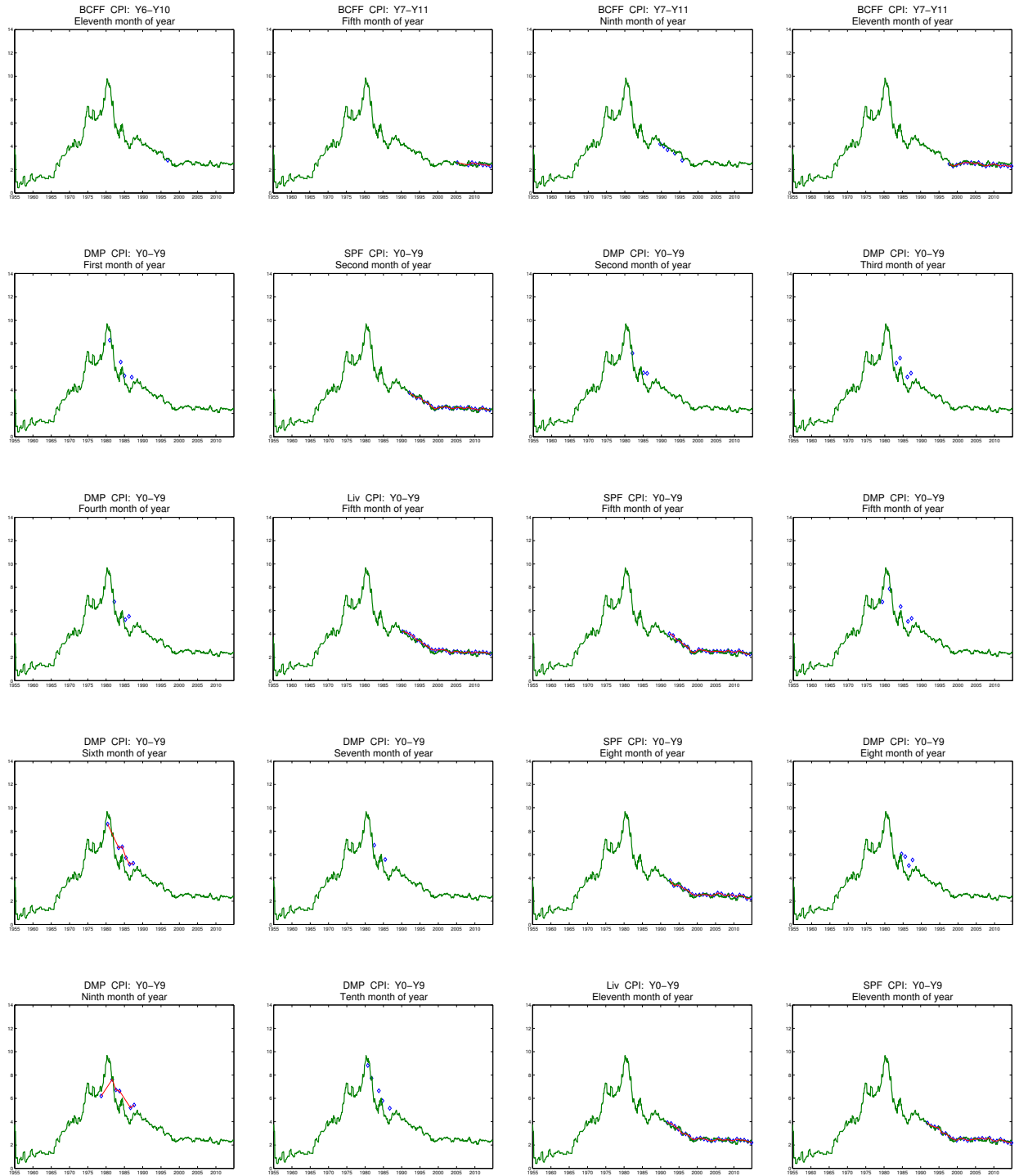


Figure 44: Fitted Survey Data
Series 381–400

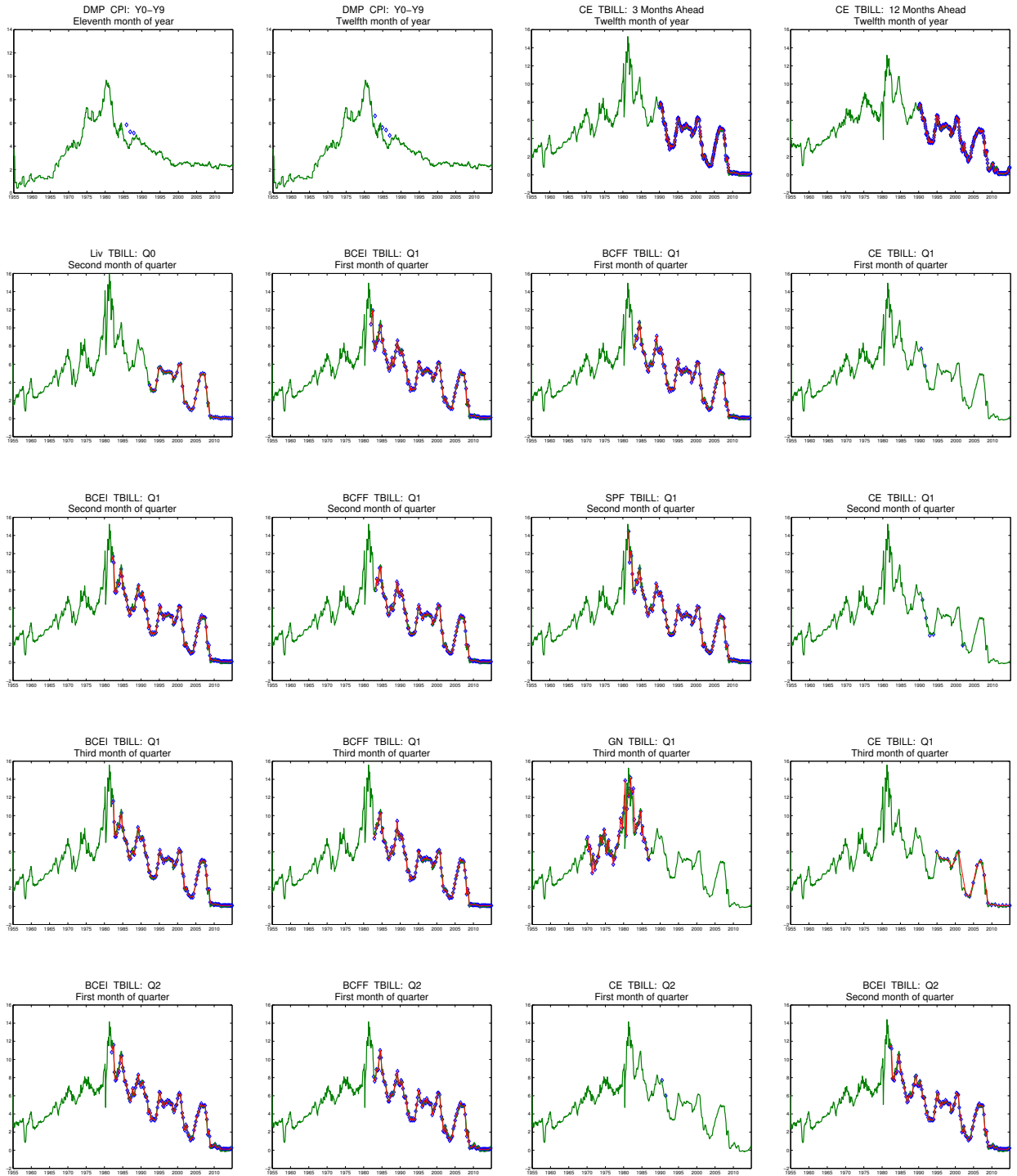


Figure 45: Fitted Survey Data
Series 401–420

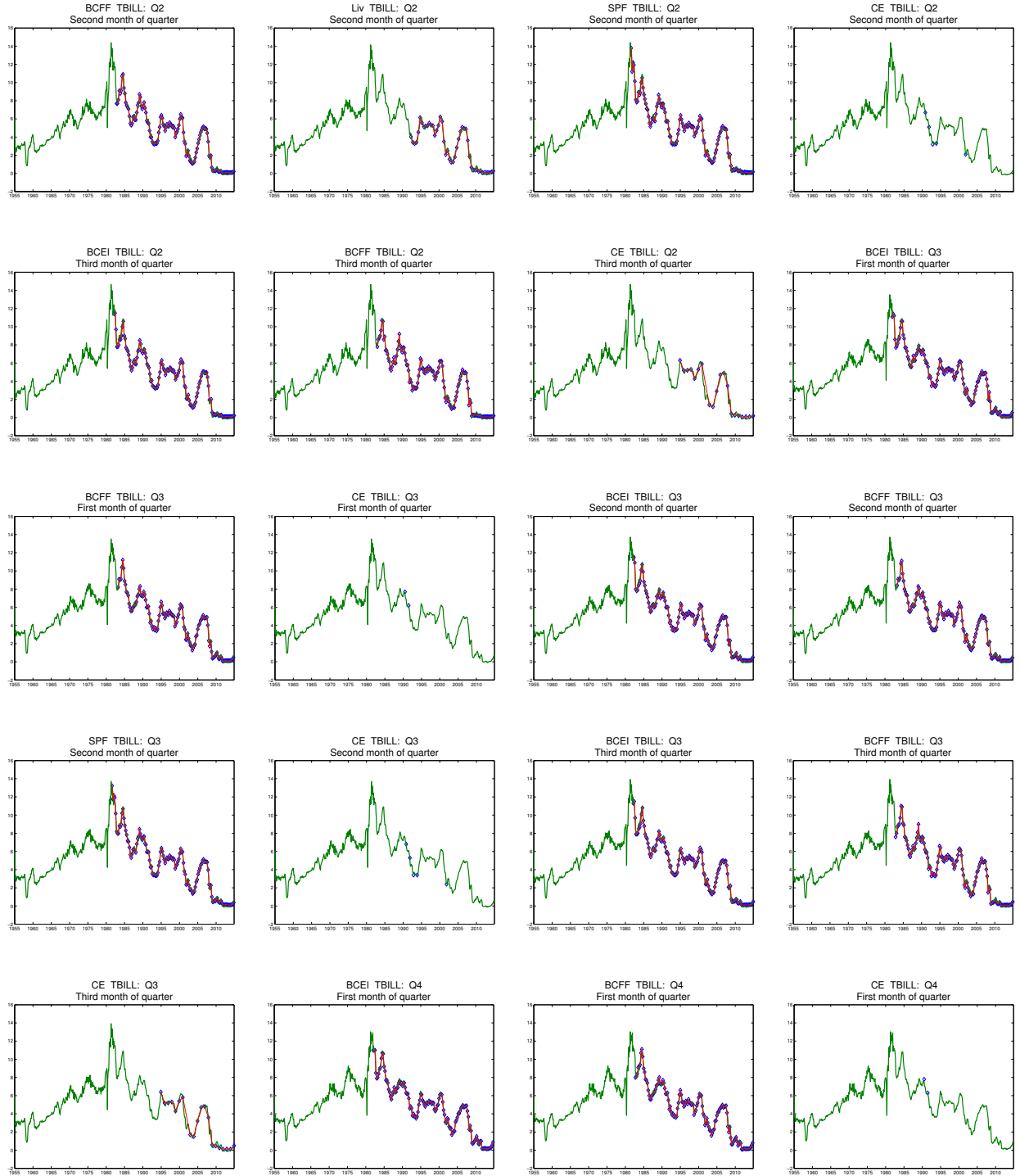


Figure 46: Fitted Survey Data
Series 421–440

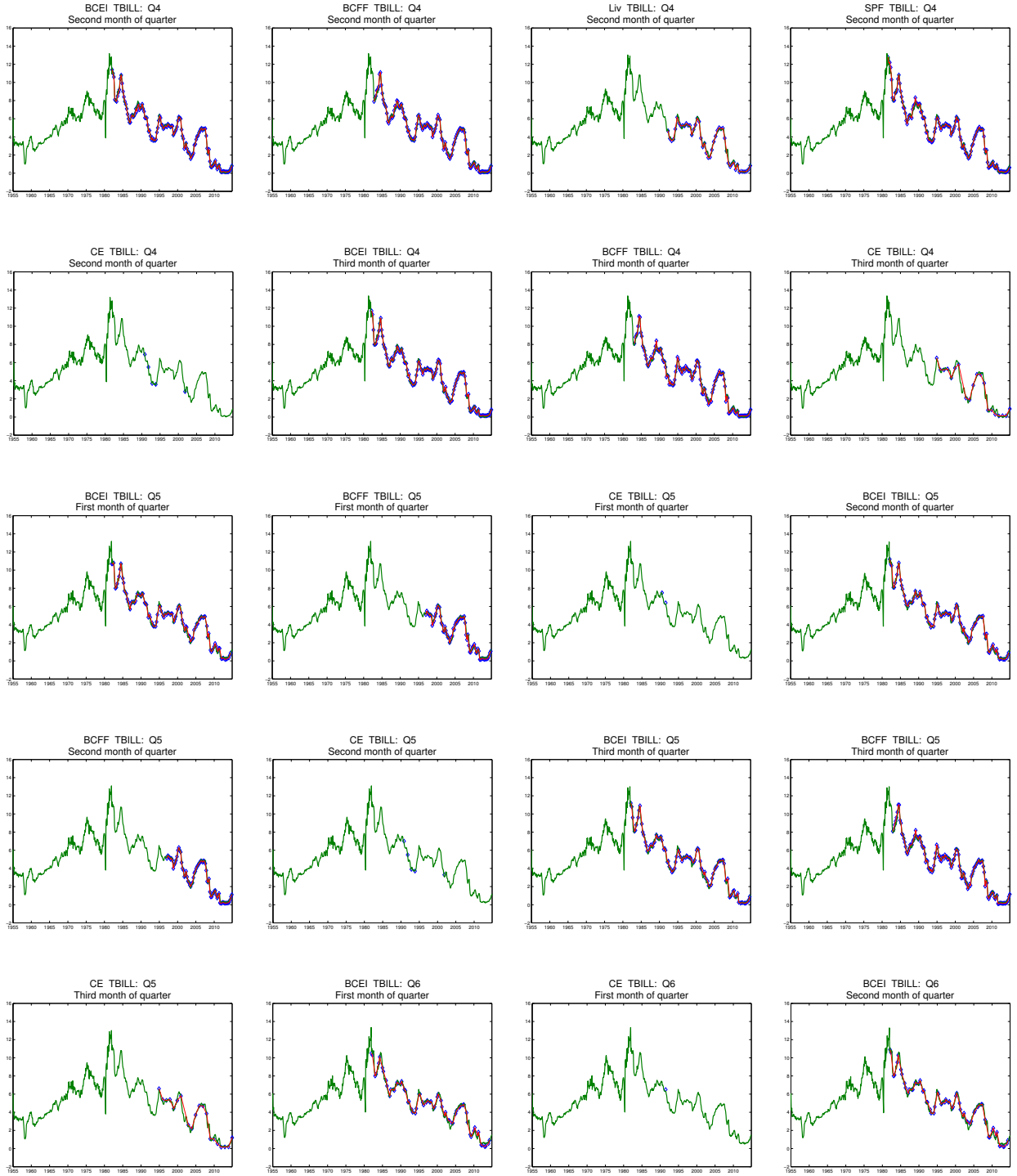


Figure 47: Fitted Survey Data
Series 441–460

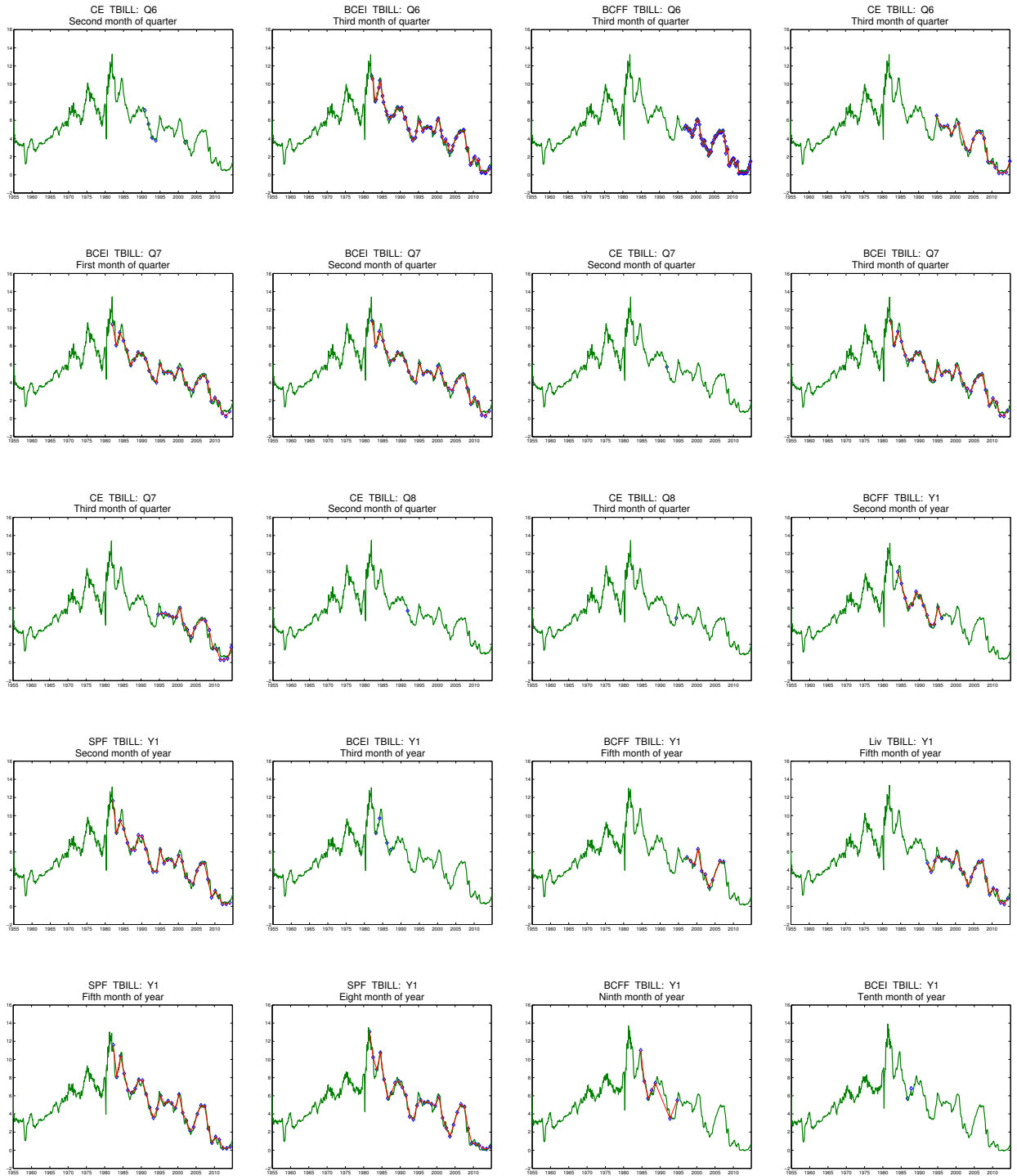


Figure 48: **Fitted Survey Data**
Series 461–480

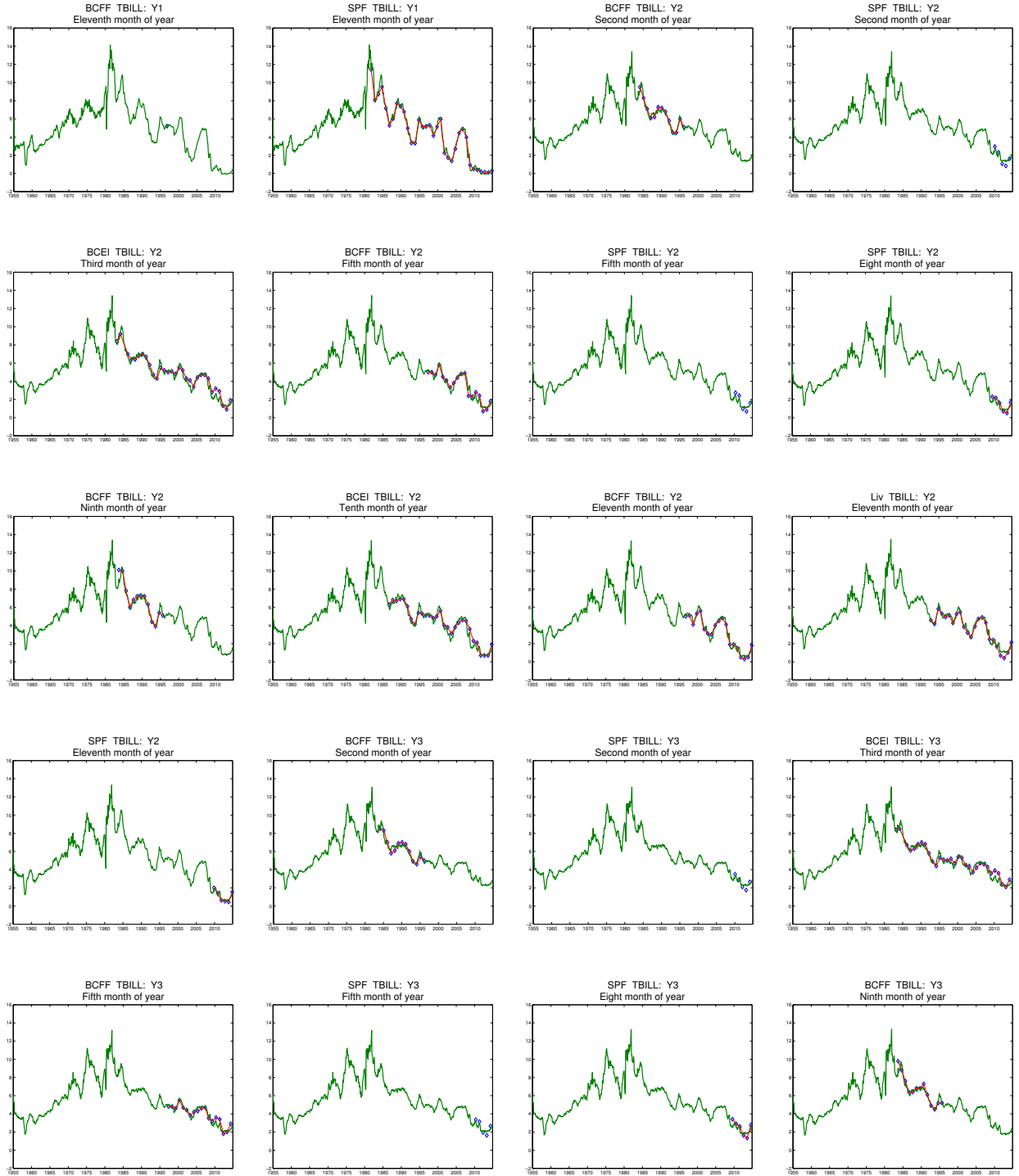


Figure 49: Fitted Survey Data
Series 481–500

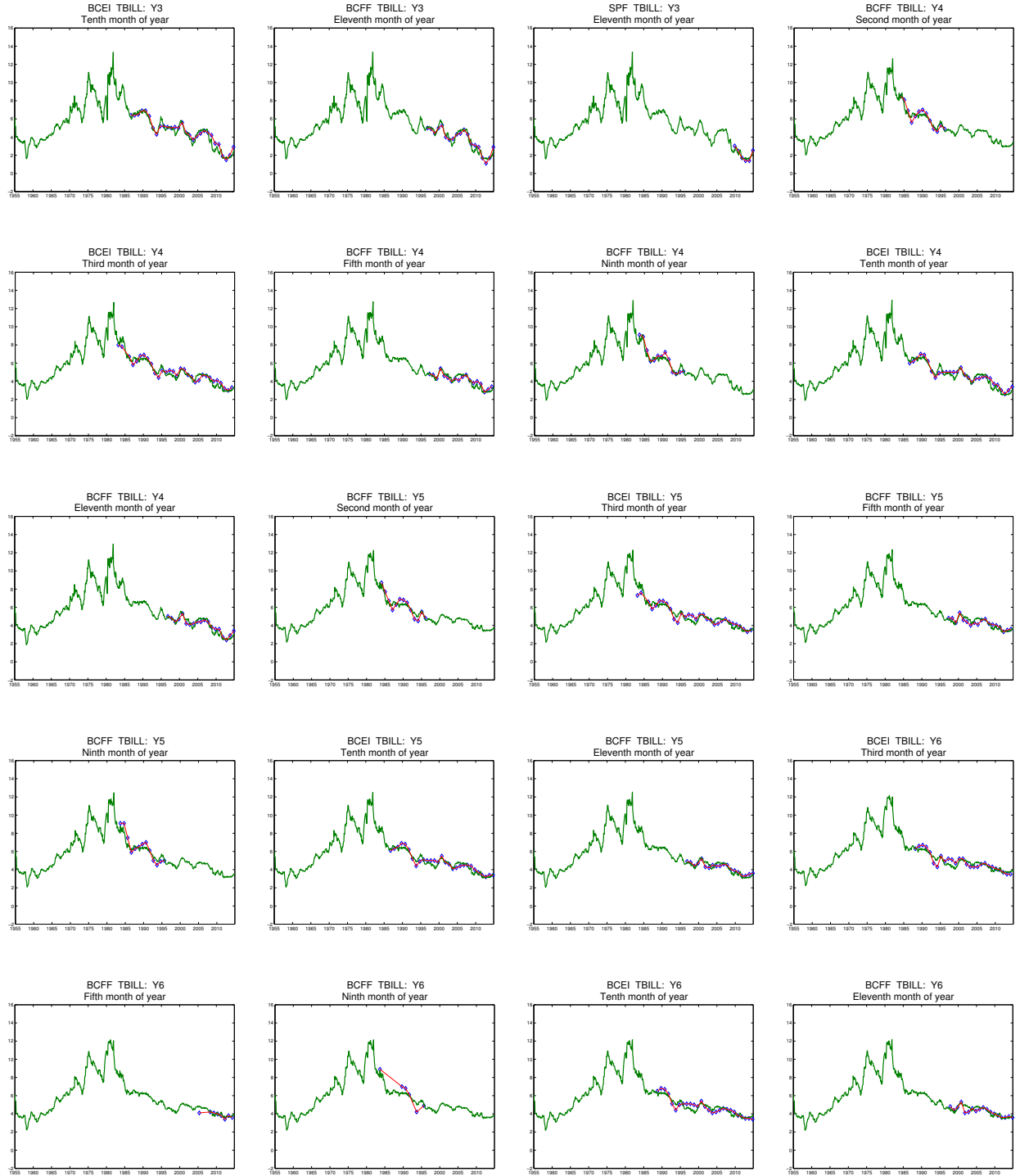


Figure 50: Fitted Survey Data
Series 501–521

