Information in the Yield Curve: A Macro-Finance Approach[*]

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Abstract

This paper uses an affine term structure model that incorporates macroeconomic and financial factors to study the term premium in the U.S. bond market. The results corroborate the known rejection of the expectation hypothesis and indicate that one factor, closely related to the Cochrane and Piazzesi (2005) factor (the CP factor), is responsible for most of the variation in bond premia. Furthermore, the model-implied bond premia are able to explain around 32% and 40% of the variability of one- and two-year excess returns and their out-of-sample performance is comparable to the one obtained with the CP factor. The model is also used to decompose yield spreads into an expectations and a term premium component in order to forecast GDP growth and inflation. Although this decomposition does not seem important to forecast GDP growth it is crucial to forecast inflation for most forecasting horizons. Also, the inclusion of control variables such as the short-term interest rate and lagged variables does not drive out the predictive power of the yield spread decomposition.

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1 Introduction

The term structure of interest rates has long been recognized as a potential source of information about future macroeconomic developments. This prevalent belief on the forward-looking characteristic of the yield curve is best represented by the expectations hypothesis (EH). According to the EH, the slope of the yield curve reflects market expectations of the average future path of short-term interest rates. Following the EH, it makes sense then to use yield curve information to forecast macroeconomic aggregates such as real economic activity and inflation.[1]

In its pure version, the EH implies that bond yields are fully determined by the expected path of the short-term interest rate with zero term premium. The extended version allows for a maturity-specific constant term premium. This extended version of the EH forms the basis of recent latent factor, semi-structural or structural models of the yield curve.[2] If, however, bond yields are composed in part by time-varying term premia not only does the EH not hold, and therefore should not be assumed in yield curve models, but also the information content of the yield curve with respect to macroeconomic aggregates may be affected. Consequently, it is crucial to determine the contribution of the expectations and term premium components in bond yields and to determine the factors driving each of these components. This should allow one to interpret more precisely the dynamics of the term structure of interest rates and to construct better information variables for macroeconomic forecasting. In this paper, we revisit this decomposition making use of an affine term structure model that incorporates macroeconomic and financial factors. We then assess the impact of this decomposition on the forecasting of GDP growth and inflation.[3]

Challenges to the expectations theory are not new and the number of papers rejecting it is large.[4] This is, however, not the focus of this paper. Despite the convincing statistical evidence rejecting the EH, it has been difficult to identify the expectations and term premium components

[1] Regarding the prediction of economic activity, see, among others, Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Plosser and Rouwenhorst (1994), and Stock and Watson (1989). For inflation, see, e.g., Fama (1990), Mishkin (1990), Estrella and Mishkin (1997), and Jorion and Mishkin (1991).

[2] See, for example, Bekaert, Cho, and Moreno (2010), Dewachter and Lyrio (2008), De Graeve, Emiris, and Wouters (2009), Hördahl, Tristani, and Vestin (2008), and Vasicek (1977).

[3] Hamilton and Kim (2002) were the first to decompose yield spreads into an expectations and a term premium component to forecast GDP growth. Ang, Piazzesi, and Wei (2006) and Favero, Kaminska, and Söderström (2005) adopt the same approach while Rudebusch, Sack, and Swanson (2007) assess the implications of structural and reduced-form models for the relationship between term premium and economic activity.

[4] See Fama (1984), Jones and Roley (1983), Mankiw and Summers (1984), and Shiller, Campbell, and Schoenholtz (1983). For more recent studies, see Cochrane and Piazzesi (2005, 2009), Duffee (2009) and Joslin, Priebsch, and Singleton (2009). These papers report statistically and economically significant time-varying risk premia.

in the yield curve. Swanson (2007) and Rudebusch, Sack, and Swanson (2007) show that term premium estimates can differ by more than four percentage points depending on the model used. This lack of identification is not surprising given the prominent role of long-run interest rate expectations in the expectations component of the yield curve and the significant differences in the long-run properties of alternative models. Our goal is, therefore, to model jointly the dynamics of the macroeconomy and the term structure with special attention to the long-run properties of the factors to determine the macroeconomic and financial drivers of each bond yield component.

To this end we use the Extended Macro-Finance (EMF) model proposed by Dewachter and Iania (2010). This model has a number of important features. First, it extends the state space adopted in standard macro-finance (MF) models with the inclusion of three financial factors and two stochastic trends of macroeconomic variables. Two of the financial factors represent liquidity factors and reflect the time variation in money market conditions. The third financial factor captures time variation in bond risk premia and measures changes in the aggregate risk aversion over time. This factor, denoted risk premium or return-forecasting factor, is similar to the one proposed by Cochrane and Piazzesi (2005), the CP factor. A distinguishing feature of our approach is that we do not construct our factor by using predictive regressions but by integrating it into the state dynamics of the model. The inclusion of two stochastic trends allows for highly persistent processes which generate time variation in long-run expectations. In that perspective and in line with the Fisher hypothesis, the model includes a factor capturing long-run inflation expectations and the natural real rate. Second, the EMF model extends the set of information variables used in the estimation to improve the identification of the eight factors in the model. Beyond the standard macroeconomic series and yield curve data, the model introduces three money market spreads to identify the liquidity factors, survey data on inflation forecasts to identify the long-run inflation expectation, and potential output growth data to identify the natural real rate. Finally, the estimation of the EMF model is performed using Bayesian techniques incorporating informative priors about impulse response functions and the shape of the yield curve which are in line with economic intuition. This avoids highly improbable outcomes and near singularities in the likelihood surface (see Chib and Ergashev (2009)), which are a reason of concern in the high-dimensional parameter space of the EMF model.

Our main findings can be summarized as follows. First, estimating the EMF model on U.S. data corroborates the rejection of the EH. In line with Cochrane and Piazzesi (2005), we identify economically and statistically significant time variation in risk premia that is mainly driven by a common factor, the return-forecasting factor. Furthermore, the model-implied bond premia are able to explain around 32% and 40% of the variability of one- and two-year excess returns and their out-of-sample performance is comparable to the one obtained with the CP factor. Second, decomposing bond yields into its expectations and term premium components we find that the expectations component of short bonds is mainly driven by monetary policy shocks while that of long bonds is affected by long-run inflation shocks. Movements in the term premium component, in contrast, are mainly driven by risk premium shocks with some limited impact of liquidity and policy rate shocks. Third, the decomposition of yield spreads into expected and term premium parts does not seem important to forecast GDP growth while it is crucial to forecast inflation for most forecasting horizons. The latter result is robust to the inclusion of control variables such as the lagged level of inflation and the short-term interest rate.[5]

The remainder of the paper is organized as follows. Section 2 explains briefly the EMF model and discusses the implied decomposition of the yield curve into expectations and term premium components. Section 3 describes the data and the Bayesian model specification used to estimate the EMF model. Section 4 discusses the main properties of the estimated model and focus on the yield decomposition and risk premia and its impact in the forecasting of GDP growth and inflation. The main findings are summarized in the conclusion.

2 Affine models for bond and term premia

2.1 Bond and term premia

A standard decomposition of the default-free yield curve separates the expectations and the term premium (or yield risk premium) components. Applied to zero-coupon bonds, this decomposition takes the following form:

$$y_t^{(n)} = \underbrace{\frac{1}{n}\sum_{\tau=0}^{n-1} E_t\left[y_{t+\tau}^{(1)}\right]}_{\text{Expectations component}} + \underbrace{\chi_t^{(n)}}_{\text{Term premium component}}, \qquad (1)$$

[5] Estrella (2005) investigates the theoretical reasons behind the predictive power of the yield curve to forecast output and inflation. The analytical results support the empirical findings for most circumstances.

where $y_t^{(n)}$ denotes the yield on a n-period bond at time t. Equation (1) identifies the expectations component as the average expected one-period interest rate over the maturity of the bond and the term premium component as the additional compensation to lock in the money over n periods instead of rolling over $n-1$ times an investment in a one-period bond.[6]

The interpretation of the term premium can be reformulated in terms of one-period bond premia (see Ludvigson and Ng (2009)). Denote the one-period excess log return for a bond with maturity n as:

$$rx_{t,t+1}^{(n)} = \ln(P_{t+1}^{(n-1)}/P_t^{(n)}) - y_t^{(1)}. \tag{2}$$

The term premium consists of the average one-period bond premia (or risk premia) obtained from holding the bond to maturity:

$$\chi_t^{(n)} = \frac{1}{n}\sum_{\tau=0}^{n-1} E_t\left[rx_{t+\tau,t+\tau+1}^{(n-\tau)}\right]. \tag{3}$$

From equation (3), the term premium represents the average expected premium implied by holding a bond with declining maturity over the time to maturity of the bond.

Combining equations (1) and (3), we obtain the final yield curve decomposition in terms of the expected future path of the risk-free interest rate ($E_t\left[y_{t+\tau}^{(1)}\right]$, $\tau = 0, ..., n-1$) and the expected future path of the one-period risk premia ($E_t\left[rx_{t+\tau,t+\tau+1}^{(n-\tau)}\right]$, $\tau = 0, ..., n-1$):

$$y_t^{(n)} = \frac{1}{n}\sum_{\tau=0}^{n-1} E_t\left[y_{t+\tau}^{(1)}\right] + \frac{1}{n}\sum_{\tau=0}^{n-1} E_t\left[rx_{t+\tau,t+\tau+1}^{(n-\tau)}\right]. \tag{4}$$

Equation (4) encompasses both versions of the expectations hypothesis (EH). Under the pure EH, the yield on a n-maturity bond is fully determined by the expected path of the short-term interest rate with zero one-period risk premia at any maturity. Under the extended EH, the one-period bond premium is constant, i.e. $E_t[rx_{t+\tau,t+\tau+1}^{(n-\tau)}] = \phi(n)$, and all variation in the yield curve is generated by changes in market expectations about future short rates. A failure of the EH implies that the yield curve responds to changes in both the expected short-term rates and in the term premia.

We model the dynamics of short rates by a vector error correction model (VECM) within a macro-finance framework. The use of a VECM instead of a standard VAR reflects the presence

[6] The term premium and term spread should not be confused. The term spread refers to the difference between long- and short-run yields while the term premium measures the deviation of long-run yields from the average expected future short-term rate.

of stochastic trends driving the low frequency dynamics of the yield curve: the long-run inflation expectation and the expected equilibrium real rate (see Kozicki and Tinsley (2001) and Dewachter and Lyrio (2006)). The dynamics of one-period risk premia is driven by one specific latent factor, which we denote the risk premium or return-forecasting factor. This factor is empirically grounded in the results of Cochrane and Piazzesi (2005) and explicitly takes into account the presence of a common factor driving realized excess returns on government bonds. In the next section, we introduce the macro-finance model used in this paper and derive the model-implied components of equation (4).

2.2 The Extended Macro-Finance model of bond and term premia

The main goal of this paper is to identify the expectations and term premium components in the yield curve within a no-arbitrage framework that incorporates macroeconomic and financial factors. We, therefore, adopt the discrete-time essentially affine EMF model from Dewachter and Iania (2010). In line with Ang and Piazzesi (2003), this model includes both observable macroeconomic variables and latent factors. All latent factors, however, have a clear economic interpretation. Two of them represent long-run expectations of macroeconomic variables while the other three correspond to financial factors. Below, we first express the yield curve components based on a general macro-finance model. We then outline the salient properties of the EMF model.

2.2.1 Macro-finance framework

The class of essentially affine macro-finance models is characterized by three main assumptions. First, the pricing kernel, m_t, is assumed to be log-normally distributed and is defined as an exponentially affine function of the risk-free rate, i_t, and a set of Gaussian structural shocks, ε_{t+1}:

$$m_{t+1} = \exp(-i_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1}), \qquad \varepsilon_{t+1} \sim N(0, I). \tag{5}$$

where Λ_t are the market prices of risk for the structural shocks. Second, following Duffee (2002), the risk-free interest rate and the prices of risk are restricted to be affine functions of the factors, X_t :

$$\begin{aligned} i_t &= \delta_0 + \delta_1' X_t, \\ \Lambda_t &= \Lambda_0 + \Lambda_1 X_t. \end{aligned} \tag{6}$$

Third, the law of motion of the state vector under the historical probability measure follows a first-order VECM transition equation:

$$X_{t+1} = C + \Phi X_t + \Sigma \varepsilon_{t+1}. \tag{7}$$

Based on the assumption of no-arbitrage, we can compute the price of a n-period bond at time t by solving the following relation recursively:

$$P_t^{(n)} = E_t \left[m_{t+1} P_{t+1}^{(n-1)} \right], \tag{8}$$

with the initial condition $P_t^{(0)} = 1$. The resulting yields are linear functions of the state vector

$$y_t^{(n)} = -\frac{\ln P_t^{(n)}}{n}, \tag{9}$$

$$y_t^{(n)} = A_{y,n} + B_{y,n} X_t, \tag{10}$$

where $A_{y,n} = -a_{y,n}/n$ and $B_{y,n} = -b_{y,n}/n$, with $a_{y,n}$ and $b_{y,n}$ satisfying the following no-arbitrage difference equations:

$$\begin{aligned} a_{y,n} &= a_{y,n-1} + b_{y,n-1}(C - \Sigma\Lambda_0) + \tfrac{1}{2} b_{y,n-1} \Sigma\Sigma' b'_{y,n-1} - \delta_0, \\ b_{y,n} &= b_{y,n-1}(\Phi - \Sigma\Lambda_1) - \delta'_1, \end{aligned} \tag{11}$$

given $a_{y,0} = 0$ and $b_{y,0} = [0, ..., 0]$.

The model summarized by equations (7) and (10) allows an affine representation of the expected average future short rate and term premium components of the n-period yield in equaiton (1) and the expected excess returns in equation (3). The expectations component can be written as:

$$\frac{1}{n} \sum_{\tau=0}^{n-1} E_t \left[y_{t+\tau}^{(1)} \right] = \frac{1}{n} \sum_{\tau=0}^{n-1} \left[A_{y,1} + B_{y,1} E_t X_{t+\tau} \right] = A_{e,n} + B_{e,n} X_t \tag{12}$$

where $A_{e,n} = -a_{e,n}/n$ and $B_{e,n} = -b_{e,n}/n$, with $a_{e,n}$ and $b_{e,n}$ determined by the following difference equations:

$$\begin{aligned} a_{e,n} &= a_{e,n-1} + b_{e,n-1} C - \delta_0, \\ b_{e,n} &= b_{e,n-1} \Phi - \delta'_1, \end{aligned} \tag{13}$$

given the initial conditions $a_{e,0} = 0$ and $b_{e,0} = [0, ..., 0]$. The term premium implied by the above framework can be obtained directly from the affine representation for the yield curve and the expectations component:

$$\chi_t^{(n)} = A_{y,n} - A_{e,n} + (B_{y,n} - B_{e,n}) X_t. \tag{14}$$

Finally, the one-period expected excess return can be derived combining equations (2), (9) and (10):

$$E_t[rx_{t,t+1}^{(n)}] = E_t\left[-(n-1)y_{t+1}^{(n-1)} + ny_t^{(n)} - y_t^{(1)}\right] = A_{rx,n} + B_{rx,n}X_t, \tag{15}$$

where

$$\begin{aligned} A_{rx,n} &= b_{y,n-1}\Sigma\Lambda_0 - \tfrac{1}{2}b_{y,n-1}\Sigma\Sigma' b_{y,n-1}', \\ B_{rx,n} &= b_{y,n-1}\Sigma\Lambda_1. \end{aligned} \tag{16}$$

We next specify each factor included in the EMF model, the dynamics of the state vector, and the implications for the yield curve decomposition in equations (12) and (14), and for the expected excess return in equation (15).

2.2.2 The Extended Macro-Finance model

The EMF model incorporates eight state variables which can be sorted in three groups. The first group includes three observable macroeconomic factors (inflation, π_t, the output gap, y_t, and the central bank policy rate, i_t^{cb}). The second group consists of three latent financial factors. The first two are related to the overall liquidity and counterparty risk in the money market ($l_{1,t}$ and $l_{2,t}$, respectively) while the third ($l_{3,t}$) drives the one-period bond premia. The third group contains two stochastic trends modeling the long-run equilibrium of inflation, π_t^*, and the natural real rate, ρ_t. The state vector X_t introduced in equation (7) is, therefore, given by

$$X_t = [\pi_t,\ y_t,\ i_t^{cb},\ l_{1,t},\ l_{2,t},\ l_{3,t},\ \pi_t^*,\ \rho_t]'. \tag{17}$$

The inclusion of the three observable macroeconomic variables is standard in macro-finance models. The introduction of liquidity factors is motivated by recent evidence documenting the impact of liquidity shocks on the yield curve (see Christensen, Lopez, and Rudebusch (2009); Feldhütter and Lando (2008); Liu, Longstaff, and Mandell (2006)). Moreover, the financial crisis of 2007-2008 demonstrated the significance of liquidity shocks on financial markets and the macroeconomy as a whole. In the EMF model, the liquidity factors are linked to tensions in the money market. One important measure of these money market tensions is the TED spread, i.e. the spread between the unsecured money market rate, i_t^{mm}, and the Treasury bill (T-bill) rate, $y_t^{(1)}$. This spread is considered as a standard measure of funding liquidity in the money market. The two EMF liquidity factors decompose this TED spread into two components, each measuring a specific dimension of liquidity risk. The first spread factor ($l_{1,t}$)

represents a convenience yield from holding Treasury bonds and can be seen as a flight-to-quality component. A flight to quality (i.e. to government bonds) is typically followed by an increase in the convenience yield, which means a widening of the spread between the yield on secured or collateralized money market rate, i_t^{repo}, and the T-bill rate. The second spread factor ($l_{2,t}$) reflects a credit component and measures counterparty risk as it is given by the difference between the unsecured and the secured money market rate. Formally:

$$\begin{aligned} TED_t &= i_t^{mm} - y_t^{(1)} = l_{1,t} + l_{2,t} \\ l_{1,t} &= i_t^{repo} - y_t^{(1)} \\ l_{2,t} &= i_t^{mm} - i_t^{repo} \end{aligned} \tag{18}$$

The third financial factor ($l_{3,t}$) is motivated by evidence from Cochrane and Piazzesi (2005, 2009) and Joslin, Priebsch, and Singleton (2009) showing that a large fraction of the variation in bond risk premia cannot be explained by macroeconomic factors but should be modeled with an additional return-forecasting factor. This factor should capture the time variation in the one-period bond premia and therefore measures the risk attitude in the market. In the EMF framework, this factor is identified by restrictions on the prices of risk such that it accounts for all the variation in the one-period bond premium:[7]

$$E_t[rx_{t,t+1}^{(n)}] = A_{rx,n} + B_{rx,n}\ e_6\ l_{3,t} \tag{19}$$

where e_i is a column vector of zeros with a one on the i-th row and $A_{rx,n}$ and $B_{rx,n}$ are defined in equation (16).

We now turn to the third group of state variables. A number of recent papers have suggested modeling the yield curve dynamics as a cointegrated or near-cointegrated system. Dewachter and Lyrio (2006) and Dewachter and Iania (2010) include two exogenous stochastic trends in the state vector leading to a cointegrated system. Cochrane and Piazzesi (2009) argue for a "very persistent real transition matrix", while Joslin, Priebsch, and Singleton (2009) favor stochastic trends based on a set of formal unit root and cointegration tests. The EMF model introduces two stochastic trends, π_t^* and ρ_t, representing the long-run equilibrium inflation rate and the natural real rate, respectively. This macroeconomic interpretation is imposed by the following

[7] These restrictions are the following:

$$\Lambda_1(i,j) = 0, \qquad \forall i \text{ and } \forall j \neq 6.$$

cointegrating restrictions:[8]

$$\lim_{s\to\infty} E_t\left[\pi_{t+s}\right] = \pi_t^*,$$
$$\lim_{s\to\infty} E_t\left[i_{t+s}^{cb}\right] = \rho_t + \pi_t^*. \tag{20}$$

The introduction of stochastic trends alters the model dynamics significantly. Unlike standard macro-finance models with fixed equilibrium levels for inflation and interest rates, the EMF model allows for time variation in the long-run expectations of these variables. This may alter considerably the model-implied expectations and term premium components of the yield curve, especially at the long end of the maturity spectrum. Importantly, in the measurement equation detailed below, we use survey data on long-horizon inflation forecasts to identify π_t^*, while the growth rate of potential GDP is used to identify ρ_t.

3 Estimation methodology

3.1 Data

We estimate the EMF model on U.S. quarterly data over the period 1960:Q1-2008:Q4 (196 observations). The variables used to identify the eight factors of the model can be divided in four groups: (*i*) standard macroeconomic series; (*ii*) yield curve data; (*iii*) money market spreads; and (*iv*) a final group including survey data on inflation forecasts and potential output growth used to identify the two stochastic trends in the model. The first group of variables contains annualized inflation based on the quarterly growth of the GDP deflator, the output gap constructed from data provided by the Congressional Budget Office (CBO), and the central bank policy rate represented by the effective federal funds rate. The data are obtained from the Federal Reserve Bank of St. Louis FRED database. The second group includes per annum zero-coupon yield data for maturities of 1, 4, 8, 12, 16, 20, and 40 quarters from the Fama-Bliss Center for Research in Security Prices (CRSP) bond files with the exception of 40-quarter yields obtained from Gürkaynak, Sack, and Wright (2007). The third group consists of money market rates used to identify the decomposition of the TED spread into a convenience yield ($l_{1,t}$) and a credit-crunch or counterparty risk factor ($l_{2,t}$). We use the 1-quarter Eurodollar (Ed) rate and the 1-quarter London Interbank offered rate - LIBOR (Lb) from Datastream to identify the credit-crunch factor. We supplement the LIBOR data with data on the Eurodollar

[8] Details on the identification restrictions for the stochastic trends can be found in Dewachter and Iania (2010).

given that the latter series dates back further in time.[9] Furthermore, we use the 1-quarter T-bill rate to identify the convenience yield. All spreads are computed relative to the secured money market rate represented by the government-backed collateral repo rate (GC-repo) from Bloomberg (ticker RPGT03M). The fourth group includes survey data on the average 4- and 40-quarter inflation forecasts and data on potential output growth. The data on inflation forecasts are retrieved from the Survey of Professional Forecasters (Federal Reserve Bank of Philadelphia) and are used to identify long-run inflation expectations. The data on potential output growth, measured as the quarterly growth of CBO potential output, are included to identify the natural real rate.

3.2 Econometric setting

The EMF model contains a total of 92 parameters represented by the vector θ. We estimate the model using standard Bayesian techniques based on informative priors. We use a large number of observable variables over a long time span to generate sufficient degrees of freedom in the estimation. The posterior density of θ, $p(\theta \mid Z^T)$, can be written as:

$$p(\theta \mid Z^T) = \frac{L(\theta \mid Z^T)p(\theta)}{p(Z^T)}, \tag{21}$$

where Z^T denotes the data set, $L(\theta \mid Z^T)$ the likelihood function, $p(\theta)$ the priors, and $p(Z^T)$ the marginal density of the data. Following Smets and Wouters (2007), among others, we use a two-step procedure to simulate the posterior density of the parameters. In a first step, we find the mode of the posterior distribution of θ using a combination of Newton-Raphson and simulated annealing optimization procedures. Subsequently, we use the random walk Metropolis-Hastings procedure to trace the posterior density of θ. Given the large number of parameters, we use a large amount of draws and check convergence by means of the standard battery of convergence tests.[10] Next, we present the likelihood function and the set of priors used to estimate the model.

3.2.1 The likelihood function

The likelihood function is obtained from the prediction error decomposition implied by the measurement equation. We rewrite the state space dynamics in equation (7) now making explicit

[9] Given that the Eurodollar and the LIBOR rates are closely related, we use the former as an additional proxy for the credit-crunch factor.

[10] The method used is similar to the one discussed in Dewachter and Iania (2010).

the dependence on the parameter vector θ:

$$X_{t+1} = C(\theta) + \Phi(\theta)X_t + \Sigma(\theta)\varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim N(0, I). \tag{22}$$

The measurement equation relates the observed data Z_t to the state vector X_t:

$$Z_t = A(\theta) + B(\theta)X_t + S(\theta)\eta_t, \qquad \eta_t \sim N(0, I). \tag{23}$$

As mentioned before, we use four groups of information variables in the measurement equation. The observed series in Z_t consist of (i) macroeconomic variables $(Z_{mac,t})$, (ii) yield curve data $(Z_{y,t})$, (iii) money market spreads $(Z_{mm,t})$, and (iv) data used to identify the two long-run trends in the model $(Z_{LR,t})$:

$$Z_t' = [Z_{mac,t}',\ Z_{y,t}',\ Z_{mm,t}',\ Z_{LR,t}'], \tag{24}$$

where

$$\begin{aligned} Z_{mac,t}' &= [\pi_t,\ y_t,\ i_t^{cb}], \qquad Z_{y,t}' = [y_t^{(1)},\ y_t^{(4)},\ y_t^{(8)},\ y_t^{(12)},\ y_t^{(16)},\ y_t^{(20)},\ y_t^{(40)}], \\ Z_{mm,t}' &= [i_t^{Lb} - y_t^{(1)},\ i_t^{Ed} - y_t^{(1)},\ i_t^{GC} - y_t^{(1)}], \qquad Z_{LR,t}' = [F_{\pi,t}^{(4)},\ F_{\pi,t}^{(40)},\ \Delta y_t^{pot}]. \end{aligned} \tag{25}$$

The vector of constants $A(\theta)$, the matrix of factor loadings $B(\theta)$, and the matrix $S(\theta)$ are accordingly partitioned in four blocks:

$$\begin{aligned} A'(\theta) &= [A_{mac}',\ A_y',\ A_{mm}',\ A_{LR}'], \\ B'(\theta) &= [B_{mac}',\ B_y',\ B_{mm}',\ B_{LR}'], \\ S(\theta) &= diag(S_{mac}',\ S_y',\ S_{mm}',\ S_{LR}'). \end{aligned} \tag{26}$$

A number of observations can be made. First, we assume that the three macroeconomic variables (inflation, the output gap, and the central bank policy rate) are observed without errors, implying that $A_{mac} = 0_{3\times1}$, $B_{mac} = [I_{3\times3}, 0_{3\times5}]$, and $S_{mac} = 0_{3\times1}$. Second, all yields are measured with an error and are related to the state variables through the no-arbitrage equation (10). Third, we use three money market spreads to identify the convenience yield and credit-crunch factors ($l_{1,t}$ and $l_{2,t}$, respectively). We use two measures for the TED spread since LIBOR rates are only available from 1986:Q2 onwards. For the period 1971:Q2-1986:Q1, we use the TED spread based on the Eurodollar rate $(i_t^{Ed} - y_t^{(1)})$. After that, the TED spread is based on the LIBOR rate $(i_t^{Lb} - y_t^{(1)})$. Both are used to identify the credit-crunch factor $(l_{2,t})$. We assume there is a spread between the Eurodollar and LIBOR rates equal to a constant, c_{Ed}, plus an idiosyncratic shock, $\eta_{Ed,t}$.[11]

$$i_t^{Ed} = y_t^{(1)} + c_{Ed} + l_{1,t} + l_{2,t} + \sigma_{Ed}\eta_{Ed,t}. \tag{27}$$

The third spread is based on the GC-repo rate ($i_t^{GC} - y_t^{(1)}$) and identifies the convenience yield ($l_{1,t}$) perfectly. The above identification implies that

$$A_{mm} = \begin{bmatrix} 0 \\ c_{Ed} \\ 0 \end{bmatrix}, \qquad B_{mm} = \begin{bmatrix} 0_{1\times 3} & 1 & 1 & 0_{1\times 3} \\ 0_{1\times 3} & 1 & 1 & 0_{1\times 3} \\ 0_{1\times 3} & 1 & 0 & 0_{1\times 3} \end{bmatrix}, \qquad S_{mm} = \begin{bmatrix} 0 \\ \sigma_{Ed} \\ 0 \end{bmatrix}. \tag{28}$$

Finally, survey data on 4- and 40-quarter average inflation forecasts $F_{\pi,t}^{(4)}$ and $F_{\pi,t}^{(40)}$ are used to identify the stochastic trend for inflation. The loadings for these survey expectations are implied by the transition equation (7). The stochastic trend for the real rate is identified by the growth rate of potential output:

$$\Delta y_t^{pot} = \alpha + \beta_\rho \rho_t + \sigma_{\Delta y^{pot}} \eta_{\Delta y^{pot},t} \tag{29}$$

where y_t^{pot} denotes log potential output. We allow for measurement errors in each of the series: $S_{LR} = [\sigma_{F_{\pi,t}^{(4)}},\ \sigma_{F_{\pi,t}^{(40)}},\ \sigma_{\Delta y^{pot}}]$.

The log-likelihood function is obtained by exploiting the linearity and normality of the system composed by equations (22) and (23):

$$l(Z_t|\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\det(V_{Z,t|t})) + (Z_t - Z_{t|t-1})'(V_{Z,t|t})^{-1}(Z_t - Z_{t|t-1})\right] \tag{30}$$

with the prediction error, $Z_t - Z_{t|t-1}$, and its variance, $V_{Z,t|t}$, given by Kalman Filter recursions (see Harvey (1991)).

3.2.2 Prior distributions

Table 1 lists the type of distribution, mean and standard deviation for the prior of the parameter vector θ. Overall, we use relatively loose priors, characterized by large standard deviations of the prior distributions. Most of the priors reflect standard beliefs regarding macroeconomic dynamics. The priors incorporate significant inertia in the dynamics of macroeconomic variables and impose a delayed deflationary impact of changes in the policy rate. Also, the priors for the

[11] The LIBOR rate is an average of rates at which banks offer funds (offer side), while Eurodollar deposits refer to a rate at which banks want to borrow funds (bid side). Typically, the Eurodollar rate is about one basis point below the LIBOR rate.

dynamics of the policy rate reflect a Taylor-rule type of monetary policy. The prior distributions on the impact matrix Σ identify a supply, a demand and a policy rate shock, while modeling the financial shocks as demand shocks affecting inflation and the output gap negatively. Finally, the priors for the prices of risk are constructed such that the EMF model implies an upward-sloping yield curve (see also Chib and Ergashev (2009)).

Insert Table 1

Informative priors are imposed for some of the standard deviations. For the standard deviation of the stochastic trends, we use a Inverse Gamma distribution with a mean of 20 basis points and a standard deviation of 0.2. This type of prior implies a peaked prior around a mean of 20 basis points but still allowing for a relatively broad confidence interval. The 90% confidence interval for the standard deviation of the stochastic trends ranges from 7 to 78 basis points. This reflects the view that stochastic trends should display a significant degree of smoothness. We impose a standard deviation of the measurement error equal to zero for the three observable macroeconomic variables, the LIBOR-based TED spread, and the convenience yield. Implicitly, we assume that these observed economic variables do not contain measurement errors.

4 Empirical results

In this section, we discuss the implications of the estimated EMF model and the implied decomposition of the yield curve for the prediction of excess bond returns, GDP growth, and inflation. In section 4.1, we assess the time variation in the model-implied bond premia and the predictive power of the EMF model to forecast excess returns. We find significant time variation in bond premia (as e.g. in Cochrane and Piazzesi (2005, 2009)) suggesting a rejection of the expectations hypothesis, and find that the extracted return-forecasting factor is closely related to the CP factor in terms of forecasting power of realized excess returns. In section 4.2, we first examine the relative importance of the expectations and term premia components for the time variation in long-term yields. This allows us to assess the extent to which changes in long-maturity yields reflect shifts in expectations about future short-term rates or in term premia. We then assess the impact of this decomposition to predict GDP growth and inflation.

4.1 Bond risk premia

The parameter estimates for the EMF model are presented in Tables 2 to 4. The EMF model clearly rejects the extended expectations hypothesis. The model generates significant time variation in the risk premia capturing a significant part of the variability of realized excess returns. These risk premia are driven by a common factor that is closely related to the return-forecasting factor of Cochrane and Piazzesi (2005).

Insert Tables 2, 3, and 4

Figure 1 illustrates the time variation in bond premia implied by the EMF model. This figure shows the expected excess return over a 4-quarter holding period for 8- to 20-quarter bonds against the corresponding realized excess return. The risk premia are statistically significant and display strong time variation and collinearity across maturities. The latter feature is indicative of a dominant factor in bond premia, i.e. the return-forecasting factor. Figure 2 compares the return-forecasting factor implied by the EMF model with that of Cochrane and Piazzesi (2005). The correlation between the two series is 67%. Statistical significance of the time variation in bond premia can be assessed based on the 99% error bands shown in Figure 1. Based on the error bands, the EH-implied null hypothesis of constant bond premia is rejected. More formal evidence against the EH is obtained by analyzing the posterior of the prices of risk (see Table 4). This can be seen by observing that the time-varying prices of risk related to inflation and interest rates, i.e. $\Lambda_1(1,6)$ and $\Lambda_1(3,6)$, are different from zero and mainly concentrated on the positive and negative sides of the support, respectively.[12] This suggests that bond premia comove with the return-forecasting factor. Finally, in line with the literature we observe that risk premia tend to be countercyclical in the EMF model. The 4-quarter expected excess return for 8- to 20-quarter bonds implied by the EFM model has a correlation of around -45% with the output gap.

Insert Figures 1 and 2

A more formal comparison between the Cochrane and Piazzesi (2005) and the EMF models can be found in Table 5, where we report in-sample and out-of-sample results for excess bond returns. The top three panels of this table report the adjusted R^2 expressing the fraction of realized excess returns explained by the EMF model and a model based on the CP factor. This

[12] Note that all risk components are priced, i.e. carry at least a constant risk premium. The constant prices of risk (Λ_0) are statistically significant for each of the shocks.

is done for a 4-, 8-, and 16-quarter holding periods and for bonds with maturities between 8 to 20 quarters. In general, we find that the EMF model explains a substantial amount of the variation in realized excess returns. This finding is in line with Cochrane and Piazzesi (2005, 2009) and Ludvigson and Ng (2009), who show that a limited number of factors can forecast a significant part of realized excess returns. For the 4-quarter horizon, the performance of both models is comparable, predicting on average above 30% of the in-sample variation in the realized excess returns. For the 8-quarter horizon, while the CP factor explains on average 21% of the variability in realized excess returns, the EMF factor explains on average almost 40%.

Insert Table 5

As an additional test, we check the unbiasedness of the EMF model-implied bond risk premia. To this end, we regress realized excess returns on expected excess returns as implied by the EMF model:

$$rx_{t,t+k}^{(n)} = \alpha + \beta E_t\left[rx_{t,t+k}^{(n)}\right] + \varepsilon_{t+k}, \qquad n = 8,\ 12,\ 16,\ 20 \text{ qtr}, \qquad k = 4,\ 8,\ 16 \text{ qtr}, \qquad n > k \tag{31}$$

where n denotes the maturity of the bond, k represents the holding period, $rx_{t,t+k}^{(n)}$ denotes the realized return in excess of the k-quarter risk-free rate of buying a n-quarter bond at time t and selling it back after k quarters, and $E_t\left[rx_{t,t+k}^{(n)}\right]$ represents the EMF model-implied risk premia on a n-quarter bond over a k-quarter period. To validate the EMF model, we test the joint hypothesis that $\alpha = 0$ and $\beta = 1$. Table 6 shows that the risk premia implied by the EMF model are unbiased: (i) all α coefficients are statistically insignificant while the β coefficients are not statistically different from one, and (ii) based on a standard F-test, we cannot reject the joint hypothesis that $\alpha = 0$ and $\beta = 1$ at any significance level for any regression.

Insert Table 6

Next to performing an in-sample analysis, we also perform an out-of-sample analysis for the 4- and 8-quarter excess return over the period 1996:Q1-2008:Q4. We compare the performance in terms of the mean square error (MSE) of the EMF model against the CP factor and a random walk model with drift (i.e. with constant risk premia). The bottom two panels of Table 5 show that for the 4-quarter horizon, the EMF model has a slightly superior performance against the other two models, except against the random walk model for a 20-quarter horizon. For the 8-quarter horizon, the EFM model does a better job in forecasting excess returns for all maturity bonds. Therefore, the EMF model succeeds in integrating a return-forecasting factor within the standard macro-finance framework.

An important implication of the EMF model is that bond premia are mainly driven by financial shocks; macroeconomic shocks, in contrast, only contribute marginally to the dynamics of the risk premia. Table 7 illustrates the relevance of financial shocks for risk premia by means of a variance decomposition of the 4-quarter bond premia of 8- to 20-quarter maturity bonds. The results highlight the importance of three types of shocks for bond premia dynamics: return-forecasting factor shocks (i.e. risk premium shocks), liquidity shocks, and policy rate shocks.[13] The return-forecasting factor shocks are the dominant source of variation in bond premia. Depending on the prediction horizon, this type of shock explains between 60% and 80% of the total variation in bond premia. Liquidity shocks explain between 12% and 20% of the bond premium variation. Finally, for horizons longer than 10 quarters, we observe a significant role for monetary policy shocks, i.e. explaining around 15% of the variation in bond premia.

Insert Table 7

4.2 Term premia

The rejection of the EH raises the question of the relative importance of the expectations and term premium components in the yield curve dynamics. This question is particularly relevant when assessing the informational content of the time variation in long-term yields. Specifically, yield curve changes might have different interpretations depending on the source of its variation, namely expectations or risk premium component (see Rudebusch, Sack, and Swanson (2007) and Ludvigson and Ng (2009) for a detailed treatment of the topic).[14] This section analyses the macroeconomic information content of the yield curve. We first assess the relative importance of the expectations and term premium components of term spreads. We then assess the information content of such decompositions to forecast GDP growth and inflation.

[13] Note that, by construction, shocks to the return-forecasting factor explain fully the variation in the quarterly holding period return. Since we analyze yearly holding period returns, other factors (shocks) may impact the bond premia through their impact on the dynamics of the return-forecasting factor.

[14] A decrease in long-term yields generated by a decrease in the expectations component or term premia leads to different interpretations. Decreases in risk premia will be stimulating and hence may call for restrictive monetary measures. This point has been stressed by Bernanke (2006): "...when the term premium declines, a higher short-term rate is required to obtain the long-term rate and the overall mix of financial conditions consistent with maximum sustainable employment and stable prices". On the contrary, decreases in the expectations component typically signal expectations about a future economic slow down and would call for more expansionary measures.

4.2.1 Decomposing the yield curve

The decomposition of the yield curve into expectations and term premium components is defined in equation (4). We illustrate this decomposition in Figure 3. The top panel of this figure displays the fitted time series of the 40-quarter yield and the middle panel plots the expectations component of this yield. The bottom panel displays the term premium implied by the EMF model and compares it to the Kim and Wright (2005) measure (KW).[15] According to Rudebusch, Sack, and Swanson (2007), among five measures of term premia considered by these authors the KW measure seems to be the most representative of them (see also Rosenberg and Maurer (2008)). We note that, despite the significant differences in structure between the EMF and KW models,[16] there is a close link between the two term premium measures. This result might be surprising, especially in light of the findings of Rudebusch, Sack, and Swanson (2007). They compare different measures of the term premium and find that the behavior of the KW and the Bernanke, Reinhart, and Sack (2004) measure is remarkably similar while that of the Cochrane and Piazzesi (2005) measure is harder to understand because it is well below the other measures and is far too volatile. Our EMF model is able to filter a return-forecasting factor similar to the CP factor while generating a term premia measure similar to that of Kim and Wright (2005).

The time variation in our term premia series is substantial, which indicates that the rejection of the EH documented above has significant economic implications. In particular, the one-to-one relation between yields and expected short rates (implying a constant, maturity-specific term premium) breaks down, especially for long-term bonds.

Insert Figure 3

Tables 8 and 9 show the variance decomposition of the expectations and term premium components, respectively, for bonds with maturities of 4, 20, and 40 quarters.[17] The expectations component of 4-quarter bonds is dominated by monetary policy shocks while of long-term (40-quarter) bonds is dominated by long-run inflation shocks. In line with the findings of the previous section, the term premium component is driven mainly by risk premium shocks both for short- and long-term bonds. Liquidity and policy rate shocks have a smaller effect over all horizons while macroeconomic shocks are insignificant. Therefore, the substantial time varia-

[15] The Federal Reserve Board provides data to generate the term premium from the Kim and Wright (2005) model.

[16] The Kim and Wright (2005) model is a purely latent factor model, whereas the EMF model combines macroeconomic, yield curve, and survey data.

[17] The ordering of the variables is the same as the one in the state vector (Eq. (17)).

tion in the term premia and the fact that this variation is primarily linked to financial and not macroeconomic shocks contaminates the informational content of the yield curve with respect to future macroeconomic developments. In particular, yield spreads, including expectations and term premium components aggregate two types of shocks: macroeconomic and financial shocks, where their relative importance varies over time. By decomposing the yield spread into expectations and term premium components, we obtain information at a more disaggregated level, allowing for a better identification of the shocks. This increases the information extracted from the yield curve. In the next section, we assess the information content of yield spreads and their decomposition for macroeconomic predictions.

Insert Tables 8 and 9

4.2.2 Macroeconomic information in the yield curve

We follow the literature and assess the predictive content of yield spreads to forecast GDP growth and inflation changes. The top panel of Figure 4 shows the 40-quarter yield spread implied by the EMF model. The middle and bottom panels display its expectations and term premium components, respectively. This figure suggests that a significant part of the yield spread variation is due to the time variation in the term premium. This blurs the informational content of the spreads with respect to future macroeconomic variables for two reasons. First, as stated above, the time variation in the term premium breaks the one-to-one relation between the expectations component and the yield spread. Second, as shown in the previous section, since the term premium is mainly determined by risk premium shocks, it introduces financial shocks into the yield spread. Both reasons suggest that a decomposition of the yield curve may help identify the macroeconomic information contained in the yield curve.

Insert Figure 4

In this section, we assess the information content of the expectations ($Spr_t^{e,(n)}$) and term premium ($\chi_t^{(n)}$) components of yield curve spreads ($Spr_t^{(n)}$) in the predictive regressions of macroeconomic aggregates, with $Spr_t^{(n)} = y_t^{(n)} - y_t^{(1)} = Spr_t^{e,(n)} + \chi_t^{(n)}$. Our work is closely related to Ang, Piazzesi, and Wei (2006), Estrella and Mishkin (1997) and Rudebusch, Sack, and Swanson (2007) for the forecast of GDP growth and to Estrella and Mishkin (1997) and Mishkin (1990) for the forecast of inflation changes.

Predicting economic growth We follow Ang, Piazzesi, and Wei (2006) in assessing the information content of the yield curve for GDP growth. We estimate several predictive regressions where the most extended version regresses log real GDP growth for the next k quarters on the yield spread components:

$$g_{t\to t+k} = \alpha + \beta^{EC}(Spr_t^{e,(n)} + \chi_t^{(n)}) + \beta^{TP}\chi_t^{(n)} + \gamma g_t + \delta y_t^{(1)} + \varepsilon_{t+k} \tag{32}$$

where $g_{t\to t+k}$ denotes log real GDP growth from t to $t+k$ and $g_t \equiv g_{t-1\to t}$, all expressed in yearly terms. In line with the literature, we use lagged GDP growth, g_t, and the short-term interest rate, $y_t^{(1)}$, as control variables.

We distinguish between four types of models. In the first two types, we assume that the yield spread is a sufficient and exhaustive information variable for output growth, i.e. $\gamma = \delta = 0$. The first type of model is the standard representation based solely on the spread. This implies that the source of the spread (i.e. expectations or term premium component) is irrelevant for growth predictions, i.e. it imposes $\beta^{TP} = 0$. The second type of model allows for differential informational content for the spread components, i.e. allows $\beta^{TP} \neq 0$. The third and fourth types allow for additional control variables (lagged GDP growth and the short-term interest rate). Similar to the first type, the third type of model does not distinguish between the sources of the spread. The last type of model is the most general one as in equation (32), differentiating between the sources of the spread and allowing for control variables. We estimate each model using either the 4-, 20-, or 40-quarter yield spread and for a GDP growth horizon of 1, 4, and 8 quarters.

Table 10 summarizes the results from the regression analysis. The estimates for model 1 report the known result that the yield spread is a valuable information variable for the prediction of GDP growth. Yield spreads are statistically significant irrespective of the prediction horizon and indicate that high yield spreads predict positive GDP growth. Despite their significant predictive content, yield spreads are not sufficient statistics for GDP growth predictions. Adding lagged GDP growth and the short-term interest rate to the regression clearly improves the performance of the predictive equations. The comparison of models 1 and 3 or 2 and 4 shows an increase in the adjusted R^2 in almost all cases. In all models, the short-term interest rate enters with a negative sign, indicating that the predictive content of yield spreads depends also on the *level* of the interest rate and needs to be lowered for higher interest rate levels. This negative relation between the interest rate level and future GDP growth is also discussed in Ang, Piazzesi, and Wei (2006). Note that the inclusion of the short-term interest rate in model 3 does not drive out the yield spread as a predicting variable. Comparing models 1 and 2 and models 3 and 4, we observe that although the decomposition of the yield spread into its two components leads in most cases to an increase in the adjusted R^2, in all cases we cannot reject the hypothesis that $\beta^{TP} = 0$. Therefore, surprisingly, the yield spread decomposition does not seem to be important for the prediction of GDP growth. This finding is in line with Rudebusch, Sack, and Swanson (2007).

Insert Table 10

Interestingly, Ang, Piazzesi, and Wei (2006) recommend for prediction purposes the use of the longest maturity yield to measure the spread. In their case, this is the 20-quarter yield. Our longest yield has a maturity of 40 quarters but we find that in 9 out of 12 cases the best spread to be used in order to forecast GDP growth is the 20-quarter spread.

Finally, we analyze whether the predictive content of the yield spread and its components changed over time. We reestimate the EFM model at every quarter using an expanding window and use expanding windows for the predictive regressions. The results are presented in Figure 5. The rows of panels in this figure define the predictive horizon used in the regression (1, 4, and 8 quarters) and the columns of panels define the maturity of the yield spread used in the regression (4, 20, and 40 quarters). The graphs show the end date of the sample period used and the resulting adjusted R^2. Therefore, the first point in each graph indicates the adjusted R^2 for the period 1960:Q1-1995:Q4.

Insert Figure 5

We observe a general decrease in the predictive power over time of the yield spread and its components to forecast GDP growth.[18] This decrease seems to be stronger after 2002. It is also clear that, allowing for control variables, the yield spread decomposition becomes more important for long-horizon forecasts. For the 1- and 4-quarter horizons (first and second rows of panels), there is little improvement from the spread decomposition (solid line in comparison with the grey dashed line). This improvement is significant for the 8-quarter horizon although such gain has decreased over time.

The opposite happens if one does not allow for control variables. For the 1-quarter horizon there is a significant improvement in the adjusted R^2 simply by decomposing the spread (red

[18] This fact was also observed by Dotsey (1998) and Haubrich and Dombrosky (1996).

dash dotted line in comparison blue dotted line). This improvement is less marked for longer forecasting horizons (second and third rows of panels).

Predicting inflation Empirically, the strongest case to make for the decomposition of the yield spread is in the prediction of inflation. In analogy with the previous section, we estimate predictive regressions of inflation changes on decomposed spreads, past inflation and the short-term interest rate:

$$\pi_t^{(k)} - \pi_t^{(4)} = \alpha + \beta^{EC}(Spr_t^{e,(k)} + \chi_t^{(k)}) + \beta^{TP}\chi_t^{(k)} + \gamma\pi_t^{(-4)} + \delta y_t^{(1)} + \varepsilon_{t+k} \qquad (33)$$

where $\pi_t^{(k)} - \pi_t^{(4)}$ is the difference between the future k-quarter inflation rate from time t to $t+k$ expressed in annual terms and the future 4-quarter inflation rate from t to $t+4$. The control variable $\pi_t^{(-4)}$ denotes past inflation between $t-4$ quarters and t. Again, we distinguish four model versions: (i) incorporating the spread (versions 1 and 3) or the decomposed spread (versions 2 and 4); and (ii) not including (version 2) or including (version 4) additional control variables. We estimate each model for a horizon of 8 to 20 quarters.

The results for model 1 in Table 11 indicate that although yield spreads significantly predict inflation changes the resulting adjusted R^2 is relatively low. In this case, the decomposition of the yield spread into an expectations and a term premium component is crucial. Without the inclusion of control variables (models 1 and 2), we observe an increase in the adjusted R^2 between 12 and 24 percentage points, reaching 34% for a 12-quarter horizon. Including control variables (models 3 and 4), the increase in the adjusted R^2, attributable to the spread decomposition, is around 10%, reaching 44% also for a 12-quarter horizon.

Insert Table 11

One reason for the difference in the relevance of the spread decomposition in the regressions for GDP growth and inflation is the fact that for the latter the expectations and the term premium components have opposite signs. While the expectations component has a positive association with future inflation, the risk premium component correlates negatively with inflation; a positive expectations component of the spread signals future increases in inflation (in line with the Fisher parity), while a positive term premium indicates a decrease in future inflation. These differences in signs can obviously not be captured by the spread itself.

The results for model 3 also show that the short-term interest rate drives out the predictive power of the yield spread. But model 4 shows that this is not the case once the yield spread is decomposed. So, while yield spreads *per se* contain valuable information, decomposing the spread into expectations components and term premium clearly improves the forecasting potential of the predictive regressions for inflation.

Finally, we analyze the time evolution of the predictive content of the yield spread and its components for inflation. Each plot in Figure 6 shows the adjusted R^2 over time for a certain predictive horizon and the corresponding yield spread (8 to 20 quarters). As in Figure 5, the graphs indicate the resulting adjusted R^2 for a sample ending on the shown date. The EFM model is also reestimated at every quarter using an expanding window. We observe a slight decrease over time in the predictive power of the yield spread and its components to forecast inflation. We also note a striking improvement in the adjusted R^2 simply by decomposing the spread in its two components (red dash dotted line in comparison with the blue dotted line). As mentioned before, this is due to the fact that the expectations and the term premium components obtain opposite signs in the regressions. For a 20-quarter horizon, once you allow for control variables the gain from decomposing the spread is marginal.

Insert Figure 6

5 Conclusion

In this paper, we use the EMF model proposed by Dewachter and Iania (2010) to study the risk and term premia in the U.S. bond market. This model extends the standard macro-finance model by including next to the standard macroeconomic factors a set of financial factors. The latter includes liquidity and risk premium factors. By including these factors the model is able to capture in a better way the additional non-macroeconomic drivers of the yield curve.

The estimation results indicate that risk premia in the U.S. market display significant time variation and strong collinearity across the maturity spectrum. The former is a clear indication that the expectation hypothesis fails. More importantly, the variance decomposition of the EMF model singles out financial factors as the main drivers behind the bond premia. In particular, we find that risk premium shocks dominate. This finding is in line with the recent literature indicating that macroeconomic factors cannot account for the time variation in risk premia. The significant collinearity of bond premia suggests that a few factors drive the entire term structure of risk premia. We find that one factor, closely related to the standard CP factor (Cochrane and Piazzesi (2005)), is responsible for most of the variation in bond premia.

We use the EMF model to decompose the yield spread into expectations and term premium components. This decomposition is used to forecast GDP growth and inflation. Although the decomposition does not seem important to forecast GDP growth it is crucial to forecast inflation for most forecasting horizons. Also, in general, the inclusion of control variables such as the short-term interest rate and lagged variables does not drive out the predictive power of the yield spread decomposition.

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Table 1: Prior distribution of the parameters

		Distr	Mean	Stdev
$\Phi^{MM}(1,1)$		$\mathcal{N}$	0.500	0.300
$\Phi^{MM}(2,1)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{MM}(3,1)$		$\mathcal{N}$	0.100	0.150
$\Phi^{MM}(1,2)$		$\mathcal{N}$	0.100	0.150
$\Phi^{MM}(2,2)$		$\mathcal{N}$	0.900	0.300
$\Phi^{MM}(3,2)$		$\mathcal{N}$	0.100	0.150
$\Phi^{MM}(1,3)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{MM}(2,3)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{MM}(3,3)$		$\mathcal{N}$	0.800	0.300
$\Phi^{lM}(i,j)$	$i=1,2; j=1,2,3$	$\mathcal{N}$	0.000	0.150
$\Phi^{lM}(i,j)$	$i=3; j=1,2$	$\mathcal{N}$	-0.100	0.150
$\Phi^{lM}(3,3)$		$\mathcal{N}$	0.100	0.150
$\Phi^{Ml}(1,1)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{Ml}(2,1)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{Ml}(3,1)$		$\mathcal{N}$	0.100	0.150
$\Phi^{Ml}(1,2)$		$\mathcal{N}$	0.100	0.150
$\Phi^{Ml}(2,2)$		$\mathcal{N}$	-0.200	0.150
$\Phi^{Ml}(3,2)$		$\mathcal{N}$	-0.100	0.150
$\Phi^{ll}(i,i)$	$i=1,2,3$	$\mathcal{N}$	0.600	0.300
$\Phi^{ll}(i,j)$	$i \neq j$	$\mathcal{N}$	0.000	0.150
$\Sigma^{MM}(i,i)$	$i=1,2,3$	$\mathcal{IG}$	0.010	0.200
$\Sigma^{MM}(2,1)$		$\mathcal{N}$	-0.002	0.002

		Distr	Mean	Stdev
$\Sigma^{MM}(3,1)$		$\mathcal{N}$	0.002	0.002
$\Sigma^{MM}(3,2)$		$\mathcal{N}$	-0.002	0.002
$\Sigma^{lM}(i,j)$	$i,j=1,2$	$\mathcal{N}$	0.000	0.002
$\Sigma^{lM}(3,j)$	$j=1,2$	$\mathcal{N}$	-0.002	0.002
$\Sigma^{lM}(3,3)$		$\mathcal{N}$	0.002	0.002
$\Sigma^{ll}(i,j)$	$i>j$	$\mathcal{N}$	0.000	0.020
$\Sigma^{ll}(i,i)$	$i=1,2$	$\mathcal{IG}$	0.005	0.200
$\Sigma^{ll}(i,i)$	$i=3$	$\mathcal{IG}$	0.030	0.200
$S_{LR}(i,i)$	$i=1,2$	$\mathcal{IG}$	0.002	0.200
$\Lambda_0(i)$	$i=1,...,8$	$\mathcal{N}$	-1.000	1.000
$\Lambda_1(i,6)$	$i=1,...,6$	$\mathcal{N}$	0.000	25.000
$S(i,i)$	$i=4,...,10,15,16$	$\mathcal{U}^*$	0.000	0.005
$S(i,i)$	$i=12$	$\mathcal{U}^*$	0.000	0.002
$S(i,i)$	$i=14$	$\mathcal{U}^*$	0.000	0.015
$A(12)=c_{Ed}$		$\mathcal{N}$	0.000	0.002
$A(16)=\alpha$		$\mathcal{N}$	0.000	0.010
$B(16,8)=\beta_\rho$		$\mathcal{N}$	1.000	0.500
$X_0(i)$	$i=4,5$	$\mathcal{U}^*$	-0.050	0.050
$X_0(i)$	$i=6$	$\mathcal{U}^*$	-0.100	0.300
$X_0(i)$	$i=7,8$	$\mathcal{U}^*$	-0.010	0.050
$\bar{C}^l(i)$	$i=1,2$	$\mathcal{U}^*$	0.000	0.015
$\bar{C}^l(i)$	$i=3$	$\mathcal{U}^*$	0.000	0.200

* : For the uniform distribution, we report the lower and upper bounds of the support instead of the mean and standard deviation, respectively.

Note: The two panels of this table report the prior density of the parameters estimated in the Extended Macro-Finance (EMF) model. $\mathcal{N}$ stands for Normal , $\mathcal{IG}$ for Inverse Gamma, and $\mathcal{U}$ for Uniform distribution. The parameters refer to the following state space system:

$$\begin{aligned} Z_t &= A + BX_t + S\eta_t, \qquad \eta_t \sim \mathcal{N}(0,I) && \text{(Meas. Eq.)} \\ X_t &= C + \Phi X_{t-1} + \Sigma\varepsilon_t, \qquad \varepsilon_t \sim N(0,I) && \text{(Trans. Eq.)} \end{aligned}$$

where the observable and state vectors are

$$\begin{aligned} Z_t &= [\pi_t, y_t, i_t^{cb}, y_t^{(1)}, ..., y_t^{(40)}, i_t^{Lb} - y_t^{(1)}, i_t^{Ed} - y_t^{(1)}, i_t^{GC} - y_t^{(1)}, F_{\pi,t}^{(4)}, F_{\pi,t}^{(40)}, \Delta y_t^{pot}]' \\ X_t &= [\underbrace{\pi_t,\ y_t,\ i_t^{cb}}_{M},\ \underbrace{l_{1,t},\ l_{2,t},\ l_{3,t}}_{l},\ \underbrace{\pi_t^*,\ \rho_t}_{\xi}]' \end{aligned}$$

and the parameters of the transition equation are given by:

$$C = \begin{bmatrix} C^M \\ C^l \\ 0 \end{bmatrix}, \qquad \Phi = \begin{bmatrix} \Phi^{MM} & \Phi^{Ml} & \Phi^{M\xi} \\ \Phi^{lM} & \Phi^{ll} & \Phi^{l\xi} \\ 0 & 0 & I \end{bmatrix}, \qquad \Sigma = \begin{bmatrix} \Sigma^{MM} & 0 & \Sigma^{M\xi} \\ \Sigma^{lM} & \Sigma^{ll} & \Sigma^{l\xi} \\ 0 & 0 & \Sigma^{\xi\xi} \end{bmatrix}$$

with

$$\begin{bmatrix} C^M \\ C^l \end{bmatrix} = \left(I - \begin{bmatrix} \Phi^{MM} & \Phi^{Ml} \\ \Phi^{lM} & \Phi^{ll} \end{bmatrix} \right) \begin{bmatrix} 0_{3\times1} \\ \bar{C}^l_{3\times1} \end{bmatrix}$$

Finally, the parameters Λ_0 and Λ_1 are related to the stochastic discount factor used for pricing the government bonds:

$$m_{t+1} = \exp(-i_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1})$$

with $i_t = y_t^{(1)}$ and $\Lambda_t = \Lambda_0 + \Lambda_1 X_t$.

Table 2: Prior and Posterior Distribution - Phi Matrix

	Prior			Posterior						
	Distr	Mean	Stdev	5 %	16 %	50 %	84 %	95 %	Mean	Mode
$\Phi(1,1)$	$\mathcal{N}$	0.500	0.300	0.398	0,424	0.457	0,491	0,514	0.461	0.456
$\Phi(2,1)$	$\mathcal{N}$	-0.100	0.150	-0.064	-0,039	0.000	0,038	0,061	0.000	0.000
$\Phi(3,1)$	$\mathcal{N}$	0.100	0.150	0.041	0,066	0.109	0,155	0,184	0.112	0.118
$\Phi(4,1)$	$\mathcal{N}$	0.000	0.150	-0.014	0,001	0.025	0,050	0,067	0.026	0.031
$\Phi(5,1)$	$\mathcal{N}$	0.000	0.150	0.020	0,033	0.053	0,073	0,087	0.053	0.050
$\Phi(6,1)$	$\mathcal{N}$	-0.100	0.150	-0.160	-0,143	-0.121	-0,097	-0,083	-0.120	-0.113
$\Phi(1,2)$	$\mathcal{N}$	0.100	0.150	-0.007	0,003	0.018	0,032	0,042	0.017	0.017
$\Phi(2,2)$	$\mathcal{N}$	0.900	0.300	0.876	0,891	0.913	0,935	0,949	0.914	0.918
$\Phi(3,2)$	$\mathcal{N}$	0.100	0.150	0.032	0,045	0.064	0,085	0,100	0.067	0.066
$\Phi(4,2)$	$\mathcal{N}$	0.000	0.150	-0.003	0,003	0.014	0,025	0,033	0.015	0.013
$\Phi(5,2)$	$\mathcal{N}$	0.000	0.150	-0.044	-0,036	-0.026	-0,016	-0,010	-0.026	-0.029
$\Phi(6,2)$	$\mathcal{N}$	-0.100	0.150	-0.090	-0,081	-0.072	-0,063	-0,057	-0.073	-0.069
$\Phi(1,3)$	$\mathcal{N}$	-0.100	0.150	0.073	0,087	0.108	0,128	0,141	0.107	0.108
$\Phi(2,3)$	$\mathcal{N}$	-0.100	0.150	-0.117	-0,096	-0.066	-0,036	-0,015	-0.066	-0.062
$\Phi(3,3)$	$\mathcal{N}$	0.800	0.300	0.813	0,835	0.868	0,900	0,924	0.868	0.873
$\Phi(4,3)$	$\mathcal{N}$	0.000	0.150	-0.010	0,001	0.016	0,034	0,044	0.017	0.018
$\Phi(5,3)$	$\mathcal{N}$	0.000	0.150	0.011	0,021	0.036	0,052	0,063	0.036	0.036
$\Phi(6,3)$	$\mathcal{N}$	0.100	0.150	0.011	0,021	0.036	0,050	0,062	0.035	0.033
$\Phi(1,4)$	$\mathcal{N}$	-0.100	0.150	-0.223	-0,173	-0.095	-0,017	0,036	-0.096	-0.085
$\Phi(2,4)$	$\mathcal{N}$	-0.100	0.150	-0.457	-0,392	-0.298	-0,202	-0,139	-0.300	-0.320
$\Phi(3,4)$	$\mathcal{N}$	0.100	0.150	-0.352	-0,289	-0.190	-0,088	-0,006	-0.193	-0.192
$\Phi(4,4)$	$\mathcal{N}$	0.600	0.300	0.589	0,629	0.687	0,750	0,791	0.692	0.693
$\Phi(5,4)$	$\mathcal{N}$	0.000	0.150	-0.176	-0,142	-0.088	-0,040	-0,008	-0.088	-0.086
$\Phi(6,4)$	$\mathcal{N}$	0.000	0.150	0.003	0,037	0.086	0,135	0,169	0.094	0.079
$\Phi(1,5)$	$\mathcal{N}$	0.100	0.150	0.282	0,328	0.396	0,469	0,515	0.391	0.393
$\Phi(2,5)$	$\mathcal{N}$	-0.200	0.150	-0.172	-0,112	-0.024	0,075	0,138	-0.026	-0.033
$\Phi(3,5)$	$\mathcal{N}$	-0.100	0.100	-0.238	-0,188	-0.115	-0,040	0,021	-0.110	-0.115
$\Phi(4,5)$	$\mathcal{N}$	0.000	0.150	-0.240	-0,206	-0.159	-0,113	-0,083	-0.158	-0.168
$\Phi(5,5)$	$\mathcal{N}$	0.600	0.300	0.610	0,649	0.700	0,749	0,777	0.701	0.705
$\Phi(6,5)$	$\mathcal{N}$	0.000	0.150	-0.185	-0,163	-0.134	-0,103	-0,080	-0.134	-0.134
$\Phi(6,6)$	$\mathcal{N}$	0.600	0.300	0.685	0,719	0.767	0,808	0,836	0.762	0.770

Note: This table reports the prior and posterior density of Φ in equation (7). The second to fourth columns report the type of distribution, mean and standard deviation of the prior, respectively. The fifth to ninth columns report the 5-th, 16-th, 50-th, 84-th and 95-th percentile of the posterior distribution, respectively. The last two columns report the mean and mode of the posterior distribution. The results are obtained using the Metropolis-Hastings algorithm. $\mathcal{N}$ stands for Normal distribution.

Table 3: Prior and Posterior Distribution - Impact Matrix

	Prior			Posterior						
	Distr	Mean	Stdev	5 %	16 %	50 %	84 %	95 %	Mean	Mode
$\Sigma(1,1)$	$\mathcal{IG}$	0.010	0.200	1,088	1,125	1.183	1,247	1,290	1.187	1.173
$\Sigma(2,1)$	$\mathcal{N}$	-0.002	0.002	-0,200	-0,166	-0.111	-0,055	-0,019	-0.109	-0.104
$\Sigma(3,1)$	$\mathcal{N}$	0.002	0.002	0,003	0,059	0.142	0,228	0,286	0.141	0.160
$\Sigma(4,1)$	$\mathcal{N}$	0.000	0.002	0,071	0,096	0.132	0,168	0,193	0.129	0.134
$\Sigma(5,1)$	$\mathcal{N}$	0.000	0.002	-0,024	-0,001	0.035	0,072	0,097	0.033	0.038
$\Sigma(6,1)$	$\mathcal{N}$	-0.002	0.002	-0,019	0,024	0.089	0,152	0,199	0.096	0.084
$\Sigma(2,2)$	$\mathcal{IG}$	0.010	0.200	0,651	0,672	0.708	0,746	0,774	0.709	0.690
$\Sigma(3,2)$	$\mathcal{N}$	0.002	0.002	-0,033	0,023	0.099	0,180	0,231	0.105	0.093
$\Sigma(4,2)$	$\mathcal{N}$	0.000	0.002	-0,029	-0,007	0.028	0,062	0,083	0.030	0.026
$\Sigma(5,2)$	$\mathcal{N}$	0.000	0.002	-0,139	-0,116	-0.085	-0,053	-0,029	-0.086	-0.080
$\Sigma(6,2)$	$\mathcal{N}$	-0.002	0.002	-0,073	-0,035	0.022	0,080	0,114	0.018	0.020
$\Sigma(3,3)$	$\mathcal{IG}$	0.010	0.200	1,208	1,246	1.308	1,378	1,427	1.314	1.298
$\Sigma(4,3)$	$\mathcal{N}$	0.000	0.002	0,323	0,344	0.377	0,412	0,436	0.379	0.372
$\Sigma(5,3)$	$\mathcal{N}$	0.000	0.002	-0,126	-0,103	-0.066	-0,030	-0,006	-0.070	-0.064
$\Sigma(6,3)$	$\mathcal{N}$	0.002	0.002	-0,302	-0,244	-0.162	-0,077	-0,026	-0.159	-0.155
$\Sigma(4,4)$	$\mathcal{IG}$	0.005	0.200	0,272	0,286	0.310	0,336	0,354	0.311	0.300
$\Sigma(5,4)$	$\mathcal{N}$	0.000	0.002	0,001	0,030	0.073	0,115	0,143	0.070	0.069
$\Sigma(6,4)$	$\mathcal{N}$	0.000	0.002	-0,418	-0,352	-0.258	-0,175	-0,117	-0.275	-0.249
$\Sigma(5,5)$	$\mathcal{IG}$	0.005	0.200	0,325	0,342	0.370	0,401	0,423	0.370	0.360
$\Sigma(6,5)$	$\mathcal{N}$	0.000	0.002	0,249	0,302	0.386	0,474	0,536	0.388	0.365
$\Sigma(6,6)$	$\mathcal{IG}$	0.030	0.200	0,603	0,659	0.754	0,871	0,957	0.801	0.680
$\Sigma(7,7)$	$\mathcal{IG}$	0.002	0.200	0,177	0,186	0.200	0,216	0,229	0.201	0.194
$\Sigma(8,8)$	$\mathcal{IG}$	0.002	0.200	0,048	0,052	0.060	0,069	0,075	0.060	0.060

Note: This table reports the prior and posterior density of Σ in equation (7). The second to fourth columns report the type of distribution, mean and standard deviation of the prior, respectively. The fifth to ninth columns report the 5-th, 16-th, 50-th, 84-th and 95-th percentile of the posterior distribution, respectively. The last two columns report the mean and mode of the posterior distribution. The statistics of the posterior distribution are multiplied by 100. The results are obtained using the Metropolis-Hastings algorithm. $\mathcal{N}$ stands for Normal and $\mathcal{IG}$ for Inverse Gamma distribution.

Table 4: Prior and Posterior Distribution - Remaining Parameters

	Prior			Posterior						
	Distr	Mean	Stdev	5 %	16 %	50 %	84 %	95 %	Mean	Mode
$\Lambda_0\,(1)$	$\mathcal{N}$	-1.000	1.000	0,130	0,427	0.888	1,380	1,734	0.865	1.020
$\Lambda_0\,(2)$	$\mathcal{N}$	-1.000	1.000	-2,552	-2,015	-1.259	-0,480	0,028	-1.152	-1.396
$\Lambda_0\,(3)$	$\mathcal{N}$	-1.000	1.000	-0,438	-0,316	-0.140	0,051	0,209	-0.145	-0.121
$\Lambda_0\,(4)$	$\mathcal{N}$	-1.000	1.000	-1,356	-1,149	-0.871	-0,583	-0,367	-0.863	-0.873
$\Lambda_0\,(5)$	$\mathcal{N}$	-1.000	1.000	-1,633	-1,399	-1.064	-0,736	-0,520	-1.097	-1.025
$\Lambda_0\,(6)$	$\mathcal{N}$	-1.000	1.000	0,398	0,476	0.591	0,687	0,775	0.579	0.580
$\Lambda_0\,(7)$	$\mathcal{N}$	-1.000	1.000	-1,225	-1,002	-0.753	-0,481	-0,275	-0.760	-0.743
$\Lambda_0\,(8)$	$\mathcal{N}$	-1.000	1.000	-2,448	-1,903	-1.061	-0,230	0,390	-1.034	-0.946
$\Lambda_1\,(1,6)$	$\mathcal{N}$	0.000	25.000	-5,347	7,851	26.515	44,379	55,710	26.001	24.498
$\Lambda_1\,(2,6)$	$\mathcal{N}$	0.000	25.000	-35,621	-18,808	4.262	27,527	42,581	2.687	8.498
$\Lambda_1\,(3,6)$	$\mathcal{N}$	0.000	25.000	-63,959	-57,537	-47.764	-38,969	-33,245	-47.722	-51.128
$\Lambda_1\,(4,6)$	$\mathcal{N}$	0.000	25.000	-20,216	-8,077	9.444	26,279	38,876	8.397	11.511
$\Lambda_1\,(5,6)$	$\mathcal{N}$	0.000	25.000	-10,855	-0,159	15.947	29,594	40,290	12.501	16.735
$\Lambda_1\,(6,6)$	$\mathcal{N}$	0.000	25.000	-11,558	-6,939	-0.839	5,380	10,295	-1.052	-1.251
$S\,(4,4)$	$\mathcal{U}^*$	0.000	0.005	0,370	0,385	0.410	0,437	0,456	0.413	0.405
$S\,(5,5)$	$\mathcal{U}^*$	0.000	0.005	0,173	0,180	0.193	0,206	0,215	0.193	0.192
$S\,(6,6)$	$\mathcal{U}^*$	0.000	0.005	0,091	0,096	0.104	0,112	0,117	0.104	0.104
$S\,(7,7)$	$\mathcal{U}^*$	0.000	0.005	0,039	0,044	0.050	0,056	0,061	0.050	0.050
$S\,(8,8)$	$\mathcal{U}^*$	0.000	0.005	0,075	0,078	0.084	0,090	0,095	0.084	0.084
$S\,(9,9)$	$\mathcal{U}^*$	0.000	0.005	0,075	0,082	0.090	0,098	0,104	0.090	0.091
$S\,(10,10)$	$\mathcal{U}^*$	0.000	0.005	0,233	0,246	0.266	0,286	0,300	0.265	0.265
$S\,(12,12)$	$\mathcal{U}^*$	0.000	0.002	0,190	0,194	0.197	0,199	0,200	0.196	0.200
$S\,(14,14)$	$\mathcal{U}^*$	0.000	0.015	0,327	0,342	0.369	0,398	0,421	0.372	0.357
$S\,(15,15)$	$\mathcal{U}^*$	0.000	0.005	0,031	0,056	0.095	0,155	0,205	0.107	0.088
$S\,(16,16)$	$\mathcal{U}^*$	0.000	0.005	0,001	0,002	0.004	0,008	0,010	0.005	0.001
$\bar{C}^l\,(1)$	$\mathcal{U}^*$	0.000	0.015	0,002	0,003	0.004	0,005	0,005	0.004	0.004
$\bar{C}^l\,(2)$	$\mathcal{U}^*$	0.000	0.015	0,006	0,007	0.008	0,009	0,009	0.008	0.008
$\bar{C}^l\,(3)$	$\mathcal{U}^*$	0.000	0.200	0,003	0,006	0.009	0,013	0,015	0.009	0.009
$X_0\,(4)$	$\mathcal{U}^*$	-0.050	0.050	0,003	0,008	0.015	0,023	0,027	0.015	0.017
$X_0\,(5)$	$\mathcal{U}^*$	-0.050	0.050	-0,005	0,004	0.018	0,030	0,039	0.018	0.020
$X_0\,(6)$	$\mathcal{U}^*$	-0.100	0.300	-0,007	0,002	0.017	0,032	0,042	0.018	0.018
$X_0\,(7)$	$\mathcal{U}^*$	-0.010	0.050	0,001	0,004	0.009	0,015	0,018	0.009	0.010
$X_0\,(8)$	$\mathcal{U}^*$	-0.010	0.050	0,023	0,025	0.029	0,032	0,034	0.029	0.029
$A(12)$	$\mathcal{N}$	0.000	0.002	-0,001	-0,001	-0.001	-0,001	0,000	-0.001	-0.001
$A(16)$	$\mathcal{N}$	0.000	0.010	-0,016	-0,012	-0.005	0,000	0,003	-0.006	-0.006
$B(16,8)$	$\mathcal{N}$	1.000	0.500	1,234	1,339	1.521	1,735	1,879	1.537	1.500

* : For the uniform distribution, we report the lower and upper bounds of the support instead of the mean and standard deviation, respectively.

Note: This table reports the prior and posterior density of S in equation (23), Λ_0 and Λ_1 in equation (6), C in equation (22), and the initial values of the state variables, X_0. The second to fourth columns report the type of distribution, mean and standard deviation of the prior, respectively. The fifth to ninth columns report the 5-th, 16-th, 50-th, 84-th, and 95-th percentile of the posterior distribution, respectively. The last two columns report the mean and mode of the posterior distribution. All results are obtained using the Metropolis-Hastings algorithm. The statistics of the posterior distribution of S and A are multiplied by 100. $\mathcal{N}$ stands for Normal and $\mathcal{U}$ for Uniform distribution.

Table 5: Excess returns: in-sample and out-of-sample analysis

In-sample statistics

	Adj. R^2: 4-qtr holding period (k)			
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
CP	29.90%	31.21%	33.07%	30.50%
EMF	36.15%	31.78%	31.51%	31.53%

	Adj. R^2: 8-qtr holding period (k)			
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
CP	-	20,29%	22,05%	20,53%
EMF	-	40,89%	38,87%	39,44%

	Adj. R^2: 16-qtr holding period (k)			
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
CP	-	-	-	-
EMF	-	-	-	47,30%

Out-of-sample statistics

	4-qtr holding period (k)			
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
EMF (RMSE)	1.54%	3.00%	4.14%	5.08%
CP (RMSE)/EMF (RMSE)	1.03	1.03	1.03	1.03
RW (RMSE)/EMF (RMSE)	1.02	1.01	1.00	0.99

	8-qtr holding period (k)			
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
EMF (RMSE)	-	2.46%	4.36%	5.70%
CP (RMSE)/EMF (RMSE)	-	1.02	1.02	1.03
RW (RMSE)/EMF (RMSE)	-	1.10	1.08	1.05

Note: This table reports in-sample (top three panels) and out-of-sample (bottom two panels) statistics for the excess bond returns. The top three panels report the adjusted R^2 of the following regression:

$$rx_{t,t+k}^{(n)} = \alpha + \beta f_t^{(n)} + \varepsilon_{t+k}, \qquad n = 8,\ 12,\ 16,\ 20 \text{ qtr}; \qquad k = 4,\ 8,\ 16 \text{ qtr}; \qquad n > k$$

where $rx_{t,t+k}^{(n)}$ denotes the realized excess return (in excess of the k-quarter risk-free rate) of buying a n-quarter bond at time t and selling it back after k quarters, and $f_t^{(n)}$ represents the unsmoothed Cochrane and Piazzesi (2005) factor (CP) or the EMF model-implied expected excess returns (first and second rows in each panel). When regressing the realized excess returns on the model-implied ones we fixed the coefficients α and β to 0 and 1, respectively. The sample period goes from 1960:Q1 to 2008:Q4.
The bottom two panels report the out-of-sample forecasts of the realized excess returns using the EMF model, the CP model, and the random walk model (RW). For the EMF and the CP models, the forecasts are obtained (*i*) by estimating the models over the period 1960:Q1-1995:Q4 and (*ii*) by producing the model-implied forecasts of the excess returns for the period 1996:Q1-2008:Q4. Every quarter the information is updated and the models are reestimated. The first row of the panel reports the root mean squared error (RMSE) of the EMF model. The following two rows present the ratios of the RMSE of the CP model over the EMF model and of the RW model over the EMF model, respectively.

Table 6: Unbiasedness of expected excess returns

4-qtr holding period (k)				
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
α	0,000	0,001	0,002	0,000
	(0,002)	(0,004)	(0,005)	(0,006)
β	1,058	1,031	1,009	0,969
	(0,155)	(0,177)	(0,185)	(0,172)
p-value ($\alpha = 0, \beta = 1$)	0,915	0,924	0,950	0,984

8-qtr holding period (k)				
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
α	-	0,000	0,000	0,000
	-	(0,002)	(0,003)	(0,004)
β	-	1,108	1,061	1,003
	-	(0,169)	(0,195)	(0,284)
p-value ($\alpha = 0, \beta = 1$)	-	0,409	0,389	0,394

16-qtr holding period (k)				
maturity (n)	8 qtr	12 qtr	16 qtr	20 qtr
α	-	-	-	0,000
	-	-	-	(0,001)
β	-	-	-	1,208
	-	-	-	(0,160)
p-value ($\alpha = 0, \beta = 1$)	-	-	-	0.386

Note: This table reports coefficients and respective Newey-West standard errors of the following regression:

$$rx_{t,t+k}^{(n)} = \alpha + \beta E_t \left[rx_{t,t+k}^{(n)} \right] + \varepsilon_{t+k}, \qquad n = 8,\ 12,\ 16,\ 20 \text{ qtr}; \qquad k = 4,\ 8,\ 16 \text{ qtr}; \qquad n > k$$

where $rx_{t,t+k}^{(n)}$ denotes the realized excess return (in excess of the k-quarter risk-free rate) of buying a n-quarter bond at time t and selling it back after k quarters, and $E_t \left[rx_{t,t+k}^{(n)} \right]$ represents the EMF model-implied expected excess return as given by equation (15). In the last row of each panel, we report the p-value of the joint test $\alpha = 0$ and $\beta = 1$. The standard errors of the coefficients are in parentheses. The sample period goes from 1960:Q1 to 2008:Q4.

Table 7: Variance decomposition of bond premia

8-qtr bond (4-qtr holding period)

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	0,6%	0,2%	0,0%	19,2%	79,8%	0,1%	0,0%
2Q	1,6%	0,5%	0,9%	16,0%	80,9%	0,1%	0,0%
4Q	2,6%	1,1%	5,0%	12,3%	78,8%	0,2%	0,0%
10Q	2,4%	1,4%	15,6%	15,0%	65,3%	0,2%	0,0%
40Q	2,5%	1,4%	17,2%	19,1%	59,6%	0,3%	0,0%
100Q	2,5%	1,4%	17,2%	19,1%	59,6%	0,3%	0,0%

12-qtr bond (4-qtr holding period)

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	0,5%	0,2%	0,0%	19,8%	79,4%	0,1%	0,0%
2Q	1,5%	0,4%	0,8%	16,6%	80,6%	0,1%	0,0%
4Q	2,5%	1,0%	4,7%	12,8%	78,8%	0,1%	0,0%
10Q	2,4%	1,4%	15,1%	15,2%	65,7%	0,2%	0,0%
40Q	2,4%	1,4%	16,7%	19,2%	60,0%	0,3%	0,0%
100Q	2,4%	1,4%	16,8%	19,2%	60,0%	0,3%	0,0%

16-qtr bond (4-qtr holding period)

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	0,5%	0,2%	0,0%	20,0%	79,2%	0,1%	0,0%
2Q	1,5%	0,4%	0,7%	16,8%	80,4%	0,1%	0,0%
4Q	2,5%	1,0%	4,5%	13,0%	78,8%	0,1%	0,0%
10Q	2,4%	1,4%	14,9%	15,3%	65,8%	0,2%	0,0%
40Q	2,4%	1,4%	16,6%	19,2%	60,2%	0,3%	0,0%
100Q	2,4%	1,4%	16,6%	19,2%	60,2%	0,3%	0,0%

20-qtr bond (4-qtr holding period)

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	0,5%	0,2%	0,0%	20,2%	79,1%	0,1%	0,0%
2Q	1,4%	0,4%	0,7%	17,0%	80,4%	0,1%	0,0%
4Q	2,4%	1,0%	4,5%	13,1%	78,8%	0,1%	0,0%
10Q	2,4%	1,4%	14,8%	15,4%	65,9%	0,2%	0,0%
40Q	2,4%	1,3%	16,5%	19,3%	60,3%	0,3%	0,0%
100Q	2,4%	1,3%	16,5%	19,3%	60,3%	0,3%	0,0%

Note: This table reports the forecasting error variance decomposition (computed at the mode of the posterior distribution of the parameters) of the 4-quarter bond premia of 8-, 12, 16 and 20-quarter maturity bonds. Sup. sh.: supply shocks; Dem. sh.: demand shocks; Pol. rate sh.: policy rates shocks; Liq. sh.: flight-to-quality and credit-crunch shocks; LR inf. sh.: long-run inflation shocks; and Eq. real rate sh.: equilibrium real rate shocks.

Table 8: Variance decomposition of the expectations component

Expected average short-term rate over 4 quarters

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	1,8%	1,4%	85,9%	10,5%	0,0%	0,2%	0,1%
2Q	2,6%	1,8%	83,9%	11,1%	0,0%	0,4%	0,1%
4Q	3,5%	2,7%	79,8%	12,8%	0,0%	1,0%	0,2%
10Q	3,7%	4,5%	68,7%	17,8%	0,0%	4,8%	0,6%
40Q	2,5%	3,5%	44,5%	15,8%	0,0%	30,6%	3,1%
100Q	1,5%	2,1%	26,4%	9,4%	0,0%	55,3%	5,4%

Expected average short-term rate over 20 quarters

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	2,8%	5,2%	52,7%	24,6%	0,0%	13,2%	1,5%
2Q	3,0%	5,6%	48,2%	25,7%	0,0%	15,6%	1,8%
4Q	3,0%	6,0%	40,3%	27,4%	0,0%	20,8%	2,3%
10Q	2,2%	5,5%	25,2%	27,3%	0,0%	35,9%	3,8%
40Q	0,8%	2,1%	8,8%	11,9%	0,0%	69,5%	6,9%
100Q	0,4%	0,9%	3,7%	5,1%	0,0%	81,9%	8,0%

Expected average short-term rate over 40 quarters

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	1,8%	3,1%	28,0%	18,3%	0,0%	44,2%	4,6%
2Q	1,8%	3,1%	24,4%	18,0%	0,0%	47,7%	5,0%
4Q	1,7%	3,0%	18,6%	17,2%	0,0%	53,9%	5,6%
10Q	1,1%	2,2%	9,7%	13,7%	0,0%	66,7%	6,8%
40Q	0,3%	0,6%	2,6%	4,5%	0,0%	83,8%	8,2%
100Q	0,1%	0,2%	1,0%	1,8%	0,0%	88,3%	8,5%

Note: This table reports the forecasting error variance decomposition (computed at the mode of the posterior distribution of the parameters) of the average expected 1-quarter interest rate over 4 quarters (top panel), 20 quarters (middel panel), and 40 quarters (bottom panel). Sup. sh.: supply shocks; Dem. sh.: demand shocks; Pol. rate sh.: policy rates shocks; Liq. sh.: flight-to-quality and credit-crunch shocks; LR inf. sh.: long-run inflation shocks; and Eq. real rate sh.: equilibrium real rate shocks.

Table 9: Variance decomposition of the term premium component

4-qtr term premium

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	0,0%	0,0%	1,3%	25,3%	73,3%	0,1%	0,0%
2Q	0,7%	0,1%	0,9%	22,7%	75,6%	0,1%	0,0%
4Q	1,8%	0,5%	2,5%	18,6%	76,6%	0,1%	0,0%
10Q	2,0%	1,0%	10,6%	18,2%	68,0%	0,1%	0,0%
40Q	2,0%	1,0%	12,6%	21,2%	63,0%	0,2%	0,0%
100Q	2,0%	1,0%	12,6%	21,2%	63,0%	0,2%	0,0%

20-qtr term premium

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	1,3%	0,8%	7,2%	3,4%	87,1%	0,2%	0,0%
2Q	2,2%	1,1%	11,5%	2,6%	82,3%	0,3%	0,0%
4Q	2,8%	1,4%	19,2%	5,1%	71,2%	0,3%	0,0%
10Q	2,4%	1,2%	27,0%	16,8%	52,2%	0,3%	0,0%
40Q	2,8%	1,2%	26,2%	22,4%	46,8%	0,6%	0,0%
100Q	2,8%	1,2%	26,2%	22,4%	46,8%	0,6%	0,0%

40-qtr term premium

Horizon	Sup. sh.	Dem. sh.	Pol. rate sh.	Liq. sh.	Risk pr. sh.	LR inf. sh.	Eq. real rate sh.
1Q	2,2%	0,6%	10,6%	1,3%	84,8%	0,5%	0,0%
2Q	3,2%	0,8%	14,7%	2,9%	77,9%	0,5%	0,0%
4Q	3,8%	0,9%	20,7%	8,8%	65,2%	0,6%	0,0%
10Q	3,5%	0,7%	24,8%	23,4%	46,9%	0,7%	0,0%
40Q	4,1%	0,8%	23,4%	29,3%	41,4%	1,0%	0,0%
100Q	4,1%	0,8%	23,4%	29,3%	41,4%	1,0%	0,0%

Note: This table reports the forecasting error variance decomposition (computed at the mode of the posterior distribution of the parameters) of the 4-quarter (top panel), 20-quarter (middel panel), and 40-quarter (bottom panel) term premium. Sup. sh.: supply shocks; Dem. sh.: demand shocks; Pol. rate sh.: policy rates shocks; Liq. sh.: flight-to-quality and credit-crunch shocks; LR inf. sh.: long-run inflation shocks; and Eq. real rate sh.: equilibrium real rate shocks.

Table 10: Forecasting GDP growth (1960:Q1-2008:Q4)

Model 1	$g_{t\to t+k} = \alpha + \beta Spr_t^{(n)} + \varepsilon_{t+k}$								
horizon (k)	1 qtr			4 qtr			8 qtr		
maturity (n)	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr
α	0,026	0,023	0,023	0,025	0,023	0,023	0,026	0,024	0,025
	(0,004)	(0,004)	(0,004)	(0,004)	(0,004)	(0,004)	(0,003)	(0,003)	(0,004)
β	1,362	0,838	0,593	1,462	0,840	0,583	1,090	0,675	0,455
	(0,469)	(0,224)	(0,199)	(0,407)	(0,214)	(0,180)	(0,345)	(0,148)	(0,126)
Adj.-R^2	0,044	0,098	0,076	0,078	0,147	0,110	0,072	0,160	0,113
Model 2	$g_{t\to t+k} = \alpha + \beta^{EC}(Spr_t^{e,(n)} + \chi_t^{(n)}) + \beta^{TP}\chi_t^{(n)} + \varepsilon_{t+k}$								
horizon (k)	1 qtr			4 qtr			8 qtr		
maturity (n)	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr
α	0,025	0,025	0,024	0,025	0,024	0,024	0,027	0,025	0,024
	(0,004)	(0,004)	(0,004)	(0,004)	(0,004)	(0,004)	(0,003)	(0,003)	(0,004)
β^{EC}	2,544	1,043	0,782	2,027	0,925	0,700	1,129	0,633	0,489
	(0,677)	(0,243)	(0,205)	(0,654)	(0,220)	(0,184)	(0,597)	(0,155)	(0,127)
β^{TP}	-1,198	-0,419	-0,323	-0,705	-0,245	-0,166	-0,083	-0,010	0,042
	(0,733)	(0,255)	(0,247)	(0,663)	(0,234)	(0,228)	(0,500)	(0,176)	(0,172)
Adj.-R^2	0,097	0,132	0,118	0,108	0,159	0,143	0,093	0,153	0,142
Model 3	$g_{t\to t+k} = \alpha + \beta Spr_t^{(n)} + \gamma g_t + \delta y_t^{(1)} + \varepsilon_{t+k}$								
horizon (k)	1 qtr			4 qtr			8 qtr		
maturity (n)	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr
α	0,027	0,023	0,023	0,029	0,025	0,025	0,031	0,026	0,026
	(0,009)	(0,010)	(0,010)	(0,009)	(0,010)	(0,011)	(0,007)	(0,008)	(0,010)
β	1,158	0,601	0,389	1,290	0,670	0,434	0,992	0,622	0,410
	(0,417)	(0,219)	(0,193)	(0,393)	(0,240)	(0,205)	(0,343)	(0,206)	(0,187)
γ	0,269	0,252	0,260	0,169	0,150	0,159	0,047	0,029	0,038
	(0,084)	(0,083)	(0,084)	(0,069)	(0,068)	(0,070)	(0,051)	(0,050)	(0,052)
δ	-0,165	-0,101	-0,095	-0,159	-0,088	-0,081	-0,107	-0,036	-0,028
	(0,103)	(0,113)	(0,122)	(0,100)	(0,115)	(0,128)	(0,085)	(0,097)	(0,112)
Adj.-R^2	0,184	0,194	0,175	0,182	0,199	0,165	0,103	0,157	0,111
Model 4	$g_{t\to t+k} = \alpha + \beta^{EC}(Spr_t^{e,(n)} + \chi_t^{(n)}) + \beta^{TP}\chi_t^{(n)} + \gamma g_t + \delta y_t^{(1)} + \varepsilon_{t+k}$								
horizon (k)	1 qtr			4 qtr			8 qtr		
maturity (n)	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr	4 qtr	20 qtr	40 qtr
α	0,033	0,020	0,018	0,040	0,029	0,026	0,043	0,035	0,032
	(0,009)	(0,010)	(0,010)	(0,010)	(0,012)	(0,012)	(0,009)	(0,012)	(0,013)
β^{EC}	0,671	0,761	0,615	0,023	0,501	0,412	-0,439	0,238	0,217
	(0,898)	(0,324)	(0,273)	(0,973)	(0,386)	(0,319)	(0,971)	(0,422)	(0,353)
β^{TP}	0,536	-0,202	-0,195	1,258	0,136	0,107	1,531	0,371	0,321
	(0,866)	(0,311)	(0,280)	(0,901)	(0,359)	(0,321)	(0,822)	(0,370)	(0,336)
γ	0,248	0,236	0,241	0,156	0,149	0,152	0,043	0,040	0,040
	(0,082)	(0,087)	(0,087)	(0,064)	(0,070)	(0,071)	(0,041)	(0,046)	(0,048)
δ	-0,262	-0,039	-0,005	-0,344	-0,159	-0,124	-0,316	-0,197	-0,162
	(0,130)	(0,140)	(0,144)	(0,138)	(0,170)	(0,176)	(0,114)	(0,175)	(0,186)
Adj.-R^2	0,201	0,197	0,188	0,221	0,199	0,183	0,193	0,172	0,153

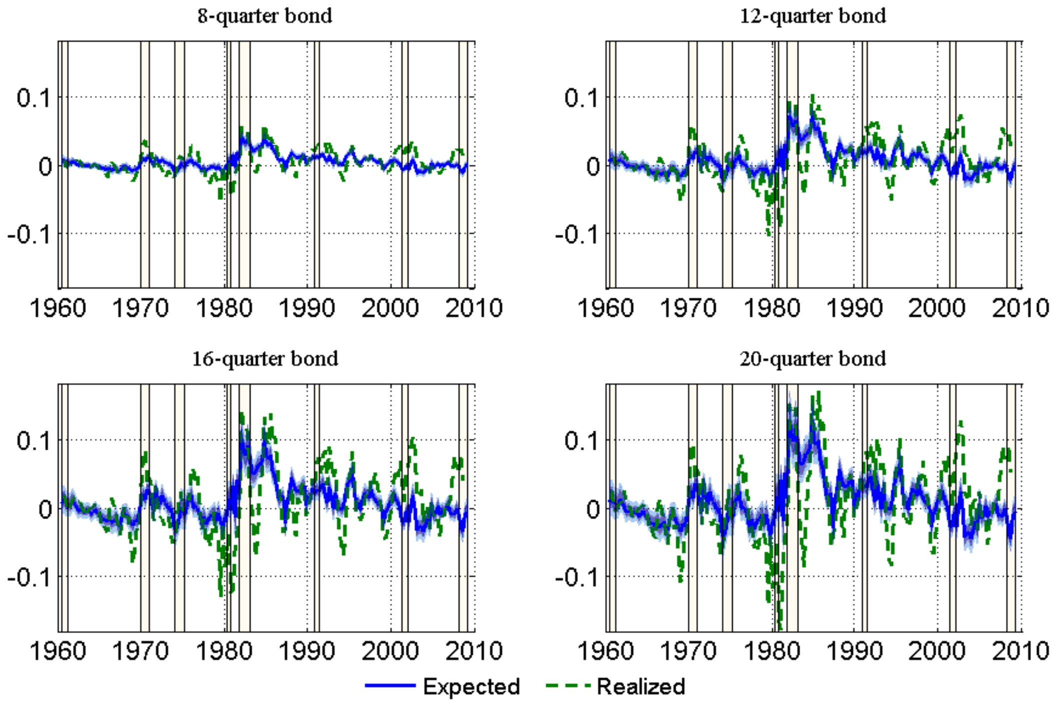
Note: This table reports the predictive coefficients, standard errors, and adjusted R^2 of four models to forecast GDP growth ($g_{t\to t+k}$) over a horizon of 1 , 4, and 8 quarters. Model 1 relates the GDP growth to the 4-, 20- and 40-quarter yield spreads ($Spr_t^{(n)} = y_t^{(n)} - y_t^{(1)}$) at time t. Model 2 links the GDP growth to the EMF model-implied 4-, 20- and 40-quarter expectations ($Spr_t^{e,(n)}$) and term premium ($\chi_t^{(n)}$) components of the yield spread. Model 3 relates the GDP growth to the 4-, 20- and 40-quarter yield spreads, the GDP growth between $t-1$ quarter and t (g_t), and the 1-quarter risk free rate ($y_t^{(1)}$). Model 4 forecasts the GDP growth by means of the EMF model-implied 4-, 20- and 40-quarter expectations and term premium components of the yield spread, the GDP growth between $t-1$ and t quarter, and the 1-quarter risk free rate. The standard errors of the coefficients are in parentheses. We estimate the model over the period 1960:Q1-2008:Q4.

Table 11: Forecasting changes in inflation (1960:Q1-2008:Q4)

Model 1	$\pi_t^{(k)} - \pi_t^{(4)} = \alpha + \beta Spr_t^{(k)} + \varepsilon_{t+k}$			
k	8 qtr	12 qtr	16 qtr	20 qtr
α	-0,001	-0,002	-0,003	-0,003
	(0,001)	(0,002)	(0,002)	(0,003)
β	0,419	0,655	0,622	0,516
	(0,203)	(0,208)	(0,215)	(0,236)
Adj.-R^2	0,063	0,161	0,155	0,113
Model 2	$\pi_t^{(k)} - \pi_t^{(4)} = \alpha + \beta^{EC}(Spr_t^{e,(k)} + \chi_t^{(k)}) + \beta^{TP}\chi_t^{(k)} + \varepsilon_{t+k}$			
k	8 qtr	12 qtr	16 qtr	20 qtr
α	-0,001	-0,001	-0,002	-0,001
	(0,001)	(0,001)	(0,002)	(0,003)
β^{EC}	1,045	1,022	0,895	0,727
	(0,239)	(0,228)	(0,229)	(0,249)
β^{TP}	-0,718	-0,693	-0,621	-0,572
	(0,157)	(0,144)	(0,132)	(0,144)
Adj.-R^2	0,302	0,343	0,298	0,233
Model 3	$\pi_t^{(k)} - \pi_t^{(4)} = \alpha + \beta_t Spr_t^{(k)} + \gamma\pi_t^{(-4)} + \delta y_t^{(1)} + \varepsilon_{t+k}$			
k	8 qtr	12 qtr	16 qtr	20 qtr
α	0,004	0,007	0,010	0,015
	(0,002)	(0,003)	(0,003)	(0,004)
β	0,253	0,353	0,246	0,054
	(0,167)	(0,183)	(0,183)	(0,179)
γ	-0,012	-0,044	-0,102	-0,170
	(0,056)	(0,076)	(0,084)	(0,087)
δ	-0,075	-0,116	-0,135	-0,153
	(0,027)	(0,039)	(0,047)	(0,053)
Adj.-R^2	0,193	0,300	0,325	0,347
Model 4	$\pi_t^{(k)} - \pi_t^{(4)} = \alpha + \beta^{EC}(Spr_t^{e,(k)} + \chi_t^{(k)}) + \beta^{TP}\chi_t^{(k)} + \gamma\pi_t^{(-4)} + \delta y_t^{(1)} + \varepsilon_{t+k}$			
k	8 qtr	12 qtr	16 qtr	20 qtr
α	-0,005	-0,005	-0,001	0,006
	(0,002)	(0,003)	(0,005)	(0,007)
β^{EC}	1,707	1,450	1,071	0,603
	(0,371)	(0,289)	(0,307)	(0,329)
β^{TP}	-1,713	-1,516	-1,233	-0,904
	(0,384)	(0,311)	(0,363)	(0,412)
γ	-0,137	-0,225	-0,280	-0,318
	(0,051)	(0,062)	(0,078)	(0,090)
δ	0,172	0,232	0,212	0,128
	(0,057)	(0,077)	(0,115)	(0,148)
Adj.-R^2	0,388	0,440	0,412	0,394

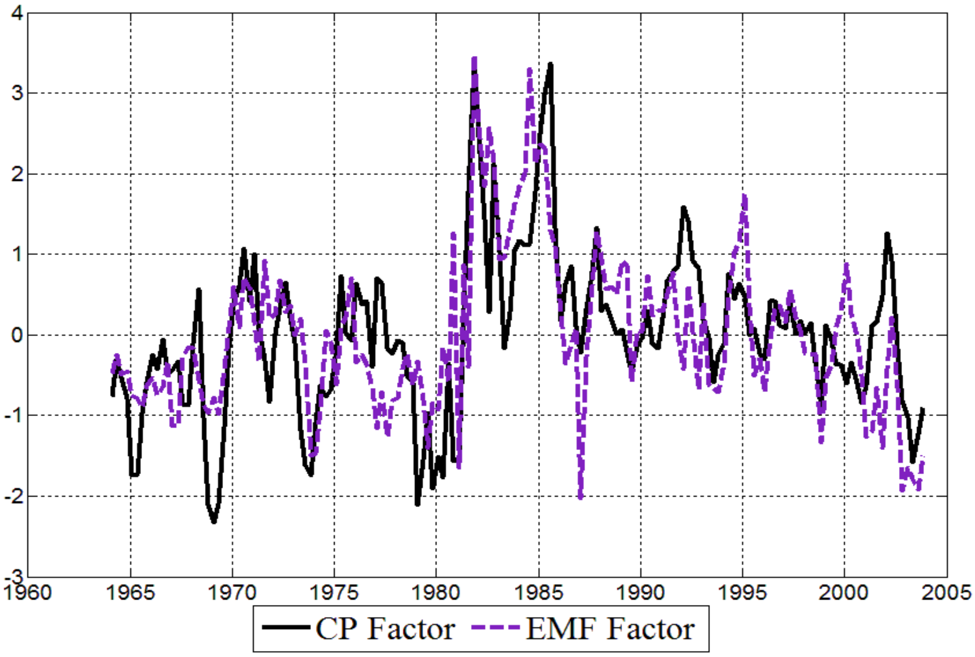
Note: This table reports the predictive coefficients, standard errors, and adjusted R^2 of four models forecasting the change in inflation (growth of the GDP deflator) over a horizon of 8, 12, 16 and 20 quarters. The methodology is directly related to Estrella and Mishkin (1997) and Mishkin (1990). The regressand is the difference between the future k-quarter inflation rate from time t to $t+k$ ($\pi_t^{(k)}$) and the future 4-quarter inflation rate from t to $t+4$ ($\pi_t^{(4)}$). Model 1 relates the change in inflation to the current 8, 12, 16 and 20-quarter yield spread over the 4-quarter yield ($Spr_t^{(k)} = y_t^{(k)} - y_t^{(4)}$). Model 2 links the change in inflation to the EMF model-implied 8, 12, 16 and 20-quarter expectations ($Spr_t^{e,(k)}$) and term premium ($\chi_t^{(k)}$) components of the yield spread at time t. Model 3 relates the change in inflation to the 8, 12, 16 and 20-quarter yield spreads, past inflation between $t-4$ quarters and t ($\pi_t^{(-4)}$), and the 1-quarter risk free rate ($y_t^{(1)}$). Model 4 forecasts the change in inflation by means of the EMF model-implied 8, 12, 16 and 20-quarter expectations and term premium components of the yield spread, past 4 quarters inflation, and the 1-quarter risk free rate. The standard errors of the coefficients are in parentheses. We estimate the model over the period 1960:Q1-2008:Q4.

Figure 1: Excess return: Expected vs. realized



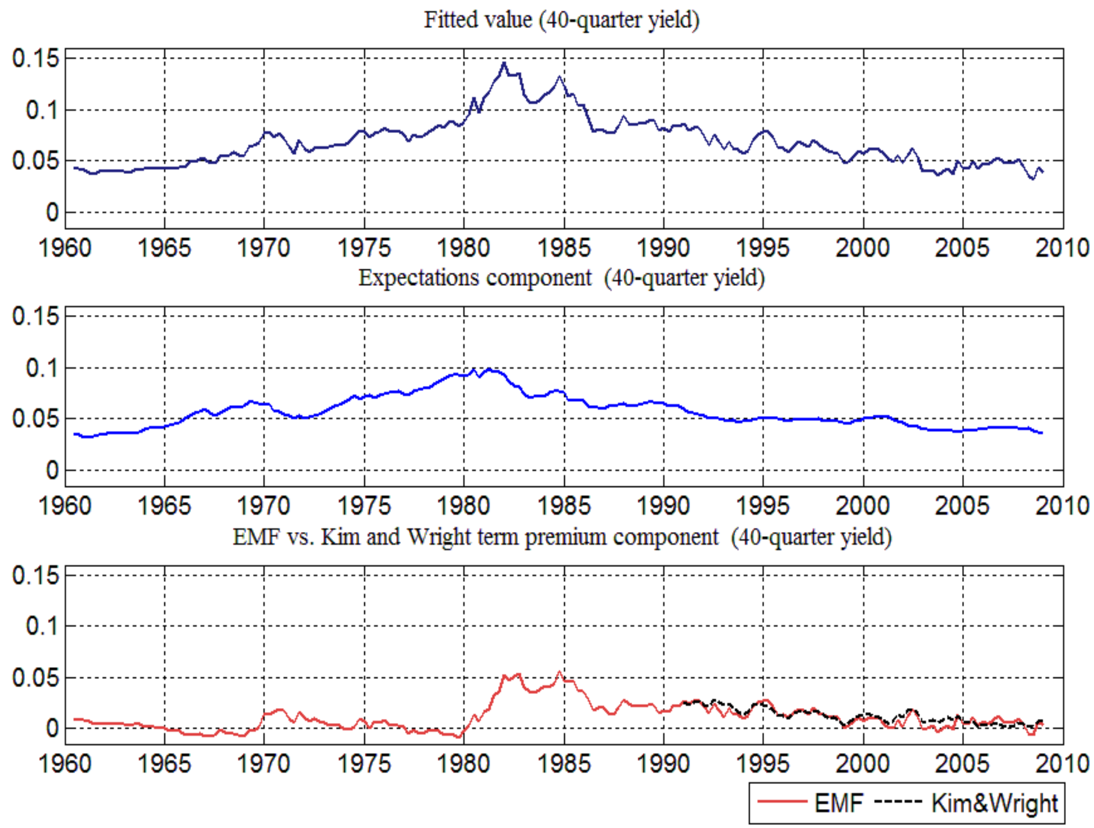
Note: This figure compares the EMF model-impled expected excess return (bond premium, continuous line) with the realized excess return (dashed line). The holding period is 4 quarters for bonds with maturities of 8, 12, 16 and 20 quarters.

Figure 2: Return-forecasting factor: CP vs. EMF factor



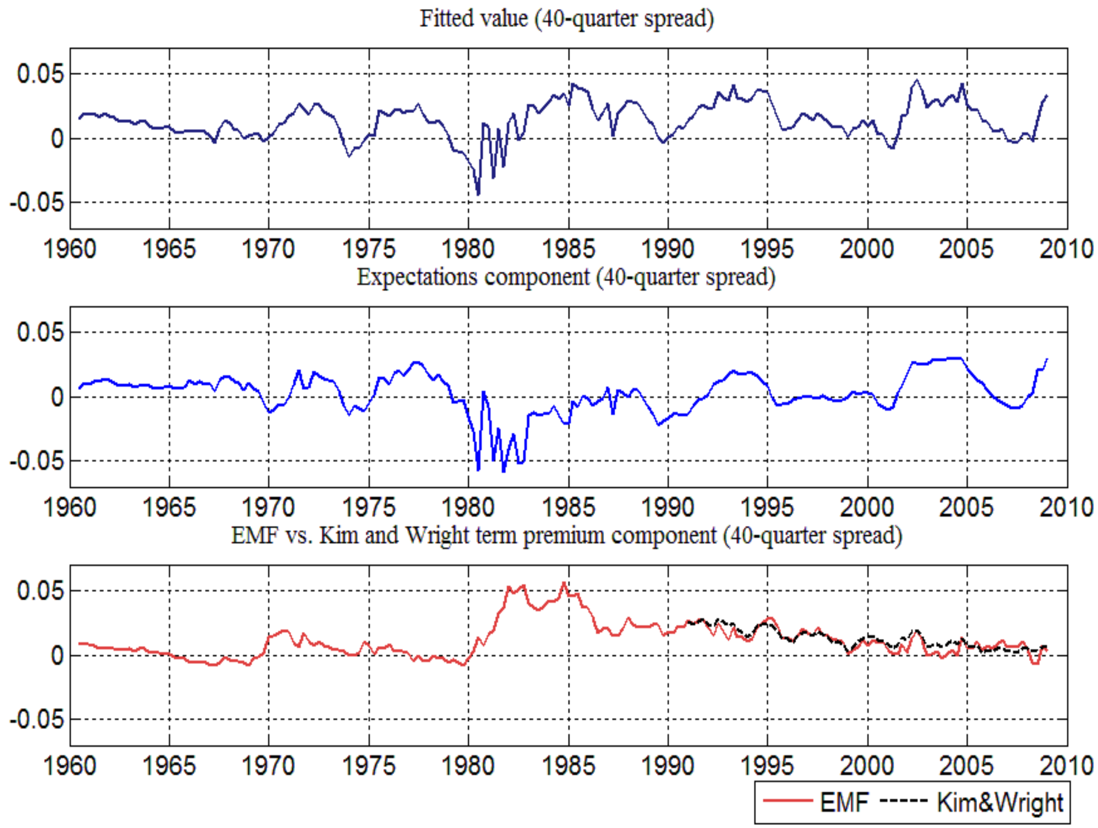
Note: This figure compares the Cochrane and Piazzesi (2005) factor (CP) with the EMF risk premium factor. Since the original CP factor is computed using monthly data and we work with quarterly frequencies, we compute the CP factor on a monthly basis and for each quarter we take the average of the monthly series. The correlation between our factor and the CP factor is 0.67.

Figure 3: Ten-year yield: fitted value, expectations component and term premium component



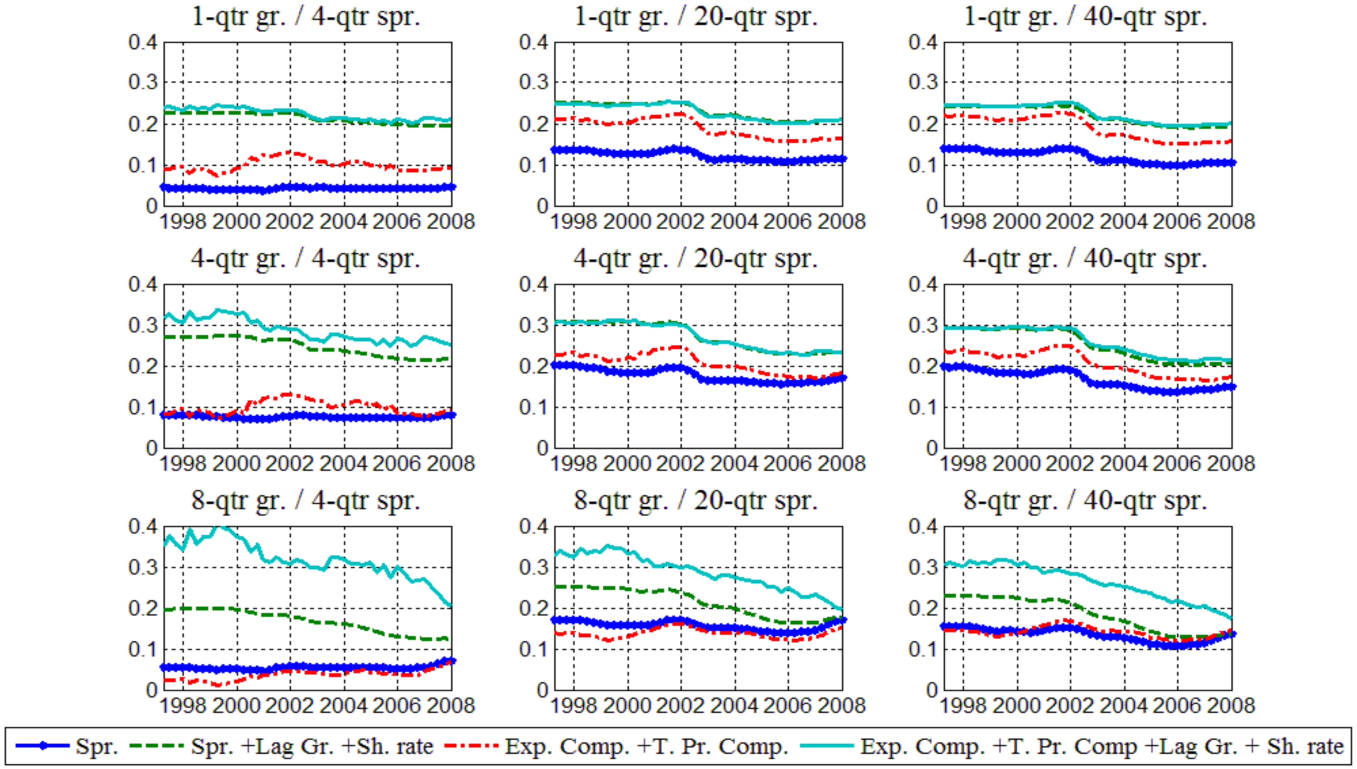
Note: The top panel of this figure plots the 40-quarter fitted yield. The middle panel depicts the EMF model-implied expected average 1-quarter yield over a period of 40 quarters. The bottom panel compares the EMF model-implied term premim for the 40-quarter bond (continuous line) with the term premium of Kim and Wright (2005) (dashed line).

Figure 4: Ten-year spread: fitted value, expectations component and term premium component



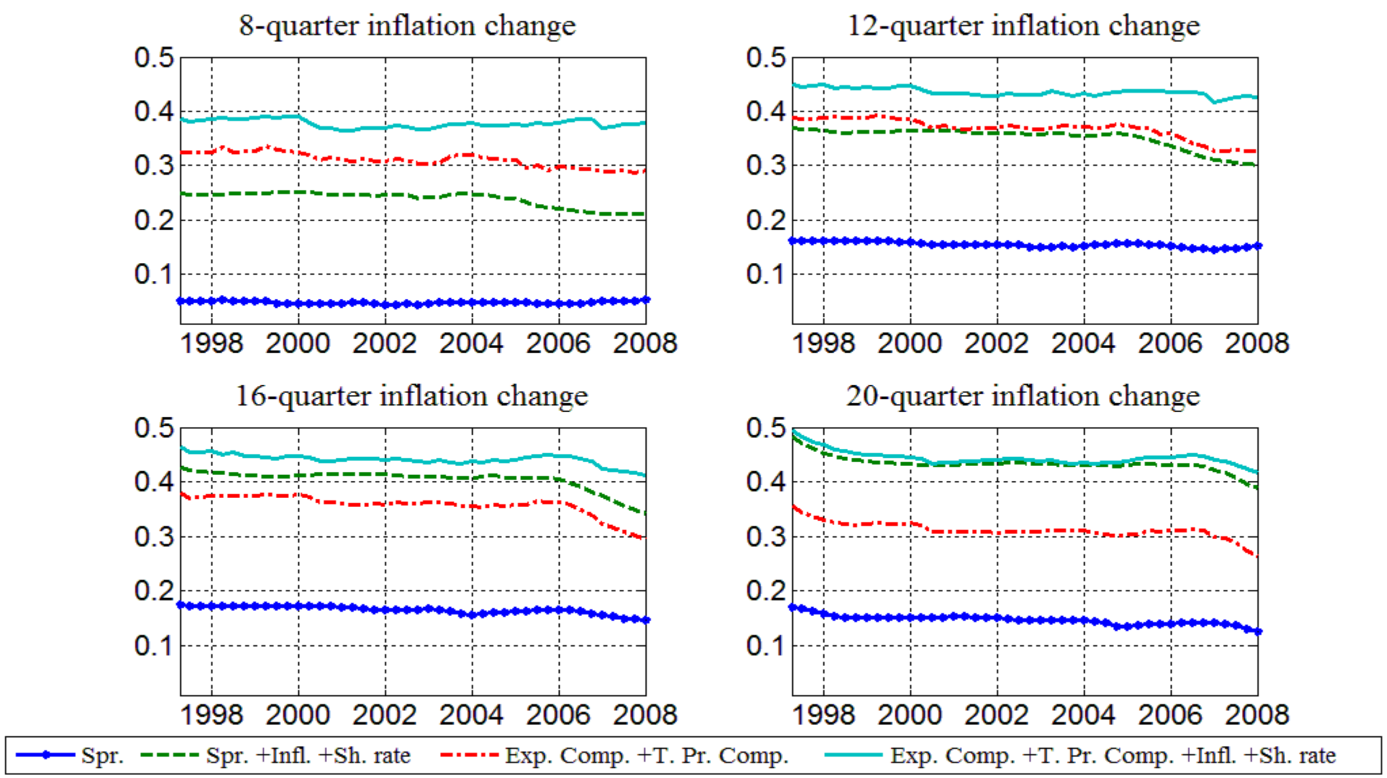
Note: The top panel of this figure plots the fitted spread of the 40-quarter yield less the 1-quarter yield. The middle panel depicts the EMF model-implied expected average 1-quarter yield over a period of 40 quarters minus the 1-quarter yield. The bottom panel compares the EMF model-impled term premium for the 40-quarter bond (continuous line) with the term premium of Kim and Wright (2005) (dashed line).

Figure 5: Forecasting real GDP growth, out-of-sample R-squared



Note: Each plot of this figure shows the adjusted R^2 over time for a certain predictive horizon using a certain yield spread. The rows of panels define the predictive horizon (1, 4, and 8 quarters) and the columns of panels the maturity of the yield spread used in the regression (4, 20, and 40 quarters). The date on the horizontal axis determines the end date of the sample period. The first point in each graph indicates the adjusted R^2 for the period 1960:Q1-1995:Q4. The EFM model is reestimated at every quarter using an expanding window.

Figure 6: FORECASTING INFLATION CHANGES, OUT-OF-SAMPLE R-SQUARED



Note: Each plot of this figure shows the adjusted R^2 over time for a certain predictive horizon and the corresponding yield spread (8, 12, 16 and 20 quarters). The date on the horizontal axis determines the end date of the sample period. The first point in each graph indicates the adjusted R^2 for the period 1960:Q1-1995:Q4. The EFM model is reestimated at every quarter using an expanding window.