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Abstract

A well-documented empirical result is that market expectations extracted from futures contracts on the federal funds rate are among the best predictors for the future course of monetary policy. We show how this information can be exploited to produce accurate forecasts of bond excess returns and to construct profitable investment strategies in bond markets. We use a tilting method for incorporating market expectations into forecasts from a standard term-structure model and then derive the implied forecasts for bond excess returns. We find that the method delivers substantial improvements in out-of-sample accuracy relative to a number of benchmarks. The accuracy improvements are both statistically and economically significant and robust across a number of maturities and forecast horizons. The method would have allowed an investor to obtain positive cumulative excess returns from simple "riding the yield curve" investment strategies over the past ten years, and in this respect it would have outperformed its competitors even after accounting for a risk-return tradeoff.

JEL Classification Codes: G1; E4; C5
Keywords: Yield curve modelling, Futures, Market Timing, Exponential tilting, Kullback-Leibler

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1 Introduction

We investigate the predictability of bonds excess returns and consider a method for exploiting data on market expectations to construct accurate out-of-sample forecasts of excess returns and to devise profitable investment strategies in bond markets.

Our study is motivated by the well-documented finding that the price of futures contracts on the federal funds rate (FFF) contains information regarding markets' expectations about future monetary policy decisions. FFF data are widely used by monetary authorities and financial markets' participants to gauge expectations concerning future monetary policy decisions (Kuttner, 2001; Bernanke and Kuttner, 2005) and their ability to anticipate policy actions has been documented in several empirical studies (Krueger and Kuttner, 1996; Söderström, 2001). They have also been found to outperform competing financial instruments (Gürkaynak et al. 2007). Because long rates are conditional expected values of future short rates - adjusted for risk premia - the entire yield curve is potentially affected by policy actions that involve changes to the federal funds rate (see Ang et al. 2007 and references therein). This paper shows how FFF data can be usefully exploited by forecasters and investors in bond markets by first incorporating them into a yield curve forecast and then converting yield curve forecasts into forecasts of excess returns for bonds of different maturities.

In order to incorporate the FFF data into a model-based forecast, we use the tilting method of Robertson et. al (2005), Giacomini and Ragusa (2013) and Altavilla et al. (2013). The method starts from a base model - in this case the Dynamic Nelson and Siegel (DNS) model of Diebold and Li (2006) for yields on bonds with different maturities, augmented by the federal funds rate. It then tilts the yield curve forecasts from the base model using the FFF-implied expectation for the relevant forecast horizon. The distinctive feature of the tilting method is that, even though the FFF is only a forecast of the very short end of the yield curve, the method incorporates the information that the FFF contains into the forecast of the entire yield curve. Given a set of forecasts for yields, we obtain the predictions for bond returns.

We document the out-of-sample accuracy gains that can be obtained from using the tilting procedure, according to a number of different metrics, and compare the FFF- tilted forecasts to three benchmarks: a forecast based on the DNS model, a forecast that imposes the expectation hypothesis (EH) and an autoregressive (AR) model forecast. We provide evidence of substantial and significant accuracy gains from using our procedure, when using either statistical or economically meaningful measures of forecast performance.

We then answer a practical question: could an investor use our method to devise profitable investment strategies in bond markets? We consider simple investment strategies consisting of "riding the yield curve" and compute cumulated returns and Sharpe ratios. We find that, over the last ten years, an investor who took position on the market according to the FFF-tilted forecasts in real time would have obtained significantly higher performance compared to the other model-based forecasts both in terms of risk-return compensation and cumulated excess returns. In almost all cases considered, our method would have delivered cumulated returns that are from twice as large to ten times as large as the cumulated returns obtained by the next best method.

There is a long literature investigating the predictability of bond excess returns, mainly from the perspective of in-sample fit. Fama and Bliss (1987), Campbell and Shiller (1991) and Fama (2004) find that the spreads between forward and spot rates have predictive power for excess returns. Cochrane and Piazzesi (2005) extend Fama and Bliss' (1987) regression by considering a combination of forward rates as predictors and show that this combination provides good in-sample fit and that it outperforms the "level", "slope" and "curvature" factors proposed by Litterman and Sheinkman (1991). Thornton and Valente (2012) evaluate the out-of-sample forecasting ability of the predictors in Fama and Bliss (1987) and Cochrane and Piazzesi (2005) in a dynamic asset allocation strategy and find that these regressions would not generate value for investors.

Because time series of bond returns can be computed from time series of yields on bonds with different maturities, the analysis of bond returns forecastability is also related to the question on how to model and forecast the yield curve. This is a vast and mature literature which features a broad range of modelling approaches.

One of the recent developments in this literature has been an emphasis towards augmenting term structure models with information that goes beyond the cross-section of yields - such as macroeconomic factors. Examples of contributions in this direction are Ang and Piazzesi (2003), DeWachter and Lyrio (2006), Ang et al. (2007), Bikbov and Chernov (2008), Duffee (2011), Ludvigson and Ng (2009), Cooper and Priestly (2009), Joslin et al. (2009). Structural models combining measures of economic activity with no-arbitrage specifications for the yield curve are proposed by Wu (2005), Hordahl et al. (2006), and Rudebusch and Wu (2008), whereas Diebold et al. (2006) and Monch (2008) incorporate macroeconomic information into the DNS model of Diebold and Li (2006).

The approach in this paper differs from the existing literature in two respects. Instead of focusing on macroeconomic information, we view the FFF-implied expectation as a summary measure of the information available at the time of forecasting which is relevant for predicting future interest rates. Instead of explicitly modifying the model to incorporate the additional information, we implicitly incorporate the information into the forecasts using the tilting method. In related research (Altavilla et al., 2013), we consider Blue Chip analysts survey data and document a persistent information gap between survey-based forecasts of short yields and yield forecasts based on the DNS model. We then show that incorporating the survey forecasts by augmenting the state space of the DNS model would not result in significant improvements in accuracy, whereas the tilting method delivers yield curve forecasts that are uniformly more accurate than those from the DNS model. The accuracy gains over the random walk however only occur at short horizons, which prompts us to seek better measures of interest rate expectations, and to move beyond yield curve forecasting and mean squared error comparisons and focus instead on bond returns, economically meaningful measures of performance and profitability of investment strategies in bond markets.

A possible concern when using futures prices to measure market expectations is the possible time variation in risk premia in FFF, which may lead to systematic forecast errors. The empirical evidence on this issue is however mixed. Piazzesi and Swanson (2008) document a predictable time variation in excess returns on FFF. Their results suggest that augmenting the information of market participants with variables available at the time they form their predictions about interest rate – they use change in nonfarm payroll - can increase the accuracy of the FFF forecasts. On the contrary, Sack (2004) and Durham (2003) find small time variation in risk premia in FFF. Krueger and Kuttner (1996) also find that FFF prices are efficient predictors of the federal funds rate although with a modest positive bias at one- and two-month horizons. In other words, the forecast errors are not significantly correlated with other variables available at the time the contracts were priced. Hamilton (2009) shows that high frequency data on near-term FFF rates reflect market participants' perception of future federal funds rates.

In the empirical analysis, we use raw FFF-implied forecasts as a measure of market expectations about the future course of monetary policy. To the extent that macroeconomic variables or risk adjustments can be used to further improve the forecasting performance of the FFF-implied forecast, the performance of the tilting method that we document in this paper could then be considered a lower bound.

The remainder of the paper is organized as follows: Section 3 introduces the data we use for the empirical analysis; Section 4 introduces to the tilting method and explains the methodology we used in the forecasting exercise. Section 5 reports the main empirical results while Section 6 concludes.

2 Data

In this section we discuss the yield data and the market expectations that we extract from the futures on the 30-day Federal Funds rate.

To measure yields, we use average of the month observations on one-day through five-year zero-coupon U.S. Treasury bonds taken from the dataset constructed by Gurkaynak, Sack and Wright (2007).[1] More precisely, we reconstruct the entire yield curve at the daily frequency starting from

[1] Dataset available at http://www.federalreserve.gov/pubs/feds/2006/.

the estimated parameters that are used to interpolate the term structure in the dataset, which use Svensson's (1994) method. We extract a total of 61 yields as well as the corresponding forward rates with maturity ranging from 1 day to 5 years. Finally, we aggregate each series at the monthly frequency. Summary statistics for the matrix of yields are reported in Table 1.

Federal Funds futures are contracts with payout at settlement date equal to the average effective federal funds rate in the month of expiration, as reported by the Federal Reserve Bank of New York. As every futures contract, they are designed to reflect expectations on the price of the underlying asset at the horizon specified by the settlement date. Federal funds futures have been traded since 1988 by the Chicago Board of Trade (CBOT). Each day, the CBOT trades futures contracts expiring in the next 36 calendar months. Data on historical futures prices are available on Bloomberg. We collected data measured on the first business day of each month for the period 1989:1-2011:12 on the 30-days Fed Funds future for the current month and the following 12 months. The futures price is reported as 100 minus the average daily federal funds rate for the month, and we thus compute the market expectation of the federal funds rate as 100 minus the futures price. Summary statistics for the futures contracts implied rates are reported in Table 2.

3 Methodology

The standard approach to studying the predictability of bond excess returns consists of estimating a predictive regression of the form:

$$rx_{t+h}^{(\tau)} = \beta Z_t + \varepsilon_{t+h}, \tag{1}$$

where $rx_{t+h}^{(\tau)}$ are excess returns on a bond with maturity τ bought at time t and sold at time $t+h$ and Z_t is a vector of variables observed at time t. For example, Fama and Bliss (1987) include individual forward rates and estimate

$$rx_{t+h}^{(\tau)} = c + \beta \left(f_t^{(\tau)} - y_t^{(h)} \right) + \varepsilon_{t+h}, \tag{2}$$

where $f_t^{(\tau)}$ is the $\tau-$period forward rate and $y_t^{(h)}$ the $h-$period spot rate[2]. Cochrane and Piazzesi (2005) find that excess returns can be predicted by a linear combination of spot and forward rates in the regression

$$rx_{t+h}^{(\tau)} = c + \beta Z_t + \varepsilon_{t+h}, \ \tau = 1, ..., 5 \tag{3}$$

where $Z_t = \left[y_t^{(1)}, f_t^{(2)}, \ldots, f_t^{(5)} \right]$.

Thornton and Valente (2012) show that the predictive power of Cochrane and Piazzesi's (2005) regression (3) does not hold out-of-sample, so we seek alternative specifications. Because of the

[2] They focus on the case in which $h = 1$

relationship between returns and yields, an alternative expression for excess returns can be obtained by starting from term structure models which express the yield curve as a function of dynamic latent shocks. Considering Diebold and Li's (2006) model, for example, one can show that excess returns can be represented in terms of the factors underlying the yield curve.

To see why, note that Diebold and Li's (2006) model is

$$\begin{array}{c} y_t^{(\tau)} = HX_t + \eta_t = L_t + \lambda_1^{(\tau)} S_t + \lambda_2^{(\tau)} C_t + \eta_t \\ X_t = c + \Phi X_{t-h} + \varepsilon_t \end{array} \tag{4}$$

where $y_t^{(\tau)}$ is a yield with maturity τ, $X_t = [L_t, S_t, C_t]^{'}$ is the vector of latent factors (level, slope and curvature), $\lambda_1^{(\tau)} = \frac{1-e^{-\gamma\tau}}{\gamma\tau}$ and $\lambda_2^{(\tau)} = \frac{1-e^{-\gamma\tau}}{\gamma\tau} - e^{-\gamma\tau}$ are the factor loadings, $c = [c_1, c_2, c_3]^{'}$ and Φ is a diagonal matrix of autoregressive coefficients with elements ϕ_1, ϕ_2 and ϕ_3. Given the definition of bond excess returns

$$rx_{t+h}^{(\tau)} = r_{t+h}^{(\tau)} - y_t^{(h)} = y_t^{(\tau)} - y_{t+h}^{(\tau-h)} - y_t^{(h)}, \quad \text{with} \quad \tau = n + h \tag{5}$$

it is easy to see that excess returns are a function of the yield curve factors:

$$rx_{t+h}^{(\tau)} = \varphi_1 + \varphi_2 L_t + \varphi_3 S_t + \varphi_4 C_t, \tag{6}$$

where $\varphi_1 = -\left(c_1 + \lambda_1^{(\tau-h)} c_2 + \lambda_2^{(\tau-h)} c_3\right)$, $\varphi_2 = -\phi_1$, $\varphi_3 = \left(\alpha_1 + \lambda_1^{(\tau-h)} \phi_2\right)$ and $\varphi_3 = \left(\alpha_2 + \lambda_2^{(\tau-h)} \phi_3\right)$, with $\alpha_1 = \left(\lambda_1^{(\tau)} - \lambda_1^{(h)}\right)$ and $\alpha_2 = \left(\lambda_2^{(\tau)} - \lambda_2^{(h)}\right)$.[3] Equation (6) is thus a predictive regression of the form (3) where $\mathbf{Z}_t$ are latent yield curve factors instead of combinations of forward rates.

The next question we address is how to incorporate the information contained in the FFF-implied expectation for the federal funds rate into forecasts for future excess returns. We start by adding the FFF-implied expectation as a regressor in (3) and find only marginal improvements in in-sample fit and only for very short maturities, which suggests that it would not be worth considering the augmented regression in an out-of-sample context, and that the conclusions would likely not differ from those of Thornton and Valente (2012).

We thus consider a different approach. We start from the DNS model of the yield curve for bonds with maturity 1-day (i.e., the federal funds rate), and 1 to 60 months. We produce a forecast

[3] From the definition of excess return we can write

$$\begin{array}{c} rx_{t+h}^{(\tau)} = \lambda_1^{(\tau)} S_t + \lambda_2^{(\tau)} C_t \\ -\lambda_1^{(h)} S_t - \lambda_2^{(h)} C_t \\ -L_{t+h} - \lambda_1^{(\tau-h)} S_{t+h} - \lambda_2^{(\tau-h)} C_{t+h}. \end{array}$$

Collecting terms

$$rx_{t+h}^{(\tau)} = -L_{t+h} + \left(\lambda_1^{(\tau)} - \lambda_1^{(h)}\right) S_t + \left(\lambda_2^{(\tau)} - \lambda_2^{(h)}\right) C_t - \lambda_1^{(\tau-h)} S_{t+h} - \lambda_2^{(\tau-h)} C_{t+h},$$

and using the autoregressive specification for the factors

$$rx_{t+h}^{(\tau)} = constant - \phi_1 L_t + (\alpha_1 + \lambda_1^{(\tau-h)} \phi_2) S_t + (\alpha_2 + \lambda_2^{(\tau-h)} \phi_3) C_t.$$

of the yield curve implied by the DNS model and then use the tilting method to anchor the yield curve forecast at the FFF-implied forecast for the federal funds rate. The procedure delivers a new forecast for the whole yield curve which equals the FFF-implied forecast for the first yield, whereas the remaining yields change in a way that makes the new yield curve forecast as close as possible (according to a Kullback-Leibler measure of divergence) to the original forecast density.

We conduct an out-of-sample forecasting exercise designed to mimic what an actual investor would have done in real time over the period 1985 - 2012. Using the first sample, which ranges from 1985:1-2003:1, we produce three out-of-sample h-step ahead forecasts for the yield curve: the first based on the DNS model, the second based on the DNS model tilted to incorporate the FFF expectation measured at 2003:1 for the forecast horizons of interest and the last based on an autoregressive model. We then augment the estimation sample with data point 2003:2 and repeat the exercise, then iterate until all observations are exhausted. We finally derive the implied forecasts of bond excess returns from the forecasts of the yields. We consider different forecast horizons: $h = 3, 6, 9, 12$ months, so that the last forecast is produced using the sample 1985:1 - 2011:12. The next section describes how we obtain the out-of-sample forecasts for both yields and returns.

3.1 The forecasts

Let FFR_t be the average federal funds rate (FFR) over month t, and Y_t a vector of yields. Denote the typical element of Y_t as $Y_t^{(\tau)}$, for maturity $\tau = 1, 2, ..., 60$ months. The yield data are average of the month zero-coupon yields constructed aggregating daily data from the Gurkaynak, Sacks and Wright (2006) dataset.

To derive $h-$step ahead forecasts of the yields, for each h we estimate the following model:

$$Z_t = \begin{bmatrix} FFR_t \\ Y_t \end{bmatrix} = HX_t + \eta_t \tag{7}$$

$$X_t = c + \Phi X_{t-h} + \varepsilon_t, \tag{8}$$

where X_t is a 3×1 vector containing three latent factors (level, slope and curvature). Each row of the matrix of factor loadings H has elements $1, \frac{1-e^{-\gamma\tau}}{\gamma\tau}$ and $\frac{1-e^{-\gamma\tau}}{\gamma\tau} - e^{-\gamma\tau}$where $\tau = \frac{1}{22}, 1, 2, ..., 60$ is the bond maturity.[4] As in Diebold and Li (2006), we set $\lambda = 0.0609$ (which is the value that maximizes the loadings on the curvature factor at 30 months) and we estimate the model in two steps, by first regressing Z_t on the columns on H and obtaining the fitted values $\widetilde{X}_t$ and then estimating (8) using the fitted $\widetilde{X}_t$ and assuming that Φ is diagonal.

The $h-$ step ahead forecasts at time t for the FFR and the yields implied by the DNS model are

[4] Note that we treat the FFR_t and a one-day-yield.

then given by

$$\widehat{Z}_{t+h}^{DNS} = \begin{bmatrix} \widehat{FFR}_{t+h}^{DNS} \\ \widehat{Y}_{t+h}^{DNS} \end{bmatrix} = H(\widehat{c} + \widehat{\Phi}\widetilde{X}_t). \tag{9}$$

The procedure for tilting the forecast $\widehat{Z}_{t+h}^{DNS}$ to incorporate market expectations is the following. Let $\widehat{FFF}_{t+h}$ indicate the FFF-implied expectation available at time t for horizon h. The tilted forecast is then given by

$$\widehat{Z}_{t+h}^{FFF} = \begin{bmatrix} \widehat{FFF}_{t+h} \\ \widehat{Y}_{t+h}^{FFF} \end{bmatrix}, \tag{10}$$

$$\widehat{Y}_{t+h}^{FFF} = \widehat{Y}_{t+h}^{DNS} - \Omega_{21}\Omega_{11}^{-1}\left(\widehat{FFR}_{t+h}^{DNS} - \widehat{FFF}_{t+h}\right),$$

with $\Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}$, where Ω_{11} is a scalar and Ω is given by

$$\Omega = \frac{1}{t-h}\sum_{j=h+1}^{t}\left(Z_j - H(\widehat{c} + \hat{\Phi}\widetilde{X}_{j-h})\right)\left(Z_j - H(\widehat{c} + \hat{\Phi}\widetilde{X}_{j-h})\right)'. \tag{11}$$

See Giacomini and Ragusa (2013) for a formal justification of the tilting procedure. To give a brief summary, the procedure starts from a density forecast $f^{DNS} \sim N(\widehat{Z}_{t+h}^{DNS}, \Omega)$ and delivers a new density forecast $f^{FFF} \sim N(\widehat{Z}_{t+h}^{FFF}, \Omega)$ which is the density with conditional mean for the first element of Z_{t+h} equal to the FFF expectation and which is closest to the density f^{DNS} according to a Kullback-Leibler measure of divergence. Giacomini and Ragusa (2013) show that if $\widehat{FFF}_{t+h}$ encompasses $\widehat{FFR}_{t+h}^{DNS}$ the whole tilted density forecast f^{FFF} is more accurate than the original density forecast f^{DNS}, when accuracy is measured by the logarithmic scoring rule of Amisano and Giacomini (2007). Encompassing is not rejected in the data, so there is scope for incorporating the FFF-implied expectation into the yield curve forecast. Whether this results in a statistically and economically significant improvement in accuracy for the individual excess returns can only be established on a case-by-case basis, and answering this question is the goal of our empirical application.

One of the benchmark models is an autoregression of order one (AR), which implies the following forecast:

$$\widehat{Z}_{t+h}^{AR} = \begin{bmatrix} \widehat{FFR}_{t+h}^{AR} \\ \widehat{Y}_{t+h}^{AR} \end{bmatrix} = \hat{\rho}^{(h)} \begin{bmatrix} FFR_t \\ Y_t \end{bmatrix}, \tag{12}$$

with $\hat{\rho}^{(h)}$ estimated from the regression

$$Z_t = \hat{\rho}^{(h)} Z_{t-h} + n_t. \tag{13}$$

The above procedure gives three $h-$ step ahead out-of-sample forecasts for the vector of yields: $\widehat{Y}_{t+h}^{(\tau)DNS}$, $\widehat{Y}_{t+h}^{(\tau)FFF}$, $\widehat{Y}_{t+h}^{(\tau)AR}$, $\tau = 1, 2, ..., 60$.

To derive the forecasts for bond excess returns, we use the fact that

$$r_{t+h}^{(\tau)} = \tau Y_t^{(\tau)} - (\tau - h) Y_{t+h}^{(\tau-h)}, \text{ for } \tau = 1 + h, 2 + h, ..., 60. \quad (14)$$

which implies that one can obtain the $h-$step ahead forecast at time t of the return on a bond with maturity τ and holding period h (i.e., a forecast of $r_{t+h}^{(\tau)}$) as

$$\widehat{r}_{t+h}^{(\tau)} = \tau Y_t^{(\tau)} - (\tau - h) \widehat{Y}_{t+h}^{(\tau-h)}, \ \tau = 1 + h, 2 + h, ..., 60. \quad (15)$$

Using formula (15) we can thus obtain three $h-$step ahead out-of-sample forecasts for the vector of returns and the corresponding forecasted excess returns

$$\widehat{rx}_{t+h}^{(\tau)} = \widehat{r}_{t+h}^{(\tau)} - hY_t^{(h)}, \ \tau = 1 + h, 2 + h, ..., 60. \quad (16)$$

that are implied by the DNS model, the DNS tilted using FFF-implied expectation and the AR: $\widehat{rx}_{t+h}^{(\tau)DNS}$, $\widehat{rx}_{t+h}^{(\tau)FFF}$, $\widehat{rx}_{t+h}^{(\tau)AR}$.

3.2 Forecast evaluation

The procedure described in the previous section gives three sequences of $h-$step ahead out-of-sample forecasts for excess returns on bonds with maturity $\tau = h + j$ with $j = 1, 3, 6, 9, 12$ and $h = 3, 6, 9, 12$ given by (16) with $\widehat{Y}_{t+h}^{(\tau-h)}$ either as in (9), (10) or (12). We also consider the additional benchmark represented by imposing the expectation hypothesis (EH), which implies that excess returns are given by the spread between spot and forward rates observable at each point in time, which is equivalent to a random walk forecast for spot rates.

We start by evaluating the forecast accuracy of each individual excess return forecast by performing the Pesaran and Timmermann's (1992) test for market timing.

We then perform a pairwise Diebold and Mariano (1995) test using both a quadratic loss and a direction of change loss.

Finally, we consider a simple investment strategy consisting of riding the yield curve: given a specified investment horizon, we take position on the market by comparing the return of a risk free bond with the returns forecasted by (9), (10) and (12).

4 Results

4.1 In-sample return predictability regressions

This section motivates the use of market expectations for forecasting bond excess returns. Summary statistics for excess returns are reported in Table 3. We consider the Cochrane and Piazzesi (2005) regression (on our different yield data and sample) and ask whether market expectations implied by federal funds future data can explain excess bond returns above and beyond the information already contained in the Cochrane and Piazzesi (2005) factor, which is a function of forward rates. Specifically, we run the regressions

$$rx_{t+h}^{(\tau)} = \beta_1^{(\tau,h)}(\gamma' f_t) + \beta_2^{(\tau,h)}\widehat{FFF}_{t+h} + \varepsilon_{t+h},\ \ \tau = 1+h, ..., 60 \tag{17}$$

where $rx_{t+h}^{(\tau)}$ are excess returns of a bond with maturity τ and a holding period h and are given by (??) and $\gamma' f_t$ is the fitted Cochrane and Piazzesi (2005) single factor obtained by regressing average excess returns across maturities on time-t forward rates for all maturities

$$\frac{1}{60-h}\sum_{j=1+h}^{60} rx_{t+h}^{(j)} = \gamma_0 + \gamma_1 Y_t^{(h)} + \gamma_2 f_t^{(1+h)} + \gamma_3 f_t^{(2+h)} + ... + \gamma_{61} f_t^{(60)} + \eta_{t+h} \tag{18}$$

$$= \gamma' f_t + \eta_{t+h} \tag{19}$$

with $f_t = [1 \quad Y_t^{(h)}\ f_t^{(1+h)}\ ...\ f_t^{(60)}]'$.

We consider the period 1995:01-2011:12. Forward rates are obtained by constructing the daily forward curves using Svensonn's (1994) method. We construct a set of 60 forward rates at each point in time, with maturities ranging from 1 month to 5 years. These daily rates are then aggregated at the monthly frequency.

Table 4 reports estimates of the coefficients $\beta_1^{(\tau,h)}$ and $\beta_2^{(\tau,h)}$ for $h = 1, 2, ..., 12$ and $\tau = j + h$ with $j = 1, 3, 6, 9, 12$.

$[INSERT\ TABLE\ 4]$

We report the results in twelve panels, corresponding to the different forecast horizons h. In each panel, for both the augmented regression (17) and the original Cochrane and Piazzesi (2005) regression we present the estimates for the coefficients and the $\bar{R}^2$. The estimates of the coefficients of the Cochrane and Piazzesi (2005) factor are always statistically significant for all the maturities and holding periods considered. The general pattern that emerges from Table 4 is that the FFF coefficient $\beta_2^{(\tau,h)}$ is significant for short maturities and short holding periods but becomes insignificant as we consider longer maturities and holding periods. A similar conclusion can be reached when considering the marginal contribution to the model's fit of adding the FFF as a predictor. The increase in the adjusted R^2 when adding the FFF is maximum at the shortest maturities (where we observe an improvement of about 7%), while the effect decreases to almost zero for long maturities.

The general conclusion from the in-sample regression analysis is that FFF has only marginal predictive power for bond returns of very short maturities and short holding periods. This suggests that if one were to utilize the augmented model (17) to predict excess bond returns out-of-sample, the addition of the FFF as a regressor would likely not be enough to overturn the conclusion of Thornton and Valente (2012) that the Cochrane and Piazzesi regression is not useful for forecasting out-of-sample nor for seeking profitable investment strategies in bond markets. Our tilting method, instead, offers the opportunity to exploit the predictive power of the FFF for returns on short maturity bonds and "transmit" the predictive ability to bonds of longer maturities.

4.2 Out-of-sample forecast performance

In this section we analyze the out-of-sample performance of the excess returns forecasts implied by the three models: the DNS model of Diebold and Li (2006) (DNS), the DNS model tilted using federal funds future-implied market expectations (FFF) and the autoregressive model (AR). The forecasts are given by (16) with $\hat{Y}_{t+h}^{(\tau-h)}$ either as in (9), (10) or (12). We also consider the additional benchmark represented by the expectation hypothesis (EH).

The forecast exercise covers the period between 2003:1-2011:12 and mimics the behavior of an investor who at each point in time forecasts the term structure at forecast horizons $h = 3, 6, 9, 12$. As for the predictive regressions, we restrict attention to a subset of excess returns with maturities $\tau = j + h$, with $j = 1, 3, 6, 9, 12$.

4.2.1 Statistical significance

We start by performing Pesaran and Timmermann's (1992) test of sign predictability on each of the four forecasts. Table 5 reports the proportion of times that the sign of excess returns is correctly predicted by the sign of the four competing forecasts. Stars indicate rejection of the null hypothesis of independence between realizations and forecasts.

[*INSERT TABLE* 5]

The table shows that the tilted forecasts clearly dominate the competitors for each maturity and for each forecast horizon. The tilted forecasts are the only ones for which the null hypothesis of independence between forecasts and realizations is rejected in all cases. For the DNS forecasts the hypothesis is never rejected, for the AR forecast it is only rejected once out of twenty cases and for the EH forecasts it is rejected in three out of twenty cases. Moreover, the proportion of correct predictions for the tilted forecasts ranges between 58% and 79%, whereas for the AR and the EH forecasts the proportion of correct predictions hovers around 50%, making these forecasts no better than a coin toss. The DNS forecasts fare poorly overall, with correct predictions as low as 17% and never higher than 49%. These conclusions are generally valid across maturities and horizons, with a slight deterioration in performance for all forecasts at the longest (12 months) forecast horizons.

We next assess the relative performance of the various forecasts in terms of both a quadratic and a direction of change loss. Table 6 reports ratios of average losses for the tilted model relative to each of the three benchmarks, together with significance levels for Diebold and Mariano's (1995) test of equal average loss.

[*INSERT TABLE* 6]

The picture that emerges from Table 6 is clear. The tilted forecasts outperform (significantly, in all but two cases) all three benchmarks for all maturities and forecast horizons in their ability to predict the direction of change of excess bond returns. A similar conclusion holds for the quadratic loss, with the difference that the tilted forecast does not perform well at the 12-month-ahead forecast horizon. This could be a consequence of the low liquidity in the market for futures contracts with a long forecast horizon.

The improvements in accuracy that can be obtained by exploiting the information contained in futures prices are generally of sizable magnitude, ranging between about 30% and 50%.

4.2.2 Economic significance

Next, we investigate whether the tilting method for incorporating market expectations into bond return forecasts can result in profitable investment strategies in bond markets. We consider the excess returns that an investor can realize by simple "riding the yield curve" strategies, relative to the benchmark case of buying a bond and bringing it to maturity.

In its simplest form, riding the yield curve consists of deciding whether to buy a bond with maturity h today and bringing it to maturity after h periods, or to buy a bond with maturity $j+h$ today and then sell it after h periods, at which point it will become a bond with maturity j. The investor will choose the latter strategy when her $h-$periods-ahead forecast for the return on a bond with maturity j is higher than the return from bringing the $h-$period bond to maturity.

We consider two scenarios. In the first one, the investor decides every h periods whether to buy a bond with h months maturity or to ride the yield curve based on a forecasting model for excess returns that she estimates on the data available at that point in time. Notice that in this case the number of trading times over the sample varies depending on h. For example, when $h = 3$ trades will occur 36 times from January 2003 until December 2011; when $h = 6$ the investor can take a position 18 times and so on. Once the decision is made, the investor is committed to either holding the h-month bond to maturity or to selling the longer maturity bond in h months. We also consider a second scenario in which the investor is able to trade every period and considers different holding periods h.

In both cases, the investment decision can be described as follows:

- At each trading time t, observe the yield of a $h-$month bond $Y_t^{(h)}$ and produce a forecast $\hat{r}_{t+h}^{(j)}$ of the return on a $j-$month bond at time $t+h$. Buy the $h-$month bond if $Y_t^{(h)} \geq \hat{r}_{t+h}^{(j)}$ or buy a $\tau = j + h$ −month bond otherwise.

- At time $t+h$, either realize a return $\bar{r}_{t+h}^{(\tau)} = Y_t^{(h)}$ from holding the $h-$months bond to maturity or $\bar{r}_{t+h}^{(\tau)} = r_{t+h}^{(\tau)}$ from selling the $j + h-$month bond.

- Repeat the previous two steps at each trading time t.

We assess the performance of the riding strategy by computing the total cumulated excess returns realized when riding the yield curve according to the different forecasts: (9), (10) and (12). We further compute Sharpe ratios for the different forecasts, defined as

$$SR^{(\tau,h)} = \frac{1}{T-h+1} \sum_{t=1}^{T-h} \frac{\bar{r}_{t+h}^{(\tau)} - Y_t^{(h)}}{\sqrt{Var\left(\bar{r}_{t+h}^{(\tau)} - Y_{t+h}^{(h)}\right)}}. \tag{20}$$

The Sharpe ratio provides an assessment of the average compensation for risk one obtains from following the riding strategy. Our benchmark case is the expectation hypothesis, which states that the investor is indifferent between holding an h period bonds to maturity and riding the yield curve, and which implies $SR^{(\tau,h)} = 0$.

As for the forecast evaluation we consider the period ranging from 2003:01-2011:12 and focus on investment horizons $h = 3, 6, 9, 12$ and bonds with maturities $\tau = j + h$, for $j = 1, 3, 6, 9, 12$.

Table 7 reports the cumulated excess returns for the different forecasts, different maturities and different holding periods. For example, the first entry (0.27) represents the cumulated excess returns from a strategy that every three months either buys a four-month bond and sells it after three months or buys a three-month bond and holds it to maturity, depending on whether the three-month-ahead tilted forecast of the return on a one-month bond is greater than the yield on a three-month bond.

[*INSERT TABLE* 7]

Table 7 shows that the tilted forecast is the only forecast to consistently yield positive excess returns for all maturities and holding periods. The DNS forecasts almost always yield negative excess returns whereas the AR forecasts yield positive returns only when trading every period. In the latter case, the excess returns from basing the trading strategy on the tilted forecasts rather than on the AR forecasts are larger, except in the case of a 24-month bond held for 12 months, which we saw in the previous section is also the horizon at which the tilted forecasts begin to deteriorate, probably due to illiquid markets for futures contracts of such length. In all other cases, the tilted forecast delivers cumulated returns that are from twice as large to ten times as large as the cumulated returns from using the AR forecasts.

Table 8 reports Sharpe ratios for the various forecasts, maturities and holding periods..

$[INSERT\ TABLE\ 8]$

Table 8 confirms that, even after accounting for risk, the tilted forecasts deliver risk-adjusted returns that are higher than those of all competitors. The Sharpe ratios for the tilted forecast are always positive, implying that it is always preferable for an investor to ride the yield curve than to buy and bring a bond to maturity, provided that the forecast of returns is formulated according to the tilted method. This is true for all investment horizons and all maturities, and regardless of whether the investor trades every period or once every h periods. The risk-adjusted returns is largest when the investor trades longer maturity bonds and holds them for longer periods, but not longer than nine months. Again this is due to the deterioration in the forecast performance of the tilting method at the 12-month horizon.

The table further reveals that Sharpe ratios for the tilted forecasts increase with the bond maturity. This implies that the investor obtains higher returns by trading in bonds with longer time to expiration without boosting the risk taken.

We conclude our analysis of the economic significance of our results by following Fleming et al. (2001), Marquering and Verbeek (2004), Della Corte et al. (2008,2009) and Thorton and Valente (2012) in computing the utility gains that a risk adverse investor would obtain by using the tilted forecast relative to the other benchmark forecasts. In particular, we compute how much a risk adverse investor would be willing to pay to switch from a forecast of excess returns based on the DNS, the AR and the expectation hypothesis to the FFF-tilted forecast. Assuming a quadratic utility function, the realized average utility for an investor endowed with one unit of wealth is

$$\bar{U}\left(\mathcal{R}_{t+h}^{(\tau)}, \lambda\right) = \frac{1}{T-h+1}\sum_{t=0}^{T-h}\left\{\mathcal{R}_{t+h}^{(\tau)} - \frac{\lambda}{2\left(1+\lambda\right)}\left(\mathcal{R}_{t+h}^{(\tau)}\right)^2\right\}, \tag{21}$$

where $\mathcal{R}_{t+h}^{(\tau)} = 1 + r_{t+h}^{(\tau)}$ and λ denotes the degree of relative risk aversion. Fleming et al. (2001) measure the economic value of alternative predictive models by equating the their average realized utility and by assuming the existence of a performance fee Δ for switching from a benchmark forecast to an alternative forecast. We compute Δ as the solution to

$$\begin{array}{c} \sum_{t=0}^{T-h}\left\{\left(\mathcal{R}_{t+h}^{(\tau),FFF} - \Delta\right) - \frac{\lambda}{2(1+\lambda)}\left(\mathcal{R}_{t+h}^{(\tau),FFF} - \Delta\right)^2\right\} = \\ \sum_{t=0}^{T-h}\left\{\left(\mathcal{R}_{t+h}^{(\tau),\mathcal{M}}\right) - \frac{\lambda}{2(1+\lambda)}\left(\mathcal{R}_{t+h}^{(\tau),\mathcal{M}}\right)^2\right\}, \end{array} \tag{22}$$

where $\mathcal{R}_{t+h}^{(\tau),FFF}$ is the gross return obtained by riding the yield curve according to the tilted forecast and $\mathcal{R}_{t+h}^{(\tau),\mathcal{M}}$ is the gross return obtained using forecast $\mathcal{M} = DNS, AR, EH$. If there is economic value to the investor in riding the yield curve according to the tilted forecast compared to a selected benchmark, then $\Delta > 0$. As in Thorton and Valente (2012) we set $\lambda = 5$[5]. Table 9 reports the results of the exercise.

$$[INSERT \quad TABLE \quad 9]$$

The table reveals that fees are always positive compared to the other benchmarks, indicating that a risk averse investor would always be willing to pay to use the tilted forecast in predicting future returns, with the only exception represented by the comparison with the AR forecasts at maturity $j = 12$ and forecast horizon $h = 12$, which is consistent with our previous results.

5 Conclusions

This paper investigates the out-of-sample predictability of bond excess returns and asks whether market-based expectations about future macroeconomic conditions can be usefully exploited by investors in bond markets.

We extract market expectations about the federal funds rate at different forecast horizons from the prices of federal funds rate futures contracts. The literature has extensively documented that these expectations are one of the most accurate available predictors for the future path of the federal funds rate, which in turn affects the entire term structure of interest rates. We exploit the link between the yield curve and bond excess returns and begin by incorporating market expectations into yield curve forecasts based on the DNS model of Diebold and Li (2006) using the tilting method of Robertson et al. (2005) and Giacomini and Ragusa (2013). The method anchors the yield curve forecast at the market expectation and results in new forecasts for all remaining yields. We then extract the forecasts of excess returns implied by the tilted yield curve forecast and evaluate their out-of-sample accuracy over the period 2003:01-2011:12. We compare the tilted excess return forecasts to those from three benchmarks: the DNS itself, the expectation hypothesis and an autoregressive model. Finally, we analyze a simple investment strategy consisting of riding the yield curve to investigate whether investors in bond markets could have adopted our method to devise profitable investment strategies in bond markets.

The empirical results paint a clear picture: our approach outperforms all competitors in terms of market timing and in terms of both statistical and economically meaningful measures of accuracy. This result is robust across holding periods and maturities. Riding the yield curve according to the tilted forecasts always results in positive cumulated excess returns and it generally outperforms the competitors when accounting for risk-return tradeoffs. In those cases, the tilted forecasts delivers cumulated returns that are from twice as large to ten times as large as the cumulated returns

[5] The results do not change qualitatively when $\lambda = 2, 3$.

obtained by the next best method. Finally, a risk adverse investor with a quadratic utility function would always be willing to pay to use the tilted forecast in predicting future returns as opposed to any other competing forecast.

One possible caveat is that the federal funds futures market becomes less liquid as the forecast horizon grows, which likely impacts the accuracy of the futures-implied forecast for the federal funds rate. This in turn can explain the slight deterioration in the forecast performance of our method at longer (12 month) horizons. For this reason, our practical recommendation is to adopt the method considered in this paper for forecasting and devising investment strategies which have short and medium horizons.

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Table 1: Yields Summary Statistics

Maturity	Mean	Median	St. Deviation	Max	Min
1	4.08	4.73	2.43	9.07	0.00
2	4.11	4.79	2.46	9.18	0.00
3	4.14	4.82	2.48	9.27	0.02
4	4.17	4.85	2.50	9.35	0.07
5	4.20	4.91	2.52	9.40	0.10
6	4.23	4.93	2.53	9.45	0.13
7	4.26	4.92	2.54	9.48	0.15
8	4.29	4.93	2.55	9.53	0.14
9	4.32	4.92	2.56	9.61	0.14
10	4.34	4.93	2.56	9.68	0.14
11	4.37	4.92	2.57	9.76	0.14
12	4.40	4.90	2.57	9.83	0.14
24	4.68	4.95	2.56	10.51	0.22
36	4.92	5.02	2.50	10.95	0.35
48	5.14	5.25	2.43	11.24	0.49
60	5.33	5.40	2.36	11.42	0.66

Notes. Descriptive statistics for monthly yields. The sample period is from 1985:01 to 2012:12

Table 2: Implied Forward Rates from Federal Fund Futures, Summary Statistics

Horizon	Mean	Median	St. Deviation	Max	Min
1	3.80	4.19	2.54	9.97	0.08
2	3.81	4.21	2.53	10.08	0.08
3	3.82	4.30	2.53	10.12	0.08
4	3.84	4.26	2.52	10.20	0.08
5	3.87	4.34	2.52	10.28	0.08
6	3.91	4.40	2.52	10.27	0.08
7	3.96	4.43	2.54	10.59	0.08
8	4.01	4.44	2.56	10.27	0.09
9	4.10	4.53	2.58	9.27	0.09
10	4.23	4.72	2.61	9.15	0.09
11	3.87	4.49	2.16	7.05	0.08
12	3.90	4.72	2.07	6.58	0.10

Notes. Descriptive statistics on federal-fufutures contracts implied forward rates.

Table 3: Excess Return Summary Statistics

Maturity	Mean	Median	St. Deviation	Max	Min	Mean	Median	St. Deviation	Max	Min
			h= 1					h= 6		
h + 1	0.02	0.01	0.04	0.21	-0.05	0.04	0.03	0.07	0.24	-0.07
h + 3	0.07	0.03	0.12	0.63	-0.16	0.13	0.08	0.20	0.71	-0.24
h + 6	0.13	0.08	0.25	1.25	-0.41	0.25	0.19	0.42	1.38	-0.55
h + 9	0.19	0.13	0.39	1.84	-0.72	0.37	0.31	0.64	2.04	-0.90
h + 12	0.25	0.19	0.55	2.42	-1.07	0.48	0.44	0.87	2.68	-1.31
			h= 9					h= 12		
h + 1	0.06	0.04	0.09	0.28	-0.10	0.08	0.06	0.11	0.34	-0.15
h + 3	0.18	0.14	0.27	0.83	-0.30	0.23	0.19	0.33	1.01	-0.47
h + 6	0.36	0.29	0.55	1.69	-0.71	0.46	0.39	0.68	2.04	-1.05
h + 9	0.53	0.46	0.84	2.55	-1.26	0.68	0.59	1.03	3.09	-1.76
h + 12	0.69	0.64	1.12	3.41	-1.79	0.89	0.81	1.36	4.16	-2.48

Notes. Descriptive statistics for excess returns. The sample period is 1985:1-2012:12.

Table 4: Predictive Regressions

	Augmented Model			CP model		Augmented Model			CP model		Augmented Model			CP model	
maturity	β_1	β_2	$\overline{R}^2$	β_1	$\overline{R}^2$	β_1	β_2	$\overline{R}^2$	β_1	$\overline{R}^2$	β_1	β_2	$\overline{R}^2$	β_1	$\overline{R}^2$
	h=1					h=2					h=3				
h + 1	**0.01**	**0.001**	0.07	**0.01**	0.03	**0.01**	**0.002**	0.15	**0.02**	0.10	**0.01**	**0.002**	0.17	**0.02**	0.10
h + 3	**0.04**	**0.002**	0.12	**0.06**	0.09	**0.06**	**0.004**	0.21	**0.07**	0.18	**0.06**	**0.006**	0.21	**0.07**	0.17
h + 6	**0.13**	**0.003**	0.17	**0.15**	0.15	**0.15**	**0.006**	0.25	**0.17**	0.24	**0.15**	**0.009**	0.24	**0.18**	0.22
h + 9	**0.23**	0.004	0.19	**0.26**	0.18	**0.26**	0.007	0.26	**0.28**	0.26	**0.26**	0.010	0.25	**0.29**	0.24
h + 12	**0.35**	0.004	0.20	**0.37**	0.20	**0.37**	0.007	0.26	**0.39**	0.26	**0.37**	0.011	0.25	**0.40**	0.25
	h=4					h=5					h=6				
h + 1	**0.01**	**0.003**	0.00	**0.02**	0.11	**0.02**	**0.004**	0.19	**0.02**	0.12	**0.02**	**0.004**	0.21	**0.03**	0.13
h + 3	**0.06**	**0.008**	0.21	**0.08**	0.17	**0.07**	**0.009**	0.23	**0.08**	0.18	**0.07**	**0.010**	0.24	**0.09**	0.20
h + 6	**0.15**	**0.012**	0.24	**0.18**	0.22	**0.16**	**0.014**	0.26	**0.19**	0.23	**0.17**	**0.016**	0.28	**0.20**	0.26
h + 9	**0.26**	0.014	0.25	**0.29**	0.24	**0.27**	**0.016**	0.27	**0.30**	0.26	**0.29**	**0.019**	0.30	**0.32**	0.29
h + 12	**0.37**	0.015	0.26	**0.41**	0.25	**0.39**	0.017	0.28	**0.42**	0.28	**0.40**	0.02	0.31	**0.44**	0.30
	h=7					h=8					h=9				
h + 1	**0.02**	**0.005**	0.23	**0.03**	0.17	**0.02**	**0.005**	0.26	**0.03**	0.21	**0.03**	**0.005**	0.29	**0.03**	0.24
h + 3	**0.08**	**0.011**	0.27	**0.10**	0.23	**0.08**	**0.012**	0.29	**0.10**	0.26	**0.09**	**0.013**	0.32	**0.11**	0.28
h + 6	**0.18**	**0.017**	0.30	**0.21**	0.28	**0.19**	**0.018**	0.32	**0.22**	0.30	**0.20**	**0.020**	0.34	**0.23**	0.33
h + 9	**0.30**	0.020	0.32	**0.33**	0.31	**0.31**	**0.022**	0.34	**0.35**	0.33	**0.32**	**0.024**	0.36	**0.36**	0.35
h + 12	**0.42**	0.021	0.33	**0.45**	0.32	**0.44**	0.022	0.35	**0.47**	0.34	**0.45**	0.025	0.37	**0.48**	0.37
	h=10					h=11					h=12				
h + 1	**0.03**	**0.006**	0.33	**0.03**	0.27	**0.03**	**0.006**	0.32	**0.04**	0.27	**0.03**	**0.005**	0.33	**0.04**	0.30
h + 3	**0.09**	**0.015**	0.36	**0.11**	0.31	**0.09**	**0.016**	0.35	**0.11**	0.31	**0.10**	**0.013**	0.36	**0.12**	0.34
h + 6	**0.20**	**0.026**	0.38	**0.24**	0.35	**0.20**	**0.028**	0.37	**0.24**	0.35	**0.22**	**0.021**	0.39	**0.25**	0.38
h + 9	**0.32**	**0.031**	0.39	**0.37**	0.37	**0.33**	**0.035**	0.39	**0.37**	0.37	**0.35**	**0.026**	0.41	**0.38**	0.40
h + 12	**0.45**	**0.033**	0.40	**0.50**	0.39	**0.45**	**0.038**	0.40	**0.50**	0.39	**0.48**	0.028	0.43	**0.52**	0.42

Notes. Results of the predictive regression using Cochrane and Piazzesi's (2005) regression (CP) and the same regression augmented with the federal funds futures for different holding period (h). Bold numbers indicate significance at the 5% level.

Table 5: Pesaran and Timmermann (1992) Test for Market Timing

Maturity	h = 3	h = 6	h = 9	h = 12
		Tilted		
h + 1	0.68***	0.65***	0.69***	0.59**
h + 3	0.69***	0.79***	0.75***	0.58*
h + 6	0.7***	0.78***	0.76***	0.66***
h + 9	0.73***	0.76***	0.79***	0.68***
h + 12	0.71***	0.73***	0.79***	0.66***
		EH		
h + 1	0.56	0.56	0.5	0.49
h + 3	0.58*	0.51	0.55	0.48
h + 6	0.56	0.59	0.53	0.48
h + 9	0.65***	0.59	0.53	0.54
h + 12	0.60*	0.57	0.56	0.56
		DNS		
h + 1	0.49	0.33	0.19	0.28
h + 3	0.44	0.2	0.18	0.27
h + 6	0.36	0.24	0.18	0.25
h + 9	0.34	0.26	0.17	0.23
h + 12	0.34	0.29	0.18	0.24
		AR		
h + 1	0.56	0.49	0.45	0.44
h + 3	0.56	0.45	0.5	0.44
h + 6	0.56	0.57	0.49	0.47
h + 9	0.62**	0.56	0.54	0.55
h + 12	0.57	0.56	0.56	0.61

Notes. Pesaran and Timmermann's (1995) market-timing test on excess return forecasts. Each panel reports the proportion of times that in a given sample the sign of realized excess returns is correctly predicted by the sign of alternative forecasts generated by three different models. ***,**,* indicate rejection of the null hypothesis of independence between forecasts and realizations at the 1%, 5% and 10% levels, respectively. EH = Expectation Hypothesis; AR= first order autoregressive model; DNS = Dynamic Nelson and Siegel; Tilted = DNS tilted using federal funds future-implied expectations.

Table 6: Diebold and Mariano Tests

	directional change loss function				quadratic loss function			
	Holding period							
Maturity	h = 3	h = 6	h = 9	h = 12	h = 3	h = 6	h = 9	h = 12
	Tilted vs EH				Tilted vs EH			
h + 1	0.86	0.9	0.78***	0.89*	0.76***	0.77***	0.78***	1.13
h + 3	0.86*	0.66***	0.74***	0.9*	0.8***	0.79***	0.8***	1.17
h + 6	0.83**	0.74***	0.71***	0.81***	0.86***	0.82***	0.82***	1.2
h + 9	0.87*	0.77***	0.67***	0.84**	0.9**	0.86***	0.84***	1.23
h + 12	0.85**	0.79***	0.7***	0.89*	0.94	0.89***	0.87***	1.25
	Tilted vs DNS				Tilted vs DNS			
h + 1	0.8**	0.73***	0.62***	0.75***	0.67***	0.66***	0.68***	1
h + 3	0.74***	0.52***	0.55***	0.75***	0.7***	0.68***	0.68***	1.02
h + 6	0.68***	0.54***	0.54***	0.68***	0.75***	0.7***	0.7***	1.04
h + 9	0.64***	0.57***	0.51***	0.65***	0.79***	0.73***	0.71***	1.05
h + 12	0.66***	0.61***	0.51***	0.67***	0.81***	0.75***	0.73***	1.04
	Tilted vs AR				Tilted vs AR			
h + 1	0.85*	0.83**	0.75***	0.86**	0.77***	0.77***	0.79***	1.15
h + 3	0.83**	0.62***	0.71***	0.86**	0.81***	0.79***	0.81***	1.19
h + 6	0.82**	0.72***	0.69***	0.81***	0.86**	0.83***	0.83***	1.23
h + 9	0.84**	0.74***	0.68***	0.85**	0.91*	0.86***	0.86***	1.26
h + 12	0.82***	0.79***	0.7***	0.94	0.94	0.9**	0.88**	1.28

Notes. Diebold and Mariano (1995) test with directional change loss function (left panel) and quadratic loss function (right panel) for models' forecasts of bond excess returns. *, **, ***, indicate significance at 10, 5, and 1% levels, respectively. EH = Expectation Hypothesis; AR= first order autoregressive model; DNS = Dynamic Nelson and Siegel; Tilted = DNS tilted using federal funds future-implied expectations. The sample period is 2003:1-2011:12

Table 7: Cumulated Excess Return - Riding the Yield Curve

	Trading every h periods				Trading every period			
Maturity	h = 3	h = 6	h = 9	h = 12	h = 3	h = 6	h = 9	h = 12
	Tilted				Tilted			
h + 1	0.27	0.24	0.13	0.21	0.61	1.06	1.52	1.73
h + 3	0.90	0.83	0.50	0.68	2.11	4.58	6.27	5.94
h + 6	1.84	1.77	1.20	1.51	4.64	11.57	14.28	16.89
h + 9	3.20	2.93	2.01	2.47	7.92	19.10	26.19	27.87
h + 12	4.68	4.20	2.90	3.55	11.72	27.30	36.11	37.56
	DNS				DNS			
h + 1	-0.12	-0.18	-0.20	-0.06	-0.36	-0.72	-0.94	0.15
h + 3	-0.34	-0.54	-0.57	-0.10	-0.93	-2.24	-2.67	0.69
h + 6	-0.61	-1.03	-1.06	-0.02	-1.58	-3.20	-4.69	0.64
h + 9	-0.83	-1.47	-1.49	0.17	-2.06	-4.21	-6.29	2.76
h + 12	-1.00	-1.85	-1.57	0.43	-2.33	-4.85	-6.32	3.09
	AR				AR			
h + 1	-0.12	-0.02	0.08	-0.06	0.01	0.14	0.47	0.65
h + 3	-0.27	0.20	0.39	-0.07	0.20	0.92	2.30	2.72
h + 6	-0.29	0.77	1.08	0.14	0.95	4.04	7.10	9.07
h + 9	0.27	1.57	1.96	0.55	3.20	8.03	14.41	21.13
h + 12	0.94	2.55	5.89	3.17	5.75	14.07	26.25	41.49

Notes. Cumulated excess returns resulting from riding the yield curve according to the different forecasts. The left panel considers an investor who only trades every h periods. The right panel considers an investor who trades every period between 2003:1-2011:12. AR= first order autoregressive model; DNS = Dynamic Nelson and Siegel; Tilted = DNS tilted using federal funds future-implied expectations.

Table 8: Sharpe Ratios - Riding the Yield Curve

	Sharp Ratios Limited number of times				Sharp Ratio Trading Every Period			
Maturity	h = 3	h = 6	h = 9	h = 12	h = 3	h = 6	h = 9	h = 12
	Tilted				Tilted			
h + 1	0.327	0.353	0.736	0.422	0.297	0.322	0.403	0.362
h + 3	0.394	0.402	0.772	0.448	0.348	0.393	0.496	0.387
h + 6	0.410	0.404	0.768	0.481	0.356	0.443	0.563	0.495
h + 9	0.481	0.427	0.732	0.510	0.374	0.473	0.636	0.522
h + 12	0.513	0.442	0.699	0.536	0.384	0.492	0.637	0.540
	DNS				DNS			
h + 1	-0.365	-0.462	-0.598	-0.103	-0.369	-0.314	-0.223	0.021
h + 3	-0.371	-0.462	-0.609	-0.056	-0.270	-0.321	-0.211	0.032
h + 6	-0.358	-0.456	-0.621	-0.006	-0.197	-0.178	-0.186	0.016
h + 9	-0.329	-0.445	-0.629	0.031	-0.161	-0.152	-0.167	0.048
h + 12	-0.293	-0.432	-0.538	0.058	-0.129	-0.128	-0.129	0.045
	AR				AR			
h + 1	-0.204	-0.020	0.135	-0.122	0.006	0.034	0.075	0.087
h + 3	-0.147	0.080	0.211	-0.044	0.031	0.071	0.120	0.120
h + 6	-0.070	0.147	0.284	0.042	0.065	0.148	0.181	0.196
h + 9	0.040	0.193	0.335	0.108	0.132	0.186	0.240	0.287
h + 12	0.095	0.229	0.487	0.354	0.164	0.234	0.307	0.396

Notes. Sharpe Ratios resulting from riding the yield curve according to the different forecasts. The left panel considers an investor who only trades every h periods. The right panel considers an investor who trades every period between 2003:1-2011:12. AR= first order autoregressive model; DNS = Dynamic Nelson and Siegel; Tilted = DNS tilted using federal funds future-implied expectations.

Table 9: Performance Fees

	Δ (Limited Number of Trading)				Δ (Trading every period)			
	Holding period							
Maturity	h = 3	h = 6	h = 9	h = 12	h = 3	h = 6	h = 9	h = 12
	Tilted vs EH				Tilted vs EH			
h + 1	0.003	0.004	0.001	0.005	0.005	0.008	0.012	0.015
h + 3	0.011	0.013	0.006	0.015	0.019	0.040	0.051	0.051
h + 6	0.023	0.029	0.014	0.035	0.042	0.116	0.116	0.153
h + 9	0.040	0.050	0.026	0.060	0.075	0.197	0.238	0.257
h + 12	0.060	0.076	0.039	0.092	0.118	0.293	0.335	0.325
	Tilted vs DNS				Tilted vs DNS			
h + 1	0.005	0.008	0.008	0.005	0.010	0.017	0.023	0.005
h + 3	0.016	0.025	0.023	0.013	0.029	0.067	0.080	0.015
h + 6	0.032	0.051	0.046	0.020	0.059	0.151	0.158	0.085
h + 9	0.053	0.080	0.069	0.024	0.096	0.235	0.281	0.121
h + 12	0.075	0.114	0.082	0.028	0.138	0.324	0.356	0.159
	Tilted vs AR				Tilted vs AR			
h + 1	0.005	0.005	0.003	0.010	0.007	0.011	0.014	0.019
h + 3	0.016	0.013	0.006	0.028	0.020	0.041	0.046	0.053
h + 6	0.029	0.021	0.008	0.052	0.037	0.093	0.074	0.116
h + 9	0.040	0.028	0.006	0.076	0.046	0.131	0.126	0.085
h + 12	0.050	0.033	-0.134	-0.019	0.054	0.152	0.065	-0.110

Notes. Performance fees - expressed in decimals - a risk adverse investor would be willing to pay for using the tilted forecast compared to the other forecasts. The left panel considers an investor who only trades every h periods. The right panel considers an investor who trades every period between 2003:1-2011:12. EH = Expectation Hypothesis; AR= first order autoregressive model; DNS = Dynamic Nelson and Siegel; Tilted = DNS tilted using federal funds future-implied expectations.