

Bond returns and market expectations*

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This Version: March 2014

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 an exponential 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 for bond maturities of up to two years and forecast horizons less than one year, and would have allowed an investor to obtain positive cumulative excess returns from simple "riding the yield curve" investment strategies over the past ten years. For long forecast horizons and bond maturities of four or five years, the preferred forecast is instead one implied by a simple autoregressive model.

JEL Classification Codes: G1; E4; C5

Keywords: Yield curve modelling, Futures, Market Timing, Exponential tilting, Out-of-sample evaluation

*We thank Allan Timmermann and two anonymous referees for useful comments and suggestions. Raffaella Giacomini gratefully acknowledges financial support from the British Academy Mid-Career Fellowship and from the Economic and Social Research Council through the ESRC Centre for Microdata Methods and Practice grant RES-589-28-0001. The views expressed in this paper do not necessarily reflect those of the European Central Bank or the Eurosystem. Address correspondence to Raffaella Giacomini, University College London, Department of Economics, Gower Street, London WC1E6BT, UK; e-mail: r.giacomini@ucl.ac.uk.

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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 about 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 exponential tilting method of Robertson et. al (2005) and Giacomini and Ragusa (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 uses exponential tilting to incorporate into the base model the FFF-implied expectation for the relevant forecast horizon. The distinctive feature of the tilting method is that, even though the FFF only provides 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. The results are particularly striking when considering bond maturities ranging from three months to two years and forecast horizons less than one year. For longer forecast horizons and bonds with maturities of four or five years, instead, the overall preferred method appears to be a simple autoregressive model.

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 always realized positive cumulative excess returns (without accounting for transactions costs) and in the majority of cases it would have outperformed its competitors in terms of risk-return compensation.

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 rate and yield 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 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), 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 popular Dynamic Nelson and Siegel (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 set 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. 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 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 could 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 discusses the data we use for the empirical analysis; Section 4 introduces the methodology we use in the forecasting exercise, including a description of the tilting method. Section 5 reports the main empirical results while Section 6 concludes.

2 Data

In this section we discuss the construction of the yield and bond return data as well as the market expectations that we extract from the FFF data.

To measure yields, we use average of the month observations on one-day through five-year zero-

coupon U.S. Treasury bonds taken both from the dataset constructed by Gurkaynak, Sack and Wright (2007) and from the Federal Reserve Economic Dataset (FRED).¹ More precisely, we reconstruct the entire yield curve at the daily frequency starting from the estimated parameters that are used to interpolate the term structure in the dataset, which use Svensson's (1994) method. We consider yields with maturity ranging from 3 months to 6 years. We then augment the dataset with the effective daily federal funds rate from FRED. Finally, we aggregate each series at the monthly frequency. We denote the yield of a bond with maturity τ at time t as $Y_t^{(\tau)}$.

From the data on yields, we construct bond excess returns as follows. Define $p_t^{(\tau)} = \log P_t^{(\tau)}$ as the log of the price of a bond with maturity τ at time t , and $f_t^{(\tau)} = p_t^{(\tau-h)} - p_t^{(\tau)}$ as the log forward rate at time t for loans between $t + \tau - h$ and $t - h$. The log holding period from buying a τ -year bond at time t and selling it after h -periods can be written as $r_{t+h}^{(\tau)} = p_{t+h}^{(\tau-h)} - p_t^{(\tau)}$. Recalling that the yield of a bond with maturity τ at time t is $Y_t^{(\tau)} = -\frac{1}{\tau}p_t^{(\tau)}$, we define the bond excess returns as $rx_{t+h}^{(\tau)} = r_{t+h}^{(\tau)} - hY_t^{(h)}$, or

$$rx_{t+h}^{(\tau)} = \tau Y_t^{(\tau)} - (\tau - h)Y_{t+h}^{(\tau-h)} - hY_t^{(h)}. \quad (1)$$

The market based expectations are constructed as follows. We consider federal funds futures, which 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 federal 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.

3 Methodology

Our interest is in investigating the predictability of bond excess returns, with the goal of providing useful tools for investors in bond markets. The standard approach to answering this question consists of estimating a predictive regression of the form:

$$rx_{t+h}^{(\tau)} = \beta Z_t + \varepsilon_{t+h}, \quad (2)$$

¹Dataset available at <http://www.federalreserve.gov/pubs/feds/2006/>.

where Z_t is a vector of variables observed at time t . For example, Fama and Bliss (1987) estimate

$$rx_{t+h}^{(\tau)} = c + \beta \left(f_t^{(\tau)} - Y_t^{(h)} \right) + \varepsilon_{t+h}, \quad (3)$$

where $f_t^{(\tau)}$ is the τ -period forward rate and $Y_t^{(h)}$ the h -period yield². Cochrane and Piazzesi (2005) find that excess returns can be predicted by a linear combination of forward rates in the regression

$$rx_{t+h}^{(\tau)} = c + \beta Z_t + \varepsilon_{t+h}, \quad \tau = 1, \dots, 5 \quad (4)$$

where $Z_t = [Y_t^{(1)}, f_t^{(2)}, \dots, f_t^{(5)}]$.

Thornton and Valente (2012) show that the predictive power of the regression (4) does not however hold out-of-sample, which makes this type of predictive regression not useful for actual forecasting. We first consider the possibility that adding the FFF-implied expectation as a regressor could increase the predictive power of the regression (4) but we document 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.

We thus adopt a different approach. Because of the relationship between returns and yields, an alternative forecast for excess returns can be obtained by starting from a term structure model which expresses the yield curve as a function of dynamic latent factors, which implies that excess returns can also be represented in terms of the same factors that underlie the yield curve.

We start from the DNS model of Diebold and Li (2006) for bonds with maturity 1-day (i.e., the federal funds rate), and 3 to 60 months. We produce a forecast of the yield curve implied by the DNS model and then use the tilting method to anchor the forecast of the 1-day rate 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 describe the methodology in greater detail below.

3.1 The forecasts

Let FFR_t be the average federal funds rate (FFR) over month t , and Y_t a vector of yields with typical element $Y_t^{(\tau)}$, for maturities $\tau = 3, \dots, 60$ months.

The starting point of our analysis is the yield curve forecast based on the DNS model of Diebold and Li (2006) for the stacked vector including FFR_t and Y_t :

$$Z_t = \begin{bmatrix} FFR_t \\ Y_t \end{bmatrix} = HX_t + \eta_t \quad (5)$$

$$X_t = c + \Phi X_{t-h} + \varepsilon_t, \quad (6)$$

²They focus on the case $h = 1$

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 $\tau = \frac{1}{22}, 1, 2, \dots, 60$ represents the bond maturity.³ 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 $\tilde{X}_t$ and then estimating (6) using the fitted $\tilde{X}_t$ and assuming that Φ is diagonal. As noted in Diebold and Li (2006), one should expect the AR(1) specification to produce superior forecasts compared to a VAR forecasting model for the factors. We performed the out-of-sample forecasting exercise without imposing restrictions on Φ and we confirmed that the VAR specification performs poorly compared to the AR forecasts, so we do not report the results for the VAR in the paper. In addition, we follow Diebold and Li (2006) and we estimate the model regressing directly the factors at time $t+h$ on factors at time t .⁴ The h -step ahead forecasts at time t for the FFR and the yields implied by the DNS model are then given by

$$\hat{Z}_{t+h}^{DNS} = \begin{bmatrix} \widehat{FFR}_{t+h}^{DNS} \\ \hat{Y}_{t+h}^{DNS} \end{bmatrix} = H(\hat{c} + \hat{\Phi}\tilde{X}_t). \quad (7)$$

The first benchmark model (AR) is an autoregression of order one, which implies the following forecast:

$$\hat{Z}_{t+h}^{AR} = \begin{bmatrix} \widehat{FFR}_{t+h}^{AR} \\ \hat{Y}_{t+h}^{AR} \end{bmatrix} = \hat{\rho}^{(h)} \begin{bmatrix} FFR_t \\ Y_t \end{bmatrix}, \quad (8)$$

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

$$Z_t = \hat{\rho}^{(h)} Z_{t-h} + n_t. \quad (9)$$

The second benchmark forecast is obtained by imposing the expectation hypothesis (EH), which implies that excess returns are given by the spread between yields and forward rates observable at each point in time and is equivalent to a random walk forecast for yields:

$$\hat{Z}_{t+h}^{EH} = Z_t. \quad (10)$$

The procedure for obtaining the tilted forecasts that incorporate the FFF-implied expectations, which we denote as $\hat{Z}_{t+h}^{FFF}$, is explained in the next section.

We will thus have four competing h -step ahead out-of-sample forecasts for the vector of yields: $\hat{Y}_{t+h}^{(\tau)DNS}$, $\hat{Y}_{t+h}^{(\tau)FFF}$, $\hat{Y}_{t+h}^{(\tau)AR}$ and $\hat{Y}_{t+h}^{(\tau)EH}$ for $\tau = 3, \dots, 60$.

³Note that we treat the FFR_t as a one-day-yield.

⁴The model for the latent factors can also be specified as

$$X_t = c + \Phi X_{t-1} + \varepsilon_t,$$

and estimated by regressing the factors at time $t+1$ on factors at time t . We performed the out-of-sample forecasting exercise by iterating h -times the one step ahead projections of the latent factors and we found little differences compared to the direct forecast procedure.

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

$$r_{t+h}^{(\tau)} = \tau Y_t^{(\tau)} - (\tau - h) Y_{t+h}^{(\tau-h)} \quad (11)$$

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

$$\widehat{r}_{t+h}^{(\tau)} = \tau Y_t^{(\tau)} - (\tau - h) \widehat{Y}_{t+h}^{(\tau-h)} \quad (12)$$

Using formula (12) we can thus obtain four competing h -step ahead out-of-sample forecasts for the vector of excess returns as

$$\widehat{rx}_{t+h}^{(\tau)} = \widehat{r}_{t+h}^{(\tau)} - h Y_t^{(h)} \quad (13)$$

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

3.2 The tilting method

This section briefly summarizes the tilting method of Robertson et al. (2006) and Giacomini and Ragusa (2013a, 2013b). See Giacomini and Ragusa (2013b) for a formal justification of the procedure in an out-of-sample evaluation context with classical inference. The tilting procedure starts from a multivariate density forecast obtained by a base model - in our case the density forecast for the vector of yields implied by the DNS model, $f^{DNS} \sim N(\widehat{Z}_{t+h}^{DNS}, \Omega)$ - and it incorporates into this forecast the information contained in moment conditions that involve a subset of the yields. In the case considered in this paper, the moment condition is the FFF-implied forecast of the first yield available at time t for horizon h , denoted $\widehat{FFF}_{t+h}$. The method delivers a new multivariate density forecast f^{FFF} which by construction sets the forecast for the first yield equal to $\widehat{FFF}_{t+h}$ and which is the closest to the initial density f^{DNS} according to a Kullback-Leibler measure of divergence. Giacomini and Ragusa (2013b) show that the solution to this constrained minimization problem is a multivariate normal density with the same variance as the original density but with different mean forecasts for all yields. Formally, the tilted density is $f^{FFF} \sim N(\widehat{Z}_{t+h}^{FFF}, \Omega)$ with

$$\begin{aligned} \widehat{Z}_{t+h}^{FFF} &= \begin{bmatrix} \widehat{FFF}_{t+h} \\ \widehat{Y}_{t+h}^{FFF} \end{bmatrix}, \\ \widehat{Y}_{t+h}^{FFF} &= \widehat{Y}_{t+h}^{DNS} - \Omega_{21} \Omega_{11}^{-1} \left(\widehat{FFR}_{t+h}^{DNS} - \widehat{FFF}_{t+h} \right), \end{aligned} \quad (14)$$

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

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

As noted by Giacomini and Ragusa (2013b), the tilted forecast in (14) is generally different from the forecast that one would obtain by estimating the DNS model subject to the constraint that the forecast for the first yield equals the futures-implied forecast.⁵ Establishing a ranking between these two different approaches is generally difficult unless one is prepared to make assumptions about the accuracy of the futures-implied forecast. See Giacomini and Ragusa (2013b) for a general discussion about the appealing properties of the tilted method over competing ways of incorporating external information into an existing forecast.

Giacomini and Ragusa (2013b) also show that, if the market-based point forecast for the first yield, $\widehat{FFF}_{t+h}$, has lower mean squared forecast error than the model-based point forecast of the same yield, $\widehat{FFR}_{t+h}^{DNS}$, 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). The fact that $\widehat{FFF}_{t+h}$ has lower mean squared error than $\widehat{FFR}_{t+h}^{DNS}$ is confirmed in our dataset, so there is scope for incorporating the FFF-implied expectations into the yield curve forecasts. 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.

4 Results

The section presents two sets of results. The first are in-sample return predictability regressions similar to those by Crochane and Piazzesi (2005) but augmented by the FFF-implied expectations.

In the rest of the section, we conduct an out-of-sample forecasting exercise designed to assess the usefulness of our method to investors in bond markets.

4.1 In-sample return predictability regressions

In this section 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

$$rx_{t+h}^{(\tau)} = \beta_1^{(\tau,h)}(\gamma' f_t) + \beta_2^{(\tau,h)} \widehat{FFF}_{t+h} + \varepsilon_{t+h}, \quad \tau = 3, \dots, 60 \quad (15)$$

⁵Consider for example the simple situation in which $Z_t = (Z_{1t}, Z_{2t})$ and there is one factor $\hat{x}_t$ with autoregressive coefficient ϕ . In this case, imposing the constraint that the one-step-ahead forecast for Z_{1t+1} equals $\widehat{FFF}_{t+1}$ yields $\phi = \frac{\widehat{FFF}_{t+1}}{\lambda_1 \hat{x}_t}$ and thus the forecast for Z_{2t+1} is $\frac{\lambda_2}{\lambda_1} \widehat{FFF}_{t+1}$, which is different from the forecast implied by the tilting method in (14).

where $rx_{t+h}^{(\tau)}$ are excess returns of a bond with maturity τ and a holding period h and are given by (11) 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

$$\frac{1}{60-h} \sum_{j=1+h}^{60} rx_{t+h}^{(j)} = \gamma_0 + \gamma_1 Y_t^{(h)} + \gamma_2 f_t^{(1+h)} + \dots + \gamma_{61} f_t^{(60)} + \eta_{t+h} \quad (16)$$

$$= \gamma'f_t + \eta_{t+h} \quad (17)$$

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

We consider the period 1995:01-2011:12.

Table 1 reports estimates of the coefficients $\beta_1^{(\tau,h)}$ and $\beta_2^{(\tau,h)}$ for $h = 3, 6, 9, 12$ and $\tau = 3, 6, 9, 12, 24, 36, 48, 60$.

[INSERT TABLE 1]

We report the results in twelve panels, corresponding to the different forecast horizons h . In each panel, for both the augmented regression (15) and the original Cochrane and Piazzesi (2005) regression we present the estimates for the coefficients and the adjusted 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 1 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 (15) 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

The exercise mimics 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 out-of-sample h -step

ahead forecasts for the yield curve based on four competing models: the DNS model of Diebold and Li (2006) (DNS), the DNS model tilted using federal funds future-implied market expectations (FFF), the autoregressive model (AR) and the forecast implied by imposing the expectation hypothesis (EH). The forecasts are given by (13) with $\hat{Y}_{t+h}^{(\tau)}$ either as in (7), (14), (8) or (10) with $\tau = 3, 6, 9, 12, 24, 36, 48, 60$ and $h = 3, 6, 9, 12$. We then expand the estimation sample with the data at time 2003:2 and repeat the exercise, then iterate until all observations are exhausted. The last forecast is produced using the sample 1985:1 - 2011:12.

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 pairwise Diebold and Mariano (1995) tests 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 positions on the market by comparing the return of a risk free bond with the returns forecasted by (7), (14) and (8).

All out-of-sample results are based on an expanding estimation window. The working paper version of this article (available at <http://raffaellagiacomini.wix.com/research#!research/c1edq>) contains a not-for-publication appendix with the corresponding results based on a rolling window estimation and using Giacomini and White's (2006) test for the pairwise comparisons. The conclusions are robust to the use of rolling window estimation.

4.2.1 Statistical significance

We start by performing Pesaran and Timmermann's (1992) test of sign predictability. Table 2 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 2]

The table shows that the tilted forecasts are the only ones for which the null hypothesis of independence between forecasts and realizations is rejected in all but one cases. The next best model is the AR, which performs well for maturities of 2 years and greater. Moreover, the proportion of correct predictions for the tilted forecasts ranges between 58% and 78%, whereas for the AR and the EH forecasts the proportion of correct predictions are heterogeneous across maturities and forecasts horizons. The DNS forecasts fare poorly overall, with correct predictions as low as 19%. 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 3 reports ratios of average losses for the tilted forecasts relative to each of the three benchmarks, together with significance levels for Diebold and Mariano's (1995) test of equal average loss.

[*INSERT TABLE 3*]

The picture that emerges from Table 3 is that the tilted forecasts outperform the competing forecasts in their ability to predict the direction of change of excess bond returns, at least for maturities up to two years. A similar conclusion holds for the quadratic loss, with the difference that the tilted forecast does not perform as well for long maturities and for the 12-month-ahead forecast horizon. This could be a consequence of the fact that information other than that contained in futures data affects the long end of the yield curve, paired with 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, up to 40%.

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. It is important to stress that we do not consider transaction costs.

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 τ today and then sell it after h periods, at which point it will become a bond with maturity $\tau - h$. The investor will choose the latter strategy when her h -periods-ahead forecast for the return on a bond with maturity τ is higher than the return from bringing the h -period bond to maturity.

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.

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 $\hat{r}_{t+h}^{(\tau)}$ of the return on a τ -month bond at time $t+h$. Buy the h -month bond if $Y_t^{(h)} \geq \hat{r}_{t+h}^{(\tau)}$ or buy a τ -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 $\tau-h$ -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: (7), (14) and (8). We further compute Sharpe ratios for the different forecasts, defined as

$$SR^{(\tau,h)} = \frac{1}{T-h+1} \sum_{t=1}^{T-h} \frac{\bar{r}_{t+h}^{(\tau)} - Y_t^{(h)}}{\sqrt{Var\left(\bar{r}_{t+h}^{(\tau)} - Y_{t+h}^{(h)}\right)}}. \quad (18)$$

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 $\tau = 3, 6, 9, 12, 24, 36, 48, 60$.

Table 4 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 4]

Table 4 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 outperform the tilted forecasts only for long maturities. The excess returns from basing the trading strategy on the tilted forecasts rather than on the AR forecasts are larger, except for bonds with maturity greater than two years, which we saw in the previous section is when the tilted forecasts begin to deteriorate. In all other cases, the tilted forecasts deliver cumulated returns that are from twice as large to ten times as large as the cumulated returns from using the AR forecasts.

Table 5 reports Sharpe ratios for the various forecasts, maturities and holding periods..

[*INSERT TABLE 5*]

Table 5 shows that, after accounting for risk, the tilted forecasts deliver risk-adjusted returns that are higher than those of all competitors, except a few cases where the autoregressive forecasts are better. 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 most investment horizons and all maturities, with few exception compared to the AR performance. Again this is due to the deterioration in the forecast performance of the tilting method for long maturities and long forecast horizons. The risk-adjusted returns are largest when the investor trades longer maturity bonds and holds them for longer periods

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 Thornton 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

$$\bar{U} \left(\mathcal{R}_{t+h}^{(\tau)}, \lambda \right) = \frac{1}{T-h+1} \sum_{t=0}^{T-h} \left\{ \mathcal{R}_{t+h}^{(\tau)} - \frac{\lambda}{2(1+\lambda)} \left(\mathcal{R}_{t+h}^{(\tau)} \right)^2 \right\}, \quad (19)$$

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

$$\sum_{t=0}^{T-h} \left\{ \left(\mathcal{R}_{t+h}^{(\tau),FFF} - \Delta \right) - \frac{\lambda}{2(1+\lambda)} \left(\mathcal{R}_{t+h}^{(\tau),FFF} - \Delta \right)^2 \right\} = \sum_{t=0}^{T-h} \left\{ \left(\mathcal{R}_{t+h}^{(\tau),\mathcal{M}} \right) - \frac{\lambda}{2(1+\lambda)} \left(\mathcal{R}_{t+h}^{(\tau),\mathcal{M}} \right)^2 \right\}, \quad (20)$$

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 $\lambda = 5^6$. Table 6 reports the results of the exercise.

[*INSERT TABLE 6*]

The table reveals that fees are 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 exception represented by the comparison with the AR forecasts for maturities greater than a year, which is consistent with our previous findings.

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 first incorporate 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 short end of the yield curve forecast - which in our case is the federal funds rate - at the market expectation for the same yield and results in new forecasts for all remaining yields. We then extract the forecasts of excess returns implied by the tilted yield curve forecasts 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, a forecast based on the expectation hypothesis and an autoregressive forecast. 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 the competitors in terms of market timing and in terms of both statistical and economically meaningful measures of accuracy. This result is robust across maturities for up to two years and forecast horizons of less than one year. For long forecast horizons and maturities of four and five years, instead, the preferred method is a simple autoregressive model. Riding the yield curve according to the tilted forecasts always results

⁶The results do not change qualitatively when $\lambda = 2, 3$.

in positive cumulated excess returns and in the majority of cases it outperforms its competitors when accounting for risk-return tradeoffs.

One of the possible reasons for the observed deterioration in the forecast performance of our method at longer forecast horizons is that the federal funds futures market becomes less liquid as the forecast horizon grows, whereas the observed dominance of a simple autoregressive forecast for bonds with long maturities could signal that factors other than the future course of monetary policy explain the dynamic behavior of the long end of the yield curve. For these reasons, our practical recommendation is to adopt the method considered in this paper for forecasting and devising investment strategies for bonds with maturities of up to two years and investment horizons less than one year.

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Table 1: Predictive Regressions

	Augmented Model			CP model		Augmented Model			CP model	
maturity	β_1	β_2	$\bar{R}^2$	β_1	$\bar{R}^2$	β_1	β_2	$\bar{R}^2$	β_1	$\bar{R}^2$
	h=3					h=6				
3	0.06	0.006	0.22	0.07	0.18	0.07	0.010	0.26	0.09	0.22
6	0.15	0.008	0.25	0.17	0.23	0.17	0.015	0.29	0.20	0.27
9	0.26	0.010	0.26	0.29	0.25	0.28	0.018	0.31	0.31	0.30
12	0.37	0.010	0.26	0.40	0.26	0.40	0.018	0.32	0.43	0.31
24	0.82	0.007	0.24	0.84	0.24	0.87	0.012	0.32	0.89	0.33
36	1.25	0.001	0.22	1.25	0.23	1.31	-0.001	0.32	1.31	0.32
48	1.64	-0.007	0.22	1.62	0.22	1.71	-0.014	0.31	1.68	0.31
60	1.99	-0.014	0.21	1.95	0.21	2.05	-0.026	0.30	2.01	0.30
	h=9					h=12				
3	0.09	0.012	0.34	0.11	0.31	0.10	0.011	0.39	0.12	0.38
6	0.20	0.019	0.37	0.23	0.35	0.22	0.019	0.42	0.25	0.42
9	0.32	0.022	0.39	0.35	0.38	0.35	0.023	0.45	0.38	0.44
12	0.45	0.022	0.40	0.48	0.39	0.48	0.024	0.46	0.51	0.46
24	0.93	0.012	0.41	0.95	0.41	0.99	0.013	0.49	1.00	0.49
36	1.37	-0.003	0.40	1.37	0.40	1.44	-0.006	0.49	1.43	0.49
48	1.75	-0.017	0.38	1.73	0.38	1.84	-0.025	0.47	1.81	0.47
60	2.08	-0.028	0.35	2.04	0.35	2.17	-0.041	0.44	2.12	0.44

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

Table 2: Pesaran and Timmermann (1992) Test for Market Timing

Maturity	h = 3	h = 6	h = 9	h = 12	h = 3	h = 6	h = 9	h = 12
Tilted					DNS			
3	0.64**	0.73***	0.69***	0.56*	0.41	0.21	0.19	0.27
6	0.64***	0.79***	0.74***	0.6**	0.34	0.24	0.19	0.26
9	0.69***	0.76***	0.78***	0.67***	0.32	0.26	0.19	0.23
12	0.72***	0.73***	0.78***	0.67***	0.33	0.29	0.17	0.25
24	0.71***	0.73***	0.75***	0.62***	0.31	0.31	0.21	0.28
36	0.59**	0.62***	0.7***	0.63***	0.35	0.35	0.24	0.28
48	0.58*	0.57	0.7***	0.65***	0.37	0.38	0.24	0.26
60	0.59**	0.59*	0.68***	0.65***	0.4	0.41	0.31	0.25
EH					AR			
3	0.58*	0.51	0.55	0.48	0.560	0.45	0.5	0.44
6	0.56	0.59*	0.53	0.48	0.560	0.57	0.49	0.47
9	0.65***	0.59*	0.53	0.54	0.62**	0.56	0.54	0.55
12	0.6**	0.57	0.56	0.56	0.570	0.56	0.56	0.61**
24	0.56	0.56	0.59*	0.60*	0.62**	0.62**	0.670	0.75***
36	0.56	0.56	0.62**	0.62**	0.58**	0.64**	0.73***	0.75***
48	0.59**	0.55	0.68**	0.66**	0.61**	0.63**	0.77***	0.76***
60	0.61**	0.58**	0.690	0.68***	0.63**	0.63**	0.78***	0.78***

Notes. Pesaran and Timmermann's (1992) 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 forecasts generated by the three different methods. ***, **, * 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 3: Diebold and Mariano Tests

	directional change loss				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			
3	0.93	0.74***	0.82**	0.92	0.84***	0.81***	0.82***	1.11
6	0.91	0.72***	0.74***	0.88**	0.86***	0.83***	0.83***	1.15
9	0.95	0.77***	0.69***	0.85**	0.89***	0.86***	0.85***	1.18
12	0.84**	0.79***	0.71***	0.88*	0.92**	0.88***	0.87***	1.2
24	0.8***	0.79***	0.78***	0.98	0.99	0.98	0.97	1.29**
36	0.96	0.92	0.88	0.99	1.04	1.04	1.07	1.37***
48	1.01	0.97	0.96	1.01	1.05*	1.06**	1.12***	1.43***
60	1.02	0.99	1.03	1.04	1.03	1.06**	1.13***	1.45***
Tilted vs DNS					Tilted vs DNS			
3	0.78***	0.58***	0.62***	0.77***	0.74***	0.7***	0.7***	0.98
6	0.74***	0.53***	0.57***	0.73***	0.75***	0.71***	0.71***	0.99
9	0.68***	0.57***	0.52***	0.66***	0.78***	0.73***	0.72***	1
12	0.65***	0.61***	0.52***	0.67***	0.81***	0.75***	0.73***	1
24	0.64***	0.63***	0.56***	0.73***	0.86***	0.8***	0.76***	0.98
36	0.79***	0.77***	0.62***	0.72***	0.88***	0.83***	0.78***	0.97
48	0.81***	0.83**	0.62***	0.69***	0.9***	0.86***	0.8***	0.96
60	0.82**	0.83**	0.68***	0.68***	0.92***	0.88***	0.82***	0.96
Tilted vs AR					Tilted vs AR			
3	0.9	0.7***	0.78***	0.88**	0.84***	0.82***	0.83***	1.14
6	0.9	0.71***	0.71***	0.87**	0.86***	0.84***	0.84***	1.17
9	0.91	0.74***	0.69***	0.86*	0.89***	0.86***	0.86***	1.2
12	0.81**	0.79***	0.71***	0.93	0.92**	0.89***	0.88**	1.22
24	0.87	0.84*	0.87	1.23*	1	0.99	0.99	1.31**
36	0.99	1.03	1.05	1.22*	1.05	1.05	1.08	1.4***
48	1.04	1.07	1.13	1.21	1.06	1.08*	1.14**	1.47***
60	1.05	1.05	1.21	1.26*	1.04	1.07*	1.16***	1.5***

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 futures-implied expectations. The sample period is 2003:1-2011:12

Table 4: Cumulated Excess Returns - Riding the Yield Curve

Maturity	h = 3	h = 6	h = 9	h = 12
Tilted				
3	0.481	0.769	0.375	0.103
6	1.760	1.704	2.718	1.237
9	2.624	2.926	4.241	2.469
12	4.312	4.201	5.808	3.555
24	10.956	10.226	12.192	8.228
36	13.142	10.837	11.033	14.320
48	17.247	14.057	15.064	20.518
60	27.518	27.410	18.804	25.933
DNS				
3	-0.451	-0.536	-0.566	-0.095
6	-1.008	-1.026	0.460	-0.020
9	-1.430	-1.465	0.743	0.169
12	-1.797	-1.854	1.055	0.431
24	-1.831	-2.881	3.013	1.747
36	-1.132	-0.071	-2.104	4.678
48	-1.139	-0.308	-2.256	5.653
60	1.094	-0.117	0.000	-1.786
AR				
3	-0.275	0.204	0.392	-0.069
6	-0.289	0.772	1.079	0.139
9	0.272	1.567	1.958	0.550
12	0.940	2.545	5.890	3.173
24	11.188	11.662	12.882	12.467
36	18.759	19.370	20.445	20.318
48	26.268	26.817	27.659	27.752
60	33.156	33.598	34.214	34.443

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

Table 5: Sharpe Ratios - Riding the Yield Curve

Maturity	h = 3	h = 6	h = 9	h = 12
Tilted				
3	0.263	0.369	0.648	0.123
6	0.396	0.387	0.531	0.393
9	0.381	0.427	0.560	0.510
12	0.472	0.442	0.580	0.536
24	0.506	0.491	0.621	0.564
36	0.415	0.537	0.560	0.632
48	0.354	0.461	0.523	0.671
60	0.402	0.512	0.498	0.674
DNS				
3	-0.410	-0.462	-0.609	-0.056
6	-0.405	-0.456	0.079	-0.006
9	-0.368	-0.445	0.087	0.031
12	-0.334	-0.432	0.096	0.058
24	-0.230	-0.365	0.153	0.118
36	-0.097	-0.013	-0.426	0.244
48	-0.146	-0.043	-0.420	0.247
60	0.056	-0.013	0.000	-0.333
AR				
3	-0.147	0.080	0.211	-0.044
6	-0.070	0.147	0.284	0.042
9	0.040	0.193	0.335	0.108
12	0.095	0.229	0.487	0.354
24	0.350	0.397	0.548	0.642
36	0.372	0.447	0.604	0.731
48	0.388	0.483	0.639	0.790
60	0.393	0.507	0.660	0.826

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

Table 6: Performance Fees

Maturity	h = 3	h = 6	h = 9	h = 12
Tilted vs EH				
3	0.005	0.012	0.004	0.000
6	0.021	0.028	0.083	0.032
9	0.033	0.050	0.134	0.060
12	0.056	0.076	0.192	0.092
24	0.174	0.245	0.508	0.283
36	0.255	0.209	0.287	0.669
48	0.492	0.386	0.557	1.329
60	-0.211	-0.424	-0.785	-0.072
Tilted vs DNS				
3	0.012	0.024	0.021	-0.002
6	0.036	0.050	0.045	0.017
9	0.053	0.080	0.068	0.024
12	0.080	0.114	0.091	0.028
24	0.196	0.303	0.183	0.061
36	0.263	0.201	0.358	0.152
48	0.507	0.372	0.662	0.417
60	1.129	1.395	1.253	1.379
Tilted vs AR				
3	0.011	0.012	0.005	0.013
6	0.028	0.021	0.076	0.049
9	0.034	0.028	0.112	0.076
12	0.046	0.033	0.000	-0.019
24	-0.071	-0.137	-0.033	-0.225
36	-0.226	-0.443	-0.471	-0.341
48	-0.323	-0.612	-0.619	-0.420
60	-0.294	-0.412	-0.738	-0.471

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 table considers an investor who only trades every h periods 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.