# The US Term Premia around the FOMC decisions*

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**Abstract**

Using the high-frequency identification from Piazzesi (2005), this study estimates a Gaussian term structure model on daily US interest rates data to explore the reaction of the estimated term premia on the Federal Open Market Committee (FOMC) policy rate decisions. All the FOMC decisions from January 1999 to December 2008 are devided into anticipated- and "surprise" policy actions, following Kuttner (2001). A separate set of parameters is estimated for the policy days. The estimation results suggest that the expansionary policy actions, considered as anticipated, cause on average a contemporaneous decline in forward term premia and a rise in the short-rate expectations on the longer-end of the curve. A surprise cut seem to provoke a parallel shift of the expected short-rates and a spike in longer term premia. This negative co-movement between the premia and the short-rate expectations, implicit in higher maturities, might provide one explaination of the so called "slope effect" of monetary policy on the US yield curve. The findings are independent of the market price of risk specification or whether the model with a single- or two parameter set is used in the assessment. Nonetheless, allowing a separate set of parameters around policy action days indicates a greater role of the slope factor in explaining the variation of long-term yields around those days.

*Keywords*: term stucture, FOMC, policy actions, term premia, Bayesian inference
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# 1 Introduction

Understanding the implications of a Central Bank policy rate decisions on the yield curve is important for assessing the key monetary policy transmission mechanism - expected path of future short-term interest rates. The rational expectations hypothesis of the term structure[1] suggests that the "expectations channel" is the main driver of the long-term interest rates, which influence both aggregate demand and aggregate investments[2].

Yet another important element of the long-term interest rates[3] represents the time-varying term premium - the difference between the long-term yields and the expected future short-term rates. By using the high-frequency identification strategy from Piazzesi (2005), this study shows that monetary policy in the US seem to affect both short-rate expectations and term premia implicit in the long-term rates. The key assumption of the identification strategy is that the Fed uses all available information, including the yield curve, to deliver a policy rate decision at a certain point in time, and that the subsequent change in yields is considered to be a reaction of the yield curve to the Fed decision.

To this end, a three-factor no-arbitrage yield curve model with two separate sets of parameters is estimated using *daily* data. The first parameter set captures the yield curve dynamics on usual days in the sample, whereas the second set is used for the days when the Federal Open Market Committee (FOMC) release the policy rate decision. There are totally 82 FOMC policy rate decisions delivered from the beginning of 1999 to the end of 2008, when the Fed funds rate reached the zero-lower bound.[4] All decisions are classified into anticipated and surprise policy actions by using the surprise indicator constructed from the Fed funds futures.[5]

In estimating the model, the level and the slope factor are backed-out from yields, while the implied volatility on longer-maturities interest rate caps is shown to be related to proxies for macroeconomic uncertainty and used as the third state variable. The likelihood function is specified following the ideas from the regime-switching term structure models[6] and using the Bayesian Markov Chain Monte Carlo (MCMC) method.[7] An over-identifying set of

[1]See Taylor (1995), Rudebusch (1995), Svensson (2003) and Woodford (2003) among many others.

[2]See for instance Goodfriend (1998), Svensson (2003) and Bernanke (2004).

[3]See Duffee (2002), Cochrane and Piazzesi (2005), Kim and Wright (2005), Ang, Bekaert and Wei (2007), Rudebusch, Sack and Swanson (2007), Swanson (2007) and Joslin, Priebsch and Singleton (2010) among many studies.

[4]It might be important to notice at this point that, if there is a strong positive relationship between the level of the yield curve and risk premia, as shown in Kim and Singleton (2010), the reactions of the premia might be somewhat compressed by the proximity of the zero lower bound. This was kindly noted by Prof. Marvin Goodfriend.

[5]See Kuttner (2001), Bernanke and Kuttner (2005) and Gürkaynak, Sack and Swanson (2002).

[6]Most notably, Ang and Bekaert (2002), Bansal and Zhou (2002) and Dai, Singleton and Yang (2007).

[7]Recent works in yield curve estimation using Bayesian MCMC methods include Ang et all (2007) as

restrictions allows for a rather quick convergence of the model with risk-neutral dynamics. This output is then used to select the market price of risk specification mostly preferred by the data. In line with Duffee (2009) and Joslin et al. (2010), *both* level and slope shocks seem to be priced in the yields. Once the model is fitted, every one-day change of the fitted yields, subsequent to an FOMC decision, is decomposed into expected future short-rate change and the term premia change.

To my best knowledge, this might be the first study to provide a rationale for the slope effect of the US monetary policy on the yield curve, using a reasonable identification strategy and a "cautios" term premia estimate[8]. Several studies though estimate a yield curve model on daily US interest rate data in order to analyse the link between the monetary policy actions and the yield curve. Piazzesi (2005) uses the exact timing of FOMC meetings to estimate a continuous time model of joint distribution of bond yields and interest rate target set by the FOMC. Bauer (2009) looks at the reaction of the US term premia to the macroeconomic news and shows that the short rate expectations, and not risk premia, account for the majority of daily volatility at the long-end of curve. Goukasin and Cialenco (2006) use an extended Nelson-Siegel and Vasicek models to show that the slope of the term structure reacts significantly to the monetary policy actions. Söderlind (2009) uses daily observations of Swiss interest rates and interest rate caps[9] and finds that an increase in policy rate causes on average a decrease in term premia for longer maturities.

There are arguably three important results in this study. There seem to be, on average, an increase in long-term future short-rate expectations and a fall in long forward term premia, whenever the Fed decision to reduce the reference rate is considered as anticipated. Presumably, the markets anticipate less uncertainty in future inflation outlook and price-in the Fed's commitment to long-term price stability and readiness to rise the Fed funds rate in the future. On the other side, a surprise cut of the policy rate seems to be followed by a decrease in future rate expectations across maturities and an increase in the term premia immanent to the mid- and long-term yields. Most importantly, this result is independent from the market price of risk specification and of weather the single- or two-parameter set model is used to track down the reaction.

Secondly, the estimated reactions to the policy rate moves of the Fed might explain the findings of previous high-frequency studies[10], which show that the longer yields' reaction to the FOMC statement releases is negligible. The results might explain the slope effect of the monetary policy actions on the yield curve, as there seem to be a negative contemporaneous movement of the estimated expectations part and the premia part of the longer-term yields.

well as Chib and Ergashev (2008).

[8]High persistency of the state variables in daily data allows for a higher amount of variation in short-rate expectations respect to those estimated on weekly, monthly or quarterly data.

[9]Söderlind (2009) is also the first study that uses the implied volatility from interest rate caps as an explicit factor in the model estimation.

[10]Most notably Flemming and Piazzesi(2005).

Finally, the separately estimated set of parameters for policy action days unveils that the portion of long-term yields variation explained by the slope factor is much higher on policy action days. The level factor, related to the medium-term inflation expectations,[11] is not the main driver of long-term yields around policy action days, which might point to a greater role of monetary policy in shaping the long-term yields around those days.

This paper is organised as follows: the first section introduces the data set; the second section introduces the Gaussian yield curve model and overlays the two-set parameter idea for the non-policy days and for the FOMC rate decisions days; the third section specifies the estimation strategy and defines the Bayesian MCMC algorithm; the fourth part elaborates the results and the final part concludes.

# 2 The Data

## 2.1 Yields

The dataset includes 2608 daily observations of the U.S. Dollar 6M LIBOR and the 1Y-10Y swap rates from plain vanilla fixed-to-floating swap contracts[12] from January 1999 to the end of December 2008. All the yields are converted to continuously compounded assuming semi-annual compounding.[13] The 6m LIBOR is corrected for the consequences of the credit disruption initiated in August 2007 and lasted until the end of the sample. For this time period, I simply used the 6m Overnight Indexed Swap (OIS) rate plus the average OIS - LIBOR spread for the period.[14] In such a way, the short rate in the sample reflects the average credit conditions throughout the sample and excludes the spike in the 6m LIBOR in the days following the Lehman Brothers bankruptcy.

In regard to the longer maturity rates, the treasury STRIPS are initially considered as readily available zero-coupon yields that are shown to remove some of the idiosyncratic variation in the yields of individual Treasury notes and bonds.[15] Yet STRIPS, as other on-the-run Treasury securities, can "go on special" in the repo market, i.e. can be used as a collateral for an overnight loan at a rate *bellow* the general collateral rate. In other words, STRIPS can be traded at a premium respect to other securities such as off-the-run

[11] See Mumtaz and Surico (2008) and Rudebusch and Wu (2007).

[12] The LIBOR rates are obtained from daily fixings by the British Bankers' Association while the swap rates are indicative mid-quotes averaged accross many data providers. Both series are available on Bloomberg and the fixing time for the swap rates is set to 17:00 hours New York time.

[13] See Hull (2006).

[14] Available also on Bloomberg from beginning 2001. The average OIS - LIBOR spread in the sample was 11 basis points.

[15] See Sack (2000) for example.

treasuries. The implications of the Repo specialness on the bonds prices in an interest rate model can be non-trivial as noted in Duffie(1996) and Jordan and Jordan (1997).

Besides repo specialness, the swap rates are appealing for other two reasons: they are often regarded as "true" constant maturity yield data[16] and thus not a subject to approximation error of the boostrapping and interpolation techniques. In addition, the swap rates imply a limited credit risk premium, as in most cases only the intermediate cash-flows are exchanged. The preliminary data inspection shows that the spread[17] between the swap rates and off-the-run treasuries of the corresponding maturity is minor, especially in September and October 2008.

## 2.2 Anticipated and Surprise Policy Actions

The dataset includes 82 policy meetings of the Federal Open Market Committee (FOMC) that resulted in an interest rate decision. The starting policy action was an interest rate hold delivered on the 3rd of February 1999, mainly due to a loosing growth momentum and contained inflationary pressures.[18] The last decision in the sample was made on 16th December 2008 in the midst of the recent financial crisis, when the Fed decided to cut the reference rate by 75 basis points to the target range 0 - 1/4 percent.

Out of 82 FOMC meetings, 11 decisions are labelled as "surprise changes" of the Federal Funds target rate. Following Kuttner (2001), I first construct a measure of the "surprise element" in Federal Funds target changes using the Federal Funds futures data from Chicago Mercantile Exchange (CME). Secondly, I characterise different policy actions as expected or unexpected.

In the construction of the policy surprise indicator, I consider the change in the Fed target rate implied by the current-month futures contract on (monthly) average Federal Funds rate. For a FOMC decision that took place at day $d$ of the month $m$, the unexpected change in the policy rate, scaled up by the factor that takes into account the number of days in the month affected by the change is calculated as:

$$\Delta i^{unexpected} = \frac{D}{D-d}(F_{m,d} - F_{m,d-1}) \tag{2.1}$$

where $D$ is the number of days in the current month and $F_{m,d}$ is the Fed Funds rate implied by the current-month futures contract value. If a policy decision was widely expected, the above change should be close to zero. In order to minimise the effect of month-end noise,

[16]Dai and Singleton (2000).
[17]As much as the change in the spread.
[18]See Fed Greenbook, February 1999, Part 1.

I calculate an unscaled change for any decisions that came in place in the last 10 calendar days of any month.[19] Results are shown in Table 1 in the Appendix.

Once constructed the surprise index, a "surprise change" is considered to be any difference calculated in (2.1) that exceeds a two thirds of the usual 25 basis points move in any direction, namely under -16 and above +16 basis points.[20] In such a way, there are 11 FOMC decisions considered as "surprise moves". Specifically, out of 23 FOMC decisions opting for an interest rate hike, only one seem to have been a "surprise hike". It was delivered on 22nd of March 2005 in a series of rate hikes lasting from June 2004 to June 2006. I consider as unexpected holds the FOMC decisions on 19th of March 2002 and 18th of September 2008. The remaining 8 policy actions are considered as surprise target rate cuts and are equally spaced between the dot-com crisis at the beginning of 2000's and the recent financial crisis. Roughly half of these are delivered after an unscheduled meeting of the FOMC.[21] There were overall 23 FOMC decisions to cut the target rate.

Finally, a brief comment regarding the FOMC decision on the 16th of December 2008, when the policy rate reached the target range 0 - 25 basis points, is warranted. The scaled one day change of the Fed futures was minus 35 basis points, which means that the futures market anticipated a policy rate cut of a smaller portion i.e. the futures market seem to have been "surprised" only by the magnitude of the rate cut. In addition to this, Taylor (2010) show that, considering the size of the reserve balances of depository institutions at Federal Reserve banks at that time, the amount of monetary easing seem to have front-runned the effective Federal funds rate. For this reason, I do not consider this last rate decision in the sample as a "surprise move".

## 2.3 Implied Volatility from Interest Rate Caps

### 2.3.1 Mechanics

An interest rate cap is a financial derivative that provides protection to the buyer, who has borrowed funds on a floating rate basis, against the risk that interests rate rise in the future. The buyer receives a positive payoff whenever an underlying interest rate (specifically the 3m LIBOR in our dataset) rises above an agreed level - known as the *cap rate*. Interest rate caps are popular instruments among both investors and financial intermidiaries.

[19] Kuttner (2001) proposes 3 days for the same purpose. 10 days are chosen to bring the measure closer to what previous studies using the tick-by-tick data produced, for example see Fleming and Piazzesi (2005).

[20] The two-thirds threshold was chosen as an arguably reasonable portion of the usual policy move, above which the move might be considered as a surprise one. Alterating the threshold to 15 or 17 basis points does not change the main result.

[21] Namely, on the 3rd of January 2001, the 18th of April 2001, the 17th of September 2001, the 22nd of January 2008 and the 8th of October 2008.

One interest rate cap is essentially a portfolio of call options, so called *caplets*, on all the future short-term rates until the expiry of the cap. For instance, an interest rate cap expiring in 1 year consists of three options on 3m LIBOR that start 3, 6 and 9 months ahead, respectively. Each of the options pays a positive difference between the 3m LIBOR and the cap rate at every single expiry, i.e. 6, 9 and 12 months ahead, respectively.

As different interest rate cap market participants use different option pricing models to determine the buying/selling price of a cap, the premium for an interest rate cap is by convention quoted in units of *implied volatility*. Specifically, it is the volatility of the underlying short-term rate "priced" by the market maker and implied by an option pricing model (usually a version of the Black-Scholes-Merton model) used by the market maker. Using again the example of a 1 year interest rate cap, the implied volatility could be thought of as the volatility of the average 3m LIBOR one year ahead.

Finally, the option data at hand consist of six time series of implied volatilities accross the cap maturities of 1Y to 4Y, 7Y and 10Y starting from January 1999.[22] Any data point represents a composite quote stemming from many data-providers (market makers) and averaged accross cap rates. The Figure 1 shows the joint dynamics of term spread and 10Y implied volatility. As it can be noticed, a relatively high term spread (in levels) seem to be related to a higher implied volatility and vice versa, with correlation coefficient at 0-lag around 0.74.

FIGURE 1 ABOUT HERE

#### 2.3.2 The Third Factor Candidate

From what previously said, implied volatility in interest rate caps can be partially considered as uncertainty in future dynamics of the short-term interest rates, over the time-span of the cap maturity.[23] Considering the findings in Hördal (2000) and Söderlind and Svensson (1997), the second moment of future short-term rates distribution might be an important indicator of market expectations concerning the future monetary policy. The third state variable in the model is the demeaned series of 10 year interest rate cap implied volatility[24]

[22]The data source is Bloomberg and the series is available from December 1995 but the contribution frequency prior to the beginning of 1999 is poor. It also publishes implied volatilities accross both maturities and cap rates starting from 2002. As in the case of swap rates, the fixing time is 17:00 hours New York time.

[23]Given that the single option caps are not "delta-neutral" strategies, this implied volatility might be considered as a proxy for the pure uncertainty of the underlying. In other words, the implied volatility quotes from the market makers also include the so called "directional risk" i.e. the risk that the underlying yield moves upwards or downwards, see Cieslak and Povala (2010).

[24]To my best knowledge, the first study that uses implied volatilities from interest rate caps in a yield curve model estimation is Söderlind (2009). The data set used contains daily observations of Swiss interest

and this section shows that this volatility explains a non-trivial portion of the time-varying "macroeconomic uncertainty".

As the macroeconomic indicators reflecting the final objectives of the Fed,[25] I consider the monthly changes in unemployment rate, headline inflation (all-items CPI), industrial production (all-sectors index) and the 10Y Treasury yield. The proxies for the macroeconomic uncertainty of the four indicators plus the federal funds target rate are constructed as squared demeaned monthly changes of the series. Alternatively, one could use the rolling-window standard deviation[26] or survey-based measures, obtained from dispersion of forecasts from economic surveys.[27] Following Blanchard and Simon (2001), I construct volatility of the monthly Industrial Production series. This proxy for macro uncertainty seems to be closely related to the considered 10Y implied volatility as the Figure 2 indicates.

FIGURE 2 ABOUT HERE

Next, I regress monthly changes and squared monthly changes in the aforementioned macroeconomic series, namely Fed funds rate, unemployment rate, headline inflation, industrial production and the 10Y yield, on single implied volatilities across maturities. The results of these univariate regressions are shown in Table 2.

TABLE 2 ABOUT HERE

As the upper panel of the Table 2 illustrates, implied volatilities explain a non-trivial part of changes in the federal funds target rate and the 10Y yield, whereas the proportion of the variation explained increase with the cap maturity. Particularly interesting is the last row of the panel, showing that the implied volatility on the 10Y cap explains roughly 40 percent of the variation in the 10Y yield. The negative sign of the slope coefficient stems from the negative correlation between the *level* shock in the 10Y yields and the implied volatilities.[28] Thus, the effect of the implied volatilities on the yield curve seems to be operating through the negative relation with the level factor. Intuitively, as both economic prospects and credit market conditions are perceived to deteriorate, the money market participants bid

rates and interest rate caps. Following the ideas in Söderlind (2009), I use the implied volatility from 10Y interest rate caps as the third and explicit factor in the model.

[25]The Federal Reserve has a dual mandate of promoting "effectively the goals of maximum employment, stable prices and moderate long-term interest rates" (Federal Reserve Act, Section 2a. Monetary Policy Objectives).

[26]See Blanchard and Simon (2001)

[27]Similarly to Boero, Smith, and Wallis (2008) and Söderlind (2010).

[28]This is broadly in line with previously reported results in Heidari and Wu (2003) and Almeida et al. (2011).

up the option caps' premiums and so increase the implied volatilities accross maturities. At the same time, the central bank eases the policy rate in an attempt to reduce the overall level of the yield curve and the policy rate decision is priced-in on the rates market.

Finally, the lower panel of the Table 2 shows close relationship of the cap implied volatilities and the uncertainty proxies. It seems that there is a statistically significant link between the 1Y implied volatility and the proxy for unemployment uncertainty, on one side. On the other, the implied volatility from the 10Y cap explains a statistically significant portion of the variation in CPI and IP volatilities, while remaining a significant independent variable in regressions against the Fed funds rate (7.1 percent of variation in terms of R-squared) and the 10Y yield (7.8 percent of variation). It might be perhaps important to emphasise that all the six implied volatility measures explain a statistically significant proportion of the variation in the proxy for inflation uncertainty.

# 3 The Model

This section introduces the general asset pricing relation, defines the pricing kernel and specifies the Gaussian diffusion process of the underlying state factors with homoscedastic volatility. Nonetheless, it derives the bond prices and overlays a simple two-parameter-set design[29].

## 3.1 General Setting and State Dynamics

Let us start with the general asset pricing equation[30] under physical probability measure $\mathbb{P}$:

$$P_{n,t} = E_t \left[ M_{t+1} P_{n-1,t+1} | I_t \right] \tag{3.1}$$

where $P_{n,t}$ is the price of an n-days to maturity zero-coupon bond in time $t$, $M_{t+1}$ is the stochastic discount factor and $I_t$ is the agents' current information set. In a risk-neutral world where investors request no risk compensation, the price of the bond $P_{n,t}$ equals:

$$P_{n,t} = E_t^{\mathbb{Q}} \left[ exp(-y_{1,t}) P_{n-1,t+1} | I_t \right] \tag{3.2}$$

where $\mathbb{Q}$ is the risk-neutral probability measure and $y_{1,t}$ is the short-term interest rate. The no-arbitrage argument assures that the two above prices are equal, as there exists an

[29]In the experimental design literature, a design (procedure) denotes a statistical method for finding the best parameter set, see for example Wang and Wu (1999) for the application of the response surface methodology of Box and Wilson (1951).

[30]See Campbell et al. (1997)

equivalent martingale measure $\mathbb{Q}$ according to which (3.2) holds[31] and:

$$\begin{aligned} exp(-y_{1,t}) &= E_t\left[M_{t+1}|I_t\right] \\ &= exp(-y_{1,t})E_t\left[(d\mathbb{Q}/d\mathbb{P})_{t+1}|I_t\right] \end{aligned} \tag{3.3}$$

where $d\mathbb{Q}/d\mathbb{P}$ is the Radon-Nykodim derivative[32] following a log-normal process:

$$(d\mathbb{Q}/d\mathbb{P})_{t+1} = exp\left(-\frac{1}{2}(\lambda_t)'\lambda_t - (\lambda_t)'\varepsilon_{t+1}\right) \tag{3.4}$$

where $\lambda_t$ is the market price of risk associated with the sources of uncertainty $\varepsilon_t$[33]. Following Duffee (2002), it is "essentially affine" in the risk factors $X_t$ as follows:

$$\lambda_t = \lambda_0 + \lambda_1 X_t \tag{3.5}$$

where $\lambda_0$ and $\lambda_1$ produce constant prices of risk if $\lambda_0 \neq 0$ and $\lambda_1 = 0$ or time-varying prices of risk if $\lambda_0 \neq 0$ and $\lambda_1 \neq 0$. The equations (3.3) to (3.5) define the pricing kernel. Another fundamental building block of the Gaussian term structure model is the state variable $X_t$ which follows a discrete version of constant volatility Ornstein-Uhlenbeck process[34]. Under the physical probability measure $\mathbb{P}$, the process is:

$$X_{t+1} = (I - \Psi)\mu + \Psi X_t + \Sigma\varepsilon_{t+1} \tag{3.6}$$

where the first term on the right-hand side is a vector of factors' means, $\Psi$ is the VAR matrix, $\Sigma$ is the covariance matrix, and $\varepsilon_t$ is an IID $N(0, 1)$.

## 3.2 Bond Prices

Assuming joint log-normality of bond prices and the pricing kernel, the $n$-days to maturity nominal bond price is an affine function of the state variables:

$$P_{n,t} = exp\left\{-\mathcal{A}_{n,t} - \mathcal{B}'_{n,t}X_t\right\} \tag{3.7}$$

where the coefficients $\mathcal{A}$ and $\mathcal{B}$ are computed using the usual recursive formula.[35] Nonetheless, the two coefficients are time dependent, as the agents can choose between two different sets of parameters to price a n-days to maturity bond $P_{n,t}$ in $t$:

[31] See Harrison and Kreps (1979).
[32] See Dai et al. (2007).
[33] See Ang and Bekaert (2002) and Ang and Piazzesi (2003).
[34] See Phillips(1972).
[35] See for example Campbell (1998) or Cochrane and Piazzesi (2004).

$$\mathcal{B}_{n,t} = \iota_t \left[ \begin{array}{c} \left(\Psi - \Sigma^j \lambda_1^j\right)' B_{n-1}^j + B_1 \\ \left(\Psi - \Sigma^k \lambda_1^k\right)' B_{n-1}^k + B_1 \end{array} \right]$$

and

$$\mathcal{A}_{n,t} = \iota_t \left[ \begin{array}{c} A_{n-1}^j + \left((I-\Psi)\mu - \Sigma^j \lambda_0^j\right)' B_{n-1}^j + \frac{1}{2} B_{n-1}^{\prime j} \Sigma^j (\Sigma^j)' B_{n-1}^j + A_1 \\ A_{n-1}^k + \left((I-\Psi)\mu - \Sigma^k \lambda_0^k\right)' B_{n-1}^k + \frac{1}{2} B_{n-1}^{\prime k} \Sigma^k (\Sigma^k)' B_{n-1}^k + A_1 \end{array} \right]$$

where $\iota_t$ is a $1 \times 2$ indicator vector, picking alternatively the $j$ or the $k$ parameter set in every $t$. It is assumed that agents use the former parameter set to price the bond on a non-policy day and letter in all the days of the FOMC policy rate decision:

$$j = \{\text{non-policy day}\} \quad \text{and} \quad k = \{\text{FOMC statement day}\}$$

As it can be noticed, the parameters in the VAR matrix as well as the parameters $\mu$, $A_1$ and $B_1$ are common in the two parameter sets. As the time interval is daily and the second parameter set is only used to price the bonds on policy action days, there is arguably no reason to believe that the persistency in the factors dynamics nor the factors mean and the average yield curve level alter significantly on an average policy action day.

Finally, given that an agent chooses between the two "models" with separate dynamics, the underlying assumption is that a particular model explains the yield dynamics until infinity. In other words, the persistency of a single "regime" is equal to unity. Yet at a cost of this approximation, there is possibly a multiple benefit. We are able to measure separately the volatilities of the underlying state variables on the usual days and on the policy days. It is possible to attribute the variation in different yields to the variation in single state variables *on* the policy action days. Above all, we can allow for different compensations for shocks to the level and to the slope of the term structure on different days.

### 3.3 No-arbitrage Argument

To assure that the no-arbitrage argument holds, I assume that the state variable $X_t$ under the risk-neutral measure $\mathbb{Q}$ follows:

$$X_{t+1}^{\mathbb{Q}} = (I - \Psi)\mu^{\mathbb{Q}s} + \Psi^{\mathbb{Q}s} X_t + \Sigma^s \varepsilon_{t+1}^{\mathbb{Q}} \tag{3.8}$$

where $s = \{j, k\}$. Note that the VAR matrix $\Psi^{\mathbb{Q}s}$ is now different in the two sets. Given equations (3.2) and (3.3), this implies that the usual no-arbitrage restrictions on the parameters describing the physical and the risk neutral measure in this case are:

$$\mu^{\mathbb{Q}s} = \mu_t - \Sigma_t^s \lambda_0^s$$

and

$$\Psi^{\mathbb{Q}s} = \Psi_t - \Sigma_t^s \lambda_{1t}^s$$

where parameters on the right hand side are estimated while the parameters $\mu^{\mathbb{Q}s}$ and $\Psi^{\mathbb{Q}s}$ are derived parameters. This might be important, since in the regime-switching literature and the stochastic regime-switching setting, Bansal and Zhou (2002), for instance, show that the regime-dependent $\Psi^{\mathbb{Q}s}$ parameter calls for a log-linearisation of the pricing kernel to get the close form solution for the recursive pricing formula. In another important study of Dai et al. (2007), the authors impose a restriction on $\mathbb{Q}$ distribution so that $\Psi^{\mathbb{Q}}$ is regime-independent. In a two-regime switching model, they estimate one of the $\Psi_t^{\mathbb{P}s}$ parameters and derive the other VAR parameter under $\mathbb{P}$ and the one-and-only under $\mathbb{Q}$.

### 3.4 Forward Term Premia

In this section, the model-implied forward term premia are derived. The reason for focusing on this particular definition of the risk premium[36] is that most of the studies of the U.S. term premia report the forward term premia.[37] According to the expectation theory of the term structure[38], an "$n - m$ period" forward rate $n$ periods ahead, $fwd_{mn,t}$, is equal to the expected future short rate plus the term premium:

$$fwd_{mn,t} = E_t\left[y_{1,t+n-1}\right] + fTP_n \tag{3.9}$$

where $fwd_{mn,t}$ is the continuosly compounded forward rate:

$$fwd_{mn,t} = \frac{n}{n-m} y_{n,t} - \frac{m}{n-m} y_{m,t} \tag{3.10}$$

Once I fit the yield curve and obtain $y_{i,t}$ for every $i = \{6m, 1Y, ...10Y\}$ and every $t = [1, T]$, the forward rates are calculated using (3.10) and the apropriate expectations part is subtracted. The expected future short term rate between 6M and 1Y time from $t$:

$$\begin{aligned} E_t[y_{6m,t+360}] &= A_1 + B_1' E_t[X_{t+180}] \\ &= A_1 + B_1' \left[(I - \Psi)\mu(I + \Psi + \Psi^2 + ... + \Psi^{180}) + \Psi^{180} X_t\right] \end{aligned}$$

[36]The term premium or the *risk* premium can be equivalently defined as a yield risk premium, a forward risk premium and a return risk premium. For a detailed discussion see Cochrane and Piazzesi (2008).

[37]See Kim and Wright (2005), Cochrane and Piazzesi (2005), and Joslin et al. (2010) among others.

[38]See Campbell and Shiller (1990) for an insightful discussion of the expectation theory of the term structure.

is subtracted from the 6M to 1Y forward rate and:

$$E_t[y_{1Y,t+360n}] = A_1 + B_1' \left[ (I - \Psi)\mu(I + \Psi + \Psi^2 + ... + \Psi^{360(n-1)}) + \Psi^{360(n-1)} X_t \right] \quad (3.11)$$

from any 1Y forward rate starting in $n = 2, 3...N$ years.

Further decomposition of the forward term premia to very state variables and parameters of the model can be found in Hördal et al. (2006).

# 4 Estimation

In this section the likelihood function used to construct the joint posterior of parameters and data is derived. In addition, the model is estimated with a simple version the Bayesian Markov-Chain Monte-Carlo (MCMC) method and this section provides the general idea, rationale and the description of the algorithm.

## 4.1 Likelihood Function

Following the ideas in Chen and Scott (1993), the 6m and the 10Y yields are set to be observable and the rest to be measured with error. Let $y_{o,t}$ be a vector of observable yields i.e. yields perfectly priced by the model. On a non-policy day, for instance, $y_{o,t} = A_o^j + (B_o^j)' X_{o,t}^j$ where $A_o^j$ is a $2 \times 1$ vector, $B_o^j$ a $2 \times 2$ matrix of factor loadings and $X_{o,t}$ are the two "latent" factors. The factors are obtained by inverting the fitted yields as:

$$X_{o,t}^j = (B_o^j)^{-1} \left( y_{o,t} - A_o^j \right)$$

To define the $X_{o,t+1}^j$ and thus the next day yield $y_{o,t+1}$, I follow the timing convention in Dai et al. (2007), according to which the conditional probability of $X_{t+1}$ satisfies:

$$f^{\mathbb{P}}\left(X_{t+1} | X_t; s_t = j; s_{t+1} = k\right) = f^{\mathbb{P}}\left(X_{t+1} | X_t; s_t = j\right) \quad (4.1)$$

The formulation differs from the original setting proposed in Hamilton (1989) where:

$$f^{\mathbb{P}}\left(X_{t+1} | X_t; s_t = j; s_{t+1} = k\right) = f^{\mathbb{P}}\left(X_{t+1} | X_t; s_{t+1} = k\right)$$

and the authors introduce it for the reasons of comparability of their model with the continuous-time yield curve models.[39] The convention proves to be useful in this setting and it can be shown that the yield $y_{o,t+1}$ reads:

$$y_{o,t+1} = \widehat{\mu_o} + \widehat{\Psi}_o y_{o,t} + (B_o^k)' \Sigma_o^j \varepsilon_{o,t+1}$$

[39]See Dai et al.(2007).

where:

$$\widehat{\mu_o} = A_o^k + B_o^k(I - \Psi)\mu^j - (B_o^k)'\Psi(B_o^j)^{-1}A_o^j$$

and

$$\widehat{\Psi_o} = (B_o^k)'\Psi(B_o^j)^{-1}$$

Consequently, the conditional probability density function of $y_{o,t+1}$ is:

$$pdf(y_{o,t+1}|y_{o,t}, s_t = j, s_{t+1} = k) = \frac{e^{-\frac{1}{2}\left(y_{o,t+1}-\widehat{\mu_o}-\widehat{\Psi_o}y_{o,t}\right)\left((B_o^k)'\Sigma_o^j(\Sigma_o^j)'B_o^k\right)^{-1}\left(y_{o,t+1}-\widehat{\mu_o}-\widehat{\Psi_o}y_{o,t}\right)'}}{\sqrt{(2\pi)^T|(B_o^k)'\Sigma_o^j(\Sigma_o^j)'B_o^k|}} \tag{4.2}$$

Finally, let the $y_{u,t}$ be a vector of the rest $N-2$ yields measured with error:

$$y_{u,t} = A_u^j + (B_u^j)'X_{o,t}^j + \xi_t^j$$

where $\xi_t^j$ is distributed as $i.i.d.$ $N(0, \omega^{j2}I)$. The normally distributed errors are assumed to have the same variance $\omega^j$ accross the unobservable yields, but which is different in the two parameter sets.[40] It is also assumed that the errors are uncorrelated cross-section and thus the covariance matrix is a diagonal matrix.

Inverting again the relation between $y_{o,t+1}$ and latent factors we have:

$$y_{u,t+1} = A_u^k - (B_u^k)'(B_o^k)^{-1}A_o^k + (B_u^k)'(B_o^k)^{-1}y_{o,t+1} + \xi_{t+1}$$

If we define again $\widehat{\mu_u} = A_u^k - (B_u^k)'(B_o^k)^{-1}A_o^k$ and $\widehat{\Psi_u} = (B_u^k)'(B_o^k)^{-1}$, the conditional density of $y_{u,t+1}$ is:

$$pdf(y_{u,t+1}|y_{o,t+1}, s_t = j, s_{t+1} = k) = \frac{e^{-\frac{1}{2}\left(y_{u,t+1}-\widehat{\mu_u}-\widehat{\Psi_u}y_{o,t+1}\right)\left(\omega^k I(\omega^k I)'\right)^{-1}\left(\left(y_{u,t+1}-\widehat{\mu_u}-\widehat{\Psi_u}y_{o,t+1}\right)\right)'}}{\sqrt{(2\pi)^T|\omega^k I(\omega^k I)'|}} \tag{4.3}$$

As already mentioned, the state variables are two latent factors and the 10Y implied volatility as the third explicit factor. The likelihood function in logs thus can be written as:

$$\begin{aligned} \ln\mathfrak{L} &= \sum_{t=0}^{T-1} \ln pdf(y_{o,t+1}, IV_{t+1}|y_{o,t}, IV_t, s_t = j, s_{t+1} = k) \\ &+ \sum_{t=0}^{T-1} \ln pdf(y_{u,t+1}|y_{o,t+1}, IV_{t+1}, s_t = j, s_{t+1} = k) \end{aligned} \tag{4.4}$$

[40] In this way, one can question weather cross-sectional pricing errors have different distributional characteristics on the non-policy versus policy action days.

## 4.2 Bayesian Inference

The yield curve implied by the model is a complicated non-linear function of the underlying parameters. As this non-linearity tend to produce a multi-modal likelihood function[41], fitting a yield curve model with a standard maximum likelihood estimation is a daunting task. In addition, the persistency of the state factors at daily frequency is widely acknowledged to be close to unit-root. Bayesian MCMC is an efficient and tractable way to tackle these issues. Nonetheless, the MCMC method might prove to be very helpful in early stages of estimation, as it secures a quick detection of possible indentification issues.

### 4.2.1 Framework

Let $\Theta$ be a vector containing all the parameters of the model:

$$\Theta = \left\{ \mu, \Psi, \Sigma^j, \Sigma^k, \lambda_0^j, \lambda_0^k, \lambda_1^j, \lambda_1^k, \omega^j, \omega^k, A_1, B_1 \right\}$$

The key idea of Bayesian estimation is to consider this vector of parameters as a multivariate random variable and use the Bayes' rule to "learn" about this random variable *given* the data:

$$p\left(\Theta \mid data\right) = \frac{p\left(data \mid \Theta\right) p\left(\Theta\right)}{p\left(data\right)} \tag{4.5}$$

where the term $p\left(\Theta\right)$ denotes the prior density of the parameters, i.e. everything we know about the parameters before looking at the data. $p\left(data \mid \Theta\right)$ is the likelihood function and $p\left(\Theta \mid data\right)$ is the posterior density of $\Theta$, summarising all we know about $\Theta$ *posterior to* seeing the data. The term $p\left(data\right)$ is known as "normalising constant"[42] and given that $p(data) = \int p(data \mid \Theta) p(\Theta) d\Theta$, it is explicitly independent of $\Theta$ and thus the (4.5) usually reads:

$$p\left(\Theta \mid data\right) \propto p\left(data \mid \Theta\right) p\left(\Theta\right)$$

In the analysis, we are interested in estimating joint posterior density $p\left(\Theta, X \mid data\right)$ of parameters $\Theta$ and the underlying factors $X$, conditional on the data. Using the Bayes' rule, this joint density can be expressed as:

$$p\left(\Theta, X \mid data\right) \propto p\left(data \mid X, \Theta\right) p\left(X \mid \Theta\right) p\left(\Theta\right) \tag{4.6}$$

where $p\left(data \mid X, \Theta\right)$ is referred to as *complete* data likelihood:[43]

$$p\left(data \mid X, \Theta\right) = \prod_{t=0}^{T-1} p_{t+1}\left(data_{t+1} \mid X_{t+1}^k, \Theta^k\right)$$

[41] See Chib and Ergashev (2009).
[42] See Koop (2003).
[43] See Frühwirth-Schnatter and Geyer (1998).

The complete data likelihood corresponds to the *cross-sectional* part of the likelihood function defined in (4.3). The term $p(X \mid \Theta)$ in (4.6) denotes the distribution of the state variables arising from the parametric state dynamics specification in (3.6). It is also known as *transition* density and given that the state variables are "backed out" from the observable yields, it corresponds to the *time series* part of the likelihood function, whose single pdf is defined in (4.2).

Finally, the priors $p(\Theta)$ are set to be non-informative or "flat" so that the posterior density of the model parameters is drawn with equal probability from the pre-defined support interval. Alternatively, I could derive the prior distributions for parameters $\Psi$, $\Sigma^s$ and $\mu$ given the normality assumption of the state VAR process in (3.6)[44] and for $\omega^s$ given the assumption of the Gaussian measurement error.[45] Chib et al. (2002) for instance, propose a scaled beta distribution as an alternative to the uniform distribution. Nevertheless, I choose not to impose lower (higher) probability areas from which the candidate values of parameters are drawn. In such a way, the estimation is entirely data-driven and proves to be computationally efficient.

For every parameter, a support interval following either no-arbitrage condition, economic reasoning or previous studies is specified. In particular, the elements of the VAR matrix are all set to be inside the unit circle, while the eigenvalues are also set to be non-negative.[46] The volatility parameters in $\Sigma^s$ and $\omega^s$ are set to be non-negative and any single element in $\Sigma^s$ is not allowed to exceed the value of three times volatility of the explicit factor. The lower bound of the parameters in $\lambda_0^s$ vector and $\lambda_1^s$ matrix are set to -100 following Chib and Ergashev(2009) whereas the upper bound for the $\lambda_0^s$ is set to 0, as the average yield curve in the sample is upward sloping.

### 4.2.2 Markov Chain Monte Carlo

Following the ideas in Frühwirth et al. (2006) and Chib and Ergaschev (2008), I use the Metropolis algorithm to draw parameter candidates from the posterior density of the model parameters. The parameter values are drawn from continuous uniform distributions $U\left(a^{\Theta}, b^{\Theta}\right)$ where the lower and the upper boundaries $a^{\Theta}$ and $b^{\Theta}$ for each parameter in $\Theta$ are previously discussed and specified in Table 4.

The Metropolis algorithm can be described in several steps:[47]

Step 1: Set the initial values of parameters $\Theta^0$. I set up two Markov chains with different

[44] For instance, see Frühwirth, et al. (2006) and Ang et al.(2007).

[45] See for example Mikkelsen (2002).

[46] Following Chib and Ergashev (2009), I impose the stationarity restriction on $(\Psi - \Sigma^s \lambda_1^s)'$ matrix in the pricing equation (3.7) as well.

[47] See Koop (2003).

starting values. The first set of starting values for the state process is obtained from OLS and the data descriptive statistics.

Step 2: Draw a candidate log-posterior density $\ln p\left(\Theta^*, X^* \mid \Theta^{mc-1}, data\right)$ conditional on previously set parameters' values $\Theta^{mc-1}$, where $mc$ is the number of Monte Carlo simulations. A single draw for any parameter $\theta_1^*$ can be described by the following Markov chain:

$$\theta_1^* = \theta_1^{mc-1} + \nu U$$

where $\nu$ is a scaling factor and $U$ is an uniformly distributed random number from interval [-1,1]. I initialise the $\nu$ factor for elements of the $\Psi$ matrix to 0.01, for elements of the $\Sigma^s$ matrix to 0.1, for the $\omega^s$ parameter to 0.00001[48] and for the elements of the market price of risk specification to 1.

Step 3: For every single parameter in $\Theta^*$, for instance $\theta_1^*$, calculate the difference between the posterior density with the candidate value and the posterior density with the previous parameter value, keeping the other parameter values fixed:

$$\begin{aligned} \alpha &= \ln p\left(\{\theta_1^*, \theta_2^{mc-1}, ..., \theta_K^{mc-1}\}, X^* \mid \Theta^{mc-1}, data\right) \\ &- \ln p\left(\{\theta_1^{mc-1}, \theta_2^{mc-1}, ..., \theta_K^{mc-1}\}, X^* \mid \Theta^{mc-1}, data\right) \end{aligned} \tag{4.7}$$

Step 4: Draw a log of the uniform random number $u \sim U(0,1)$ and accept the single parameter candidate setting $\theta_1^{mc} = \theta_1^*$ whenever:

$$min(0, \alpha) > log(u)$$

Step 5: Repeat the Steps 2 to 5 until the joint posterior density of the parameters converge in distribution.

The algorithm is ran 100,000 times and the first 40,000 are discarded as the burn-in period. The scaling parameter is automatically updated after every 5000 sweeps, from the 10,000th to the 40,000th iteration, to obtain the acceptance ratio of approximately 0.5. The two Markov chains with different starting values for both joint posterior and the single parameters' posteriors converge to literally the same posterior distributions.

[48] Proposed in Ang et al. (2007) so that it roughly corresponds to a 30 basis points bid-ask spread on Treasuries. An average spread on the OTC plain vanilla swap market might be similar, see Understanding Interest Rate Swaps: Math and Pricing, California Debt and Investment Advisory Commission, 2007.

## 4.3 Econometric Identification

### 4.3.1 Normalisations

Dynamic term structure models include unidentified structural parameters and thus the normalisation is the essential part of estimation. To this purpose, I use the standard normalisation scheme proposed in Dai and Singleton (2000) with a couple of alterations.

Regarding the diffusion process for $X_t$, the VAR matrix is set to be upper diagonal[49] and set the persistency coefficient between the two latent factors to be zero. Preliminary estimation showed that the $\Psi_{11}$ parameter, corresponding to the autoregression coefficient of the level factor, is near one. I thus simply set it to 1,[50] which is in line with the near co-integration assumption from previous studies[51] Instead of normalising the $\Sigma^s$ matrix to unit matrix, I allow for different values of diagonal elements in $\Sigma^s$ in two different parameter sets. Finally, the $\mu$ vector is normalised to zero.

When calculating the parameters of the pricing equation, I impose the usual boundary condition $A_0 = B_0 = 0$. $A_1$ is normalised to average 6m LIBOR in the sample, namely 3.64 percent, following Favero et al.(2007). Assuming that only latent factors move the short-term interest rate, the vector $B_1$ is normalised to [1 1 0]'.[52] As the third factor has no loading on the short rate, the last row of vector $\lambda_0^s$ and matrix $\lambda_1^s$ is zero.

Before estimating the entire model, the proposed normalisation sheme is used to estimate the risk neutral specification. The preliminary analysis point to a rather quick convergence of the parameters defining the $\mathbb{Q}$ measure. The mean values of parameters' posterior distributions are used as starting values in the choice of the market price of risk specification, explained in the following section.

### 4.3.2 Market Price of Risk Specification

In the second part of the preliminary analysis, all the parameters of the matrix $\lambda_1^s$ for both non-policy and policy days are estimated and the algorithm did not converge after 50,000 sweeps. The parameters $\lambda_{11}^s$ and $\lambda_{21}^s$ on one side, and $\lambda_{12}^s$ and $\lambda_{22}^s$ on the other side, seem not to be separately identified. To see this, let us consider for example the vector $B_2^s$. It is

[49] Choosing between the lower/upper diagonal $\Psi$ and lower/upper diagonal var-cov matrix $\Sigma$ is equivallent, see Dai and Singleton (2000), Appendix C.

[50] As in Diebold and Lee (2006), Blais (2009), Bauer(2009), Söderlind(2009) or Joslin et al. (2010).

[51] See for instance Giese (2008), Jardet, Monfort, and Pegoraro (2010).

[52] Alternativelly, one could normalise the covariance matrix of the diffusion process to a unity matrix and estimate the elements of $B_1$, see Ang and Bekaert (2003).

equal to the product:

$$(\Psi - \Sigma^s \lambda_1^s)' B_1 = \begin{bmatrix} \Psi_{11} - \Sigma_{11}^s \lambda_{11}^s - \Sigma_{22}^s \lambda_{21}^s \\ -\Sigma_{11}^s \lambda_{12}^s + P_{22} - \Sigma_{22}^s \lambda_{22}^s \\ P_{13} - \Sigma_{11}^s \lambda_{13}^s + P_{23} - \Sigma_{22}^s \lambda_{23}^s \end{bmatrix} \tag{4.8}$$

Arbitrage restrictions might not help as well, a large positive value of $\lambda_{11}^s$ and a large negative value $\lambda_{21}^s$ are interchangable. The same goes for $\lambda_{12}^s$ and $\lambda_{21}^s$ elements. That said, out of possible $2^6$ combinations to estimate, I isolate 35 following this logic, and estimate every specification running the algorithm 10,000 times. The specifications are then sorted according to the Bayesian Information Criterion and the results are reported in Table 3.

TABLE 3 ABOUT HERE

As it can be noticed, the first 23 specifications have similar values of the criterion and thus produce similar residual sum of squared pricing errors. As there is no obviously preferred one, I look at how many times a parameter was in the specification and thus sum the first 23 rows of the Table 3.

The market price of risk specification preferred by the data is:

$$\lambda_t^s = \begin{bmatrix} \lambda_{0,1}^s \\ \lambda_{0,2}^s \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & \lambda_{1,13}^s \\ 0 & 0 & \lambda_{1,23}^s \\ 0 & 0 & 0 \end{bmatrix} X_t \tag{4.9}$$

Consequently, both "level" and "slope" risks seem to be priced-in, i.e. the expected returns seem to be earned in compensation not only to the "level" shock[53] but also in compensation to the "slope" shock.[54]

# 5 Results

## 5.1 Parameters and State Variables

Table 4 presents the estimated transition matrix $\Psi$ in the upper panel and the other parameters in the lower panel. As already mentioned, the persistency of the level factor in the daily data is near the unit-root and for that reason it is set to 1 and excluded from estimation. Removing the stationarity restriction on the $X_{level}$ do not influence the overall estimation, as the parameter posterior distributions with or without the restriction

[53] Similarly to Cochrane and Piazzesi (2008)

[54] As in Duffee (2009) and Joslin et al. (2010).

are literally the same.[55] Given the upper panel of Figure 1, this might be a reasonable assumption.

TABLE 4 ABOUT HERE

The estimates of the $\Sigma^s$ matrix point to a relative increase in volatility of the slope factor and a sizeable increase in volatility of the explicit factor on the days of the policy rate decision. The volatility increase around FOMC meeting has been already documented by a wide literature in announcement effect. Estimated $\Psi$ and $\Sigma^s$ matrices reproduce the state variables dynamic and I plot the level and the slope factor in the upper panel of Figure 3. The correlation between factors is -0.07 from where it might be inferred that they are "telling" separate stories about yields' dynamics.

FIGURE 3 ABOUT HERE

Finally, the measurement error volatility $\omega^s$ is higher for the policy action days, which reveals that cross-sectional pricing errors seem to be systematically more volatile on the days of the FOMC decisions. In addition, all the parameters of the MPR specification are negative and not too different between the parameter sets. One might notice though, that the compensation for the "slope" risk around policy days seem to be somewhat higher than on average days. As monetary policy is considered to have a slope effect on the yield curve, this result appears reasonable.

## 5.2 Separating non-policy and policy days

### 5.2.1 Pricing Performance

By construction, the 6m and the 10Y yields are explained perfectly by the model. I therefore look at the cross-sectional fit of the yields and estimate separately the two-parameter-set model and the single-set model, using the entire data sample. Table 5 reports the mean absolute pricing errors.

TABLE 5 ABOUT HERE

As it can be noticed, the pricing errors of the alternative models are comparable. Both models fit the data increasingly better going from the short- to the long-end of the curve. A slightly better performance of the two-set model around policy action days might be

[55] This is also a by-product of the market price of risk specification, see equations (4.8) and (4.9).

explained by the fact that, the higher volatility of the level and curvature factor plus a more negative market price of risk coefficient for the slope factor translate into a more "pronounced" explicit (implied volatility) factor loading.

### 5.2.2 Relative importance of factors around policy days

Estimating a separate set of parameters for the policy action days allows for state variables to have different loadings on the yield curve. In addition, we can have an insight into the portion of yield variance explained by the factors on average days and policy action days, separately.

On the lower panel of the Figure 3, the explicit factor loadings for two different sets of parameters are illustrated. The loadings are identical for the 6-months yield by construction. Moving towards the long-end, the implied volatility factor has a stronger impact on the yield curve, both on average days in the sample and on the days of the FOMC decisions. Given the shape of the factor loading, the 10Y implied volatility might be considered as the "curvature factor".[56] The negative loadings indicate that an increased uncertainty in future short-rates is followed by a decrease in long-term rates. As the level factor is the main driver of the longer rates overall, there is a negative correlation between the level factor and the implied volatility as well.

TABLE 6 ABOUT HERE

Table 6 reports the variance decomposition of yields separately for the non-policy days and for the FOMC decisions days. The main driver of medium- and long-term yields on an average day in the sample is the level factor, explaining a half of the variation in medium-term yields and two-thirds of the 10-year yields. On policy action days, diversely, the slope factor explain roughly as much variation in the long-term yields as the level factor and more than a half of the variation in the medium-term yields. This result is driven by the higher slope and curvature factors' volatilities, estimated in the policy-day set. Accordingly, the explicit factor also becomes more important around policy action days. The variation in the long yields explained by the third factor equals 4.6 percent on an average day and slightly above 10 percent on a day of the FOMC rate call.

## 5.3 Estimated effects of the Policy Rate Announcements

Once the yield curve is fitted, the instantaneous forward rates are calculated and decomposed to expected future short-term rates and the forward term premia. To assure that

[56]Having a rather similar shape to the third unobserved factor in Ang and Piazzesi (2003).

the estimated term premia behaves similarly to what previous studies have shown, I look at the change of estimated expected rates and the forward term premia during the period June 2004 - February 2005.

In the mentioned period, the Fed increased the policy rate by 150 basis points in 6 FOMC meetings. The 6-month LIBOR increased by roughly 100 basis points while the 10Y swap rate decreased by 64 basis points. This yield curve movement was considered at the time as a "conundrum" and the subsequent studies showed that, during that time, the future expectations of the short-term rate rose parallelly across maturities while the long-term premia significantly fell. The term premia and the short-rate expectations reported here are broadly consistent with these findings.[57]

TABLE 7, FIGURE 6 AND 7 ABOUT HERE

That said, the Table 7 and Figures 6 and 7 report the estimated one-day reactions of the term premia to different policy actions,[58] while Table 8 and Figure 8 show the estimated one-day average change of the expected future short-term rates after a FOMC decision. The main result, independent from the market price of risk specification[59] or the model used to fit the yields, is two-fold.

First, the longer term premia seem to fall after an anticipated decision of the FOMC to cut the Fed funds rate. When a move of the Fed is widely anticipated, perceived uncertainty about the future outlook for the economy seem to fall, or at least to abate. The estimated reduction in premia amounts from 3.5 to 11 basis points. At the same time, the long-term expectations of the future short-rate rise, as the markets might expect that the Fed eventually increases the reference rate to fight potential inflationary preassures in the future. The average increase in the short-rate expectations is 2 basis points.

Secondly, the average response of the forward term premia to an unexpected expansionary move by the Fed is positive and it is followed by a decrease in short-rate expectations. While the forward premia reaction is statistically significant, both one-set and two-set models estimate a downward shift of the short-rate expectations which are not statistically significant, with p-values of the t-statistic slightly above the level of significance of 0.10.[60] There is an average 7.4 to 9.27 basis points increase in the 3Y term premia, an average 9.81 to 12.16 basis points increase in the 5Y term premia and an average 10.77 to 11.46 in the 7Y term premia, following a surprise interest rate cut of the Fed.

[57] This result is not reported.

[58] The 90 percent credible interval is calculated using the posterior parameters' distributions. As the parameters enter the model in a complex and non-linear way, I use every 100-th set of parameters along the first Markov chain and after burn-in, to fit the yield curve and then calculate the reaction.

[59] Very similar results are obtained for all the 23 specifications reported in Table 3.

[60] This is given by the fact that the standard deviation of the changes in expectations is somewhat higher than the changes in term premia accross the policy rate decisions.

TABLE 8 AND FIGURE 8 ABOUT HERE

The estimated negative co-movement of short-rate expectations and term premia after contractionary policy actions seem to be responsible for the “missing” reaction of the long-term yields to the FOMC decisions, especially after the surprise policy actions. As it can be noticed, the long-term yields reaction to other decisions is not statistically significant. If the high-frequency identification implemented in this study is arguably one of few reasonable ways to assess the effect of monetary policy on yield curve, this result provides rationale of why interest rate policy in the US might be a slope, and not the level, “tool” in shaping the US yield curve.

## 6 Conclusion

This study estimates a no-arbitrage Gaussian term structure model which includes an additional set of parameters to capture the yield curve dynamics around the days of the FOMC policy rate decisions, in period from January 1999 - December 2008. Given the potential multi-modality of the likelihood function, a version of Metropolis algorithm is used to estimate the model, while imposing economically meaningful restrictions on paramers’ values and the support interval. No explicit assumptions on the market price of risk are made, but the specification mostly preferred by the data is chosen i.e. the one in which the bond investors are compensated for both the level and the slope shock.

The model output indicates that anticipated Fed decisions to cut the policy rate seem to produce a fall in term premia and an increase in future short-rate expectations implicit in long-term forward rates. A suprise cut is estimated to provoke a parallel downward shift in rate expectations and an increase in medium- and long-term forward premia across maturities. Most importantly, this result seem to be independent of the market price of risk specification or weather the single- or two-set model is used in the analysis.

The results presented in this study might be further reinforced in several ways. One could elaborate the reaction of the term premia to the policy rate announcements at a higher data frequency, similar to Flemming and Piazzesi (2005). The measured speed of reaction to a FOMC decision might provide an instantaneous insight to the policy maker into the overall market conditions in which the decision is brought or perhaps into a sort of ”market assessment” of the decision. In addition, one could analyse a longer sample of daily observations, because the operating procedures of the Fed has not been changed since the 1994. Also, one could use the output from both empirical- and affine models to decompose the forward rates into expectations and premia part and then look at their reactions. All this might be the subject of author’s future research.

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## Appendix - Tables and Figures

Table 1: The reported FOMC meetings that resulted in an interest rate decision including both scheduled and unscheduled meetings. The sample covers 23 decisions to hike the policy rate, 26 cut and 45 hold decisions. Column Surprise reports the unexpected element of every decision extracted from the Fed futures market and following Kuttner (2001). Every absolute value of the surprise indicator that exceeds 2/3 of the 25 basis points categorises a decision as a Surprise Hike/Surprise Cut.

| Day | Month | Year | Decision (bp) | surprise (bp) | Surprise Hike | Surprise Cut |
|---|---|---|---|---|---|---|
| 3 | Feb | 1999 | 0 | 1 | | |
| 30 | Mar | 1999 | 0 | -1 | | |
| 18 | May | 1999 | 0 | 10 | | |
| 30 | Jun | 1999 | 25 | -8 | | |
| 24 | Aug | 1999 | 25 | 2 | | |
| 5 | Oct | 1999 | 0 | 6 | | |
| 16 | Nov | 1999 | 25 | 11 | | |
| 21 | Dec | 1999 | 0 | 12 | | |
| 2 | Feb | 2000 | 25 | 2 | | |
| 21 | Mar | 2000 | 25 | -1 | | |
| 16 | May | 2000 | 50 | 8 | | |
| 28 | Jun | 2000 | 0 | -2 | | |
| 22 | Aug | 2000 | 0 | 3 | | |
| 3 | Oct | 2000 | 0 | 2 | | |
| 15 | Nov | 2000 | 0 | 0 | | |
| 19 | Dec | 2000 | 0 | 3 | | |
| 3 | Jan | 2001 | -50 | -24 | | * |
| 31 | Jan | 2001 | -50 | -5 | | |
| 20 | Mar | 2001 | -50 | -7 | | |

| Day | Month | Year | Decision (bp) | surprise (bp) | Surprise Hike | Surprise Cut |
|---|---|---|---|---|---|---|
| 18 | Apr | 2001 | -50 | -79 | | * |
| 15 | May | 2001 | -50 | -22 | | * |
| 27 | Jun | 2001 | -25 | 9 | | |
| 21 | Aug | 2001 | -25 | -3 | | |
| 17 | Sep | 2001 | -50 | -28 | | * |
| 2 | Oct | 2001 | -50 | -14 | | |
| 6 | Nov | 2001 | -50 | -16 | | |
| 11 | Dec | 2001 | -25 | -7 | | |
| 30 | Jan | 2002 | 0 | 3 | | |
| 19 | Mar | 2002 | 0 | 53 | | |
| 7 | May | 2002 | 0 | -4 | | |
| 26 | Jun | 2002 | 0 | -9 | | |
| 13 | Aug | 2002 | 0 | -7 | | |
| 24 | Sep | 2002 | 0 | -2 | | |
| 6 | Nov | 2002 | -50 | -12 | | |
| 10 | Dec | 2002 | 0 | 0 | | |
| 29 | Jan | 2003 | 0 | 2 | | |
| 18 | Mar | 2003 | 0 | 4 | | |
| 6 | May | 2003 | 0 | -7 | | |
| 25 | Jun | 2003 | -25 | 11 | | |
| 12 | Aug | 2003 | 0 | 0 | | |
| 16 | Sep | 2003 | 0 | 0 | | |
| 28 | Oct | 2003 | 0 | -1 | | |
| 9 | Dec | 2003 | 0 | 1 | | |
| 28 | Jan | 2004 | 0 | 3 | | |
| 16 | Mar | 2004 | 0 | 0 | | |
| 4 | May | 2004 | 0 | 1 | | |
| 30 | Jun | 2004 | 25 | -8 | | |
| 10 | Aug | 2004 | 25 | 7 | | |
| 21 | Sep | 2004 | 25 | 8 | | |
| 10 | Nov | 2004 | 25 | 1 | | |
| 14 | Dec | 2004 | 25 | 0 | | |

| Day | Month | Year | Decision (bp) | surprise (bp) | Surprise Hike | Surprise Cut |
|---|---|---|---|---|---|---|
| 2 | Feb | 2005 | 25 | 1 | | |
| 22 | Mar | 2005 | 25 | 29 | * | |
| 3 | May | 2005 | 25 | 2 | | |
| 30 | Jun | 2005 | 25 | 2 | | |
| 9 | Aug | 2005 | 25 | 0 | | |
| 20 | Sep | 2005 | 25 | 7 | | |
| 1 | Nov | 2005 | 25 | 1 | | |
| 13 | Dec | 2005 | 25 | 0 | | |
| 31 | Jan | 2006 | 25 | 1 | | |
| 28 | Mar | 2006 | 25 | 6 | | |
| 10 | May | 2006 | 25 | 1 | | |
| 29 | Jun | 2006 | 25 | -7 | | |
| 8 | Aug | 2006 | 0 | -5 | | |
| 20 | Sep | 2006 | 0 | 0 | | |
| 25 | Oct | 2006 | 0 | -2 | | |
| 12 | Dec | 2006 | 0 | -1 | | |
| 31 | Jan | 2007 | 0 | 0 | | |
| 9 | May | 2007 | 0 | 1 | | |
| 28 | Jun | 2007 | 0 | 2 | | |
| 7 | Aug | 2007 | 0 | 8 | | |
| 18 | Sep | 2007 | -50 | -44 | | * |
| 31 | Oct | 2007 | -25 | 9 | | |
| 11 | Dec | 2007 | -25 | 0 | | |
| 22 | Jan | 2008 | -75 | -63 | | * |
| 30 | Jan | 2008 | -50 | -10 | | |
| 18 | Mar | 2008 | -75 | 49 | | * |
| 30 | Apr | 2008 | -25 | -7 | | |
| 25 | Jun | 2008 | 0 | -4 | | |
| 5 | Aug | 2008 | 0 | -3 | | |
| 16 | Sep | 2008 | 0 | 21 | | |
| 8 | Oct | 2008 | -50 | -17 | | * |
| 29 | Oct | 2008 | -50 | -10 | | |
| 16 | Dec | 2008 | -75 | -35 | | (as anticipated) |

Table 2: The output of univariate regressions with intercept, where monthly changes (upper panel) and squared demeaned monthly changes (lower panel) in the single U.S. macroeconomic variables: Federal Funds rate (FFR), Unemployment rate (UNEMPL), Headline inflation (CPI), Industrial production all-industries (IP) and 10Y yields from STRIPS are regressed on the implied volatilites across the available cap maturities (1Y to 4Y, 7Y and 10Y). The Table reports the regression coefficients and the coefficient of determination of the single univariate regressions. The levels of significance reported are: * 0.1, **0.05 and ***0.01.

| | | | $\hat{\beta}$ | | | |
|---|---|---|---|---|---|---|
| | $IV_{1Y}$ | $IV_{2Y}$ | $IV_{3Y}$ | $IV_{4Y}$ | $IV_{7Y}$ | $IV_{10Y}$ |
| $FFR$ | -0,005** | -0,012*** | -0,016*** | -0,020*** | -0,026*** | -0,033*** |
| $UNEMPL$ | 0,003 | 0,004 | 0,005 | 0,005 | 0,005 | 0,006 |
| $CPI$ | -0,005 | -0,018 | -0,026* | -0,032* | -0,039* | -0,054* |
| $IP$ | -0,007 | -0,012 | -0,013 | -0,024 | -0,034 | -0,042 |
| $y_{10Y}$ | -0,004 | -0,019*** | -0,038*** | -0,054*** | -0,075*** | -0,095*** |
| | | | $R^2$ | | | |
| $FFR$ | 0,030 | 0,059 | 0,070 | 0,074 | 0,070 | 0,074 |
| $UNEMPL$ | 0,016 | 0,016 | 0,014 | 0,009 | 0,006 | 0,005 |
| $CPI$ | 0,003 | 0,016 | 0,023 | 0,025 | 0,021 | 0,025 |
| $IP$ | 0,007 | 0,007 | 0,006 | 0,014 | 0,016 | 0,016 |
| $y_{10Y}$ | 0,011 | 0,094 | 0,250 | 0,358 | 0,390 | 0,405 |
| | | | $\hat{\beta}$ | | | |
| | $IV_{1Y}$ | $IV_{2Y}$ | $IV_{3Y}$ | $IV_{4Y}$ | $IV_{7Y}$ | $IV_{10Y}$ |
| $FFR^2$ | 0,004*** | 0,010*** | 0,012*** | 0,014*** | 0,019*** | 0,024*** |
| $UNEMPL^2$ | 0,001*** | 0,001* | 0,001 | 0,001 | 0,001 | 0,002 |
| $CPI^2$ | 0,039*** | 0,097*** | 0,110*** | 0,121*** | 0,128*** | 0,152*** |
| $IP^2$ | 0,020 | 0,034 | 0,055* | 0,077** | 0,114*** | 0,143*** |
| $y_{10Y}^2$ | 0,002 | 0,004 | 0,005 | 0,007* | 0,013*** | 0,021*** |
| | | | $R^2$ | | | |
| $FFR^2$ | 0,037 | 0,068 | 0,073 | 0,073 | 0,070 | 0,071 |
| $UNEMPL^2$ | 0,036 | 0,024 | 0,015 | 0,007 | 0,007 | 0,006 |
| $CPI^2$ | 0,033 | 0,075 | 0,066 | 0,056 | 0,036 | 0,032 |
| $IP^2$ | 0,012 | 0,014 | 0,025 | 0,034 | 0,042 | 0,042 |
| $y_{10Y}^2$ | 0,008 | 0,016 | 0,016 | 0,023 | 0,052 | 0,078 |

Table 3: Candidate Market Price of Risk Specifications

| Rank | $\lambda^j_{(1,1)}$ | $\lambda^j_{(2,2)}$ | $\lambda^j_{(1,3)}$ | $\lambda^j_{(2,1)}$ | $\lambda^j_{(1,2)}$ | $\lambda^j_{(2,3)}$ | BIC |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1 | 0 | 0 | 1 | -8.41 |
| 2 | 0 | 0 | 1 | 0 | 0 | 0 | -8.40 |
| 3 | 1 | 0 | 1 | 0 | 0 | 0 | -8.39 |
| **4** | **0** | **0** | **1** | **0** | **0** | **1** | **-8.39** |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | -8.39 |
| 6 | 1 | 0 | 0 | 0 | 0 | 0 | -8.37 |
| 7 | 1 | 0 | 0 | 0 | 0 | 1 | -8.34 |
| 8 | 0 | 0 | 0 | 0 | 0 | 1 | -8.34 |
| 9 | 0 | 1 | 1 | 0 | 0 | 1 | -8.20 |
| 10 | 0 | 0 | 0 | 0 | 1 | 0 | -8.19 |
| 11 | 0 | 0 | 1 | 0 | 1 | 0 | -8.17 |
| 12 | 1 | 1 | 1 | 0 | 0 | 1 | -8.17 |
| 13 | 0 | 0 | 0 | 0 | 1 | 1 | -8.16 |
| 14 | 0 | 0 | 0 | 1 | 1 | 1 | -8.13 |
| 15 | 0 | 0 | 1 | 1 | 1 | 1 | -8.12 |
| 16 | 0 | 1 | 1 | 0 | 0 | 0 | -8.08 |
| 17 | 0 | 1 | 1 | 1 | 0 | 1 | -8.07 |
| 18 | 0 | 1 | 0 | 0 | 0 | 0 | -8.06 |
| 19 | 1 | 0 | 1 | 0 | 1 | 1 | -8.04 |
| 20 | 0 | 0 | 1 | 0 | 1 | 1 | -8.01 |
| 21 | 1 | 1 | 0 | 0 | 0 | 0 | -8.00 |
| 22 | 0 | 0 | 1 | 1 | 1 | 0 | -7.97 |
| 23 | 1 | 1 | 1 | 0 | 0 | 0 | -7.91 |
| Sum | **8** | **7** | **14** | **4** | **8** | **12** | |
| 24 | 0 | 0 | 0 | 1 | 0 | 0 | -7.39 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 35 | 0 | 0 | 1 | 1 | 0 | 1 | -2.30 |

Table 4: Estimated parameters and numerical standard errors (in parethesis), along with the support interval and the acceptance ratio. The columns $IF$ denote the estimated inefficiency factor computed as $1 + 2\sum_{l=1}^{L}\rho(l)$ where $\rho(l)$ is the autocorrelation at lag $l$ in the Markov chain sequence of a parameter, and L is the value at which the autocorrelation function goes to zero. Further details can be found in Chib (2001).

| Common Parameters | | | | | |
|---|---|---|---|---|---|
| | $a^{\Theta}$ | $b^{\Theta}$ | $\theta$ | *AccRatio* | $IF$ |
| $\Psi_{1,1}$ | - | - | 1,000 | - | - |
| | | | - | | |
| $\Psi_{2,2}$ | 0,001 | 0,999 | 0,772 | 0,506 | 70,9 |
| | | | (0,002) | | |
| $\Psi_{1,3}$ | -0,999 | 0,999 | 0,000 | 0,511 | 113,4 |
| | | | (0,000) | | |
| $\Psi_{2,3}$ | -0,999 | 0,999 | -0,068 | 0,491 | 129,9 |
| | | | (0,001) | | |
| $\Psi_{3,3}$ | 0,001 | 0,999 | 0,995 | 0,521 | 16,7 |
| | | | (0,000) | | |

| Switching - Parameters | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $a^{\Theta}$ | $b^{\Theta}$ | Non-policy Days | | | Policy Days | | |
| | | | $\theta$ | *AccRatio* | $IF$ | $\theta$ | *AccRatio* | $IF$ |
| $\Sigma_{1,1}^{j}$ | 0,001 | 15,000 | 0,051 | 0,523 | 114,4 | 0,038 | 0,552 | 106,8 |
| | | | (0,000) | | | (0,002) | | |
| $\Sigma_{2,2}^{j}$ | 0,001 | 15,000 | 0,187 | 0,503 | 7,3 | 0,198 | 0,524 | 9,2 |
| | | | (0,002) | | | (0,011) | | |
| $\Sigma_{3,3}^{j}$ | 0,001 | 15,000 | 0,351 | 0,504 | 4,0 | 0,414 | 0,553 | 7,5 |
| | | | (0,003) | | | (0,023) | | |
| $\lambda_{0,2}^{j}$ | -100,000 | -0,001 | -1,897 | 0,465 | 59,5 | -1,801 | 0,522 | 63,6 |
| | | | (0,032) | | | (0,177) | | |
| $\lambda_{1,13}^{j}$ | -100,000 | 100,000 | -0,242 | 0,394 | 427,2 | -0,234 | 0,421 | 348,7 |
| | | | (0,007) | | | (0,026) | | |
| $\lambda_{1,23}^{j}$ | -100,000 | 100,000 | -0,097 | 0,439 | 472,8 | -0,105 | 0,458 | 414,9 |
| | | | (0,007) | | | (0,040) | | |
| $\omega^{j}$ | 0,001 | 10,000 | 0,370 | 0,525 | 9,0 | 0,394 | 0,539 | 5,0 |
| | | | (0,004) | | | (0,022) | | |

Table 5: Mean Absolute Pricing Errors. The values are reported for the single- and the two-set model across maturities and the pricing errors of the fitted models regard the entire dataset. The estimated one-set model is *separately* estimated and not embedded in the two-set model.

| In-Sample (Jan99 - Dec08) | | | | | |
|---|---|---|---|---|---|
| | 1Y | 3Y | 5Y | 7Y | 9Y |
| Policy Days (82) | | | | | |
| Two-Set | 20.07 | 19.14 | 9.19 | 6.38 | 1.89 |
| One-Set | 19.99 | 19.04 | 9.22 | 6.56 | 2.04 |
| - Anticipated Moves (71) | | | | | |
| Two-Set | 18.29 | 18.08 | 8.63 | 5.97 | 1.76 |
| One-Set | 18.18 | 17.96 | 8.63 | 6.16 | 1.91 |
| - Surprise Moves (11) | | | | | |
| Two-Set | 31.58 | 26.01 | 12.83 | 8.99 | 2.74 |
| One-Set | 31.73 | 26.02 | 13.05 | 9.17 | 2.83 |
| All Days (2608) | | | | | |
| Two-Set | 18.00 | 18.45 | 8.70 | 6.14 | 1.92 |
| One-Set | 17.99 | 18.39 | 8.64 | 6.09 | 1.90 |

Table 6: Variance Decomposition. The variance of yields is decomposed by dividing each single state variable shock with the overall Mean Squared Error (MSE) of forecasting the state VAR s periods ahead: $MSE_n = (B_n^j)'\Sigma^j B_n^j + (B_n^j)'\psi\Sigma^j\Psi B_n^j + ...(B_n^j)'\psi^{s-1}\Sigma^j\Psi^{s-1}B_n^j$. An instructive derivation of the MSE can be found in Dahlquist and Hasseltoft (2010).

| | Non-Policy Days | | | Policy Days | | |
|---|---|---|---|---|---|---|
| | 1 Day | | | | | |
| | 6m LIBOR | 5Y | 10Y | 6m LIBOR | 5Y | 10Y |
| $X_{level}$ | 0.289 | 0.483 | 0.627 | 0.172 | 0.317 | 0.448 |
| $X_{slope}$ | 0.690 | 0.469 | 0.327 | 0.794 | 0.595 | 0.452 |
| $IV$ | 0.022 | 0.047 | 0.046 | 0.035 | 0.088 | 0.101 |
| | 3 Months | | | | | |
| | 6m LIBOR | 5Y | 10Y | 6m LIBOR | 5Y | 10Y |
| $X_{level}$ | 0.376 | 0.546 | 0.672 | 0.234 | 0.367 | 0.487 |
| $X_{slope}$ | 0.605 | 0.410 | 0.286 | 0.735 | 0.547 | 0.415 |
| $IV$ | 0.019 | 0.044 | 0.043 | 0.031 | 0.086 | 0.098 |

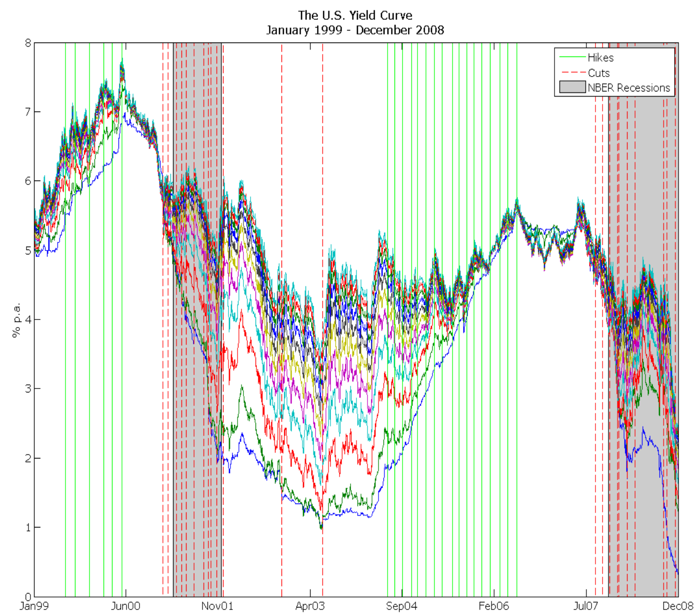
Table 7: 1-Day Average Change of the Term Premia in basis points. The table reports the difference between the mean 1-day forward premia change on a policy action day and the mean 1-day premia change on a non-policy day. The premia are estimated using both the single-set model (upper panel) and the two-parameter-set model (lower panel). The levels of significance reported are: *0.1, **0.05 and ***0.01 and come from an independent two-sample t-test.

| One-Set Model | | | | | |
|---|---|---|---|---|---|
| Occasion/Maturity | 1Y | 3Y | 5Y | 7Y | 10Y |
| All Decisions (82) | -0,13 | -0,36 | -0,46 | -0,48 | -0,46 |
| | (0,70) | (0,71) | (0,72) | (0,72) | (0,74) |
| - Hikes (23) | -0,19 | -0,58 | -0,74 | -0,79 | -0,79 |
| | (0,66) | (0,65) | (0,66) | (0,67) | (0,68) |
| - Cuts (23) | | | | | |
| – Anticipated Cuts (15) | -0,65 | -2,11 | -3.38* | -4.32* | -5.51** |
| | (0,22) | (0,17) | (0,10) | (0,05) | (0,02) |
| – Surprise Cuts (8) | 2.48* | 7.4* | 9.81* | 10.77* | 11,35 |
| | (0,07) | (0,08) | (0,08) | (0,09) | (0,10) |
| - Holds (36) | -0,04 | -0,06 | 0,04 | 0,17 | 0,39 |
| | (0,96) | (0,98) | (0,99) | (0,96) | (0,91) |
| **Two-Set Model** | | | | | |
| Occasion/Maturity | 1Y | 3Y | 5Y | 7Y | 10Y |
| All Decisions (82) | 0,04 | 1,48 | 1,86 | 0,18 | -6.14*** |
| | (0,89) | (0,13) | (0,15) | (0,89) | 0,00 |
| - Hikes (23) | -0,05 | 1,18 | 1,5 | -0,19 | -6.51*** |
| | (0,91) | (0,37) | (0,38) | (0,91) | (0,00) |
| - Cuts (23) | | | | | |
| – Anticipated Cuts (15) | -0,44 | -0,18 | -0,95 | -3,57* | -11.15*** |
| | (0,39) | (0,90) | (0,62) | (0,10) | (0,00) |
| – Surprise Cuts (8) | 2.66** | 9.27*** | 12.16*** | 11.46* | 5,68 |
| | (0,05) | (0,00) | (0,01) | (0,07) | (0,40) |
| - Holds (36) | -0,04 | -0,06 | 0,04 | 0,17 | 0,39 |
| | (0,96) | (0,98) | (0,99) | (0,96) | (0,91) |

Table 8: 1-Day Average Change of Future Short-Rate Expectations in basis points. The table reports the difference between the average 1-day change of future short-rate expectations on a policy action day and the average 1-day expectations change on a non-policy day for the single-set model (upper panel) and the two-set model (lower panel). The levels of significance reported are: *0.1, **0.05 and ***0.01 and stem from an independent two-sample t-test.

| One-Set Model | | | | | |
|---|---|---|---|---|---|
| Occasion/Maturity | 1Y | 3Y | 5Y | 7Y | 10Y |
| All Decisions (82) | -0,26 | -0,10 | 0,00 | 0,03 | 0,04 |
| | (0,65) | (0,89) | (0,99) | (0,97) | (0,95) |
| - Hikes (23) | 1,12*** | 1,05 | 1,00 | 0,99 | 0,98 |
| | (0,00) | (0,11) | (0,25) | (0,30) | (0,32) |
| - Cuts (23) | | | | | |
| – Anticipated Cuts (15) | -0,22 | 1,22 | 2.01* | 2.29* | 2.41* |
| | (0,80) | (0,22) | (0,09) | (0,07) | (0,07) |
| – Surprise Cuts (8) | -6,68 | -7,82 | -8,44 | -8,66 | -8,76 |
| | (0,13) | (0,12) | (0,12) | (0,11) | (0,11) |
| - Holds (36) | 0,16 | 0,01 | -0,07 | -0,10 | -0,11 |
| | (0,81) | (0,99) | (0,96) | (0,95) | (0,95) |
| Two-Set Model | | | | | |
| Occasion/Maturity | 1Y | 3Y | 5Y | 7Y | 10Y |
| All Decisions (82) | -0,27 | -0,12 | -0,03 | 0,00 | 0,01 |
| | (0,64) | (0,87) | (0,97) | (0,99) | (0,98) |
| - Hikes (23) | 1,13*** | 1,08* | 1,05 | 1,04 | 1,03 |
| | (0,00) | (0,10) | (0,23) | (0,27) | (0,29) |
| - Cuts (23) | | | | | |
| – Anticipated Cuts (15) | -0,24 | 1,13 | 1.89* | 2.16* | 2.28* |
| | (0,77) | (0,24) | (0,10) | (0,08) | (0,07) |
| – Surprise Cuts (8) | -6,69 | -7,85 | -8,49 | -8,72 | -8,82 |
| | (0,13) | (0,12) | (0,12) | (0,11) | (0,11) |
| - Holds (36) | 0,16 | 0,01 | -0,07 | -0,10 | -0,11 |
| | (0,81) | (0,99) | (0,96) | (0,95) | (0,95) |

Figure 1: The upper panel illustrates the U.S. yield curve dynamics from the beginning of 1999 to the end of 2008. The vertical green (solid) lines represent the FOMC decisions to hike the target rate, while the red (dashed) lines are days when the Fed opted for an interest rate cut. The lower panel shows the term spread (blue solid) on the left scale versus the 10Y implied volatility (red dashed) on the right scale.



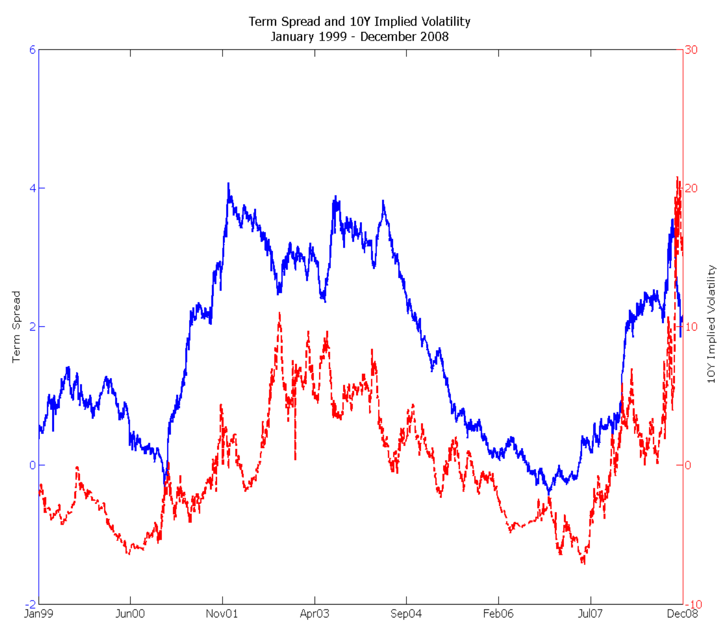



Figure 2: A proxy for macroeconomic uncertainty (blue line) versus the 10Y implied volatility (red line). The proxy is calculated by following Blanchard and Simon (2001) namely, by calculating a 36-months rolling standard deviation of the level of industrial production.

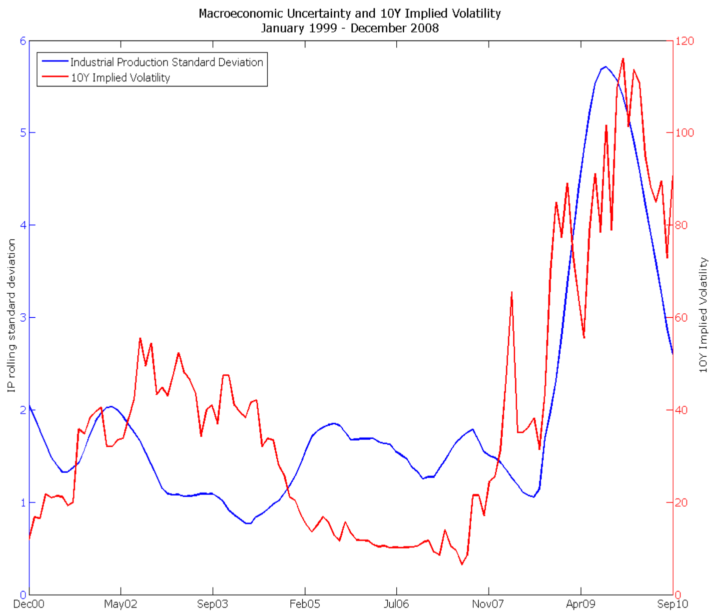


Figure 3: The upper panel shows the estimated level (solid blue) and slope (dashed green) factors backed out from 6m LIBOR and 10Y swap rate, respectively. The lower panel reports the explicit factor loadings for all-days parameters (solid red) and FOMC decision days parameters (dashed red).

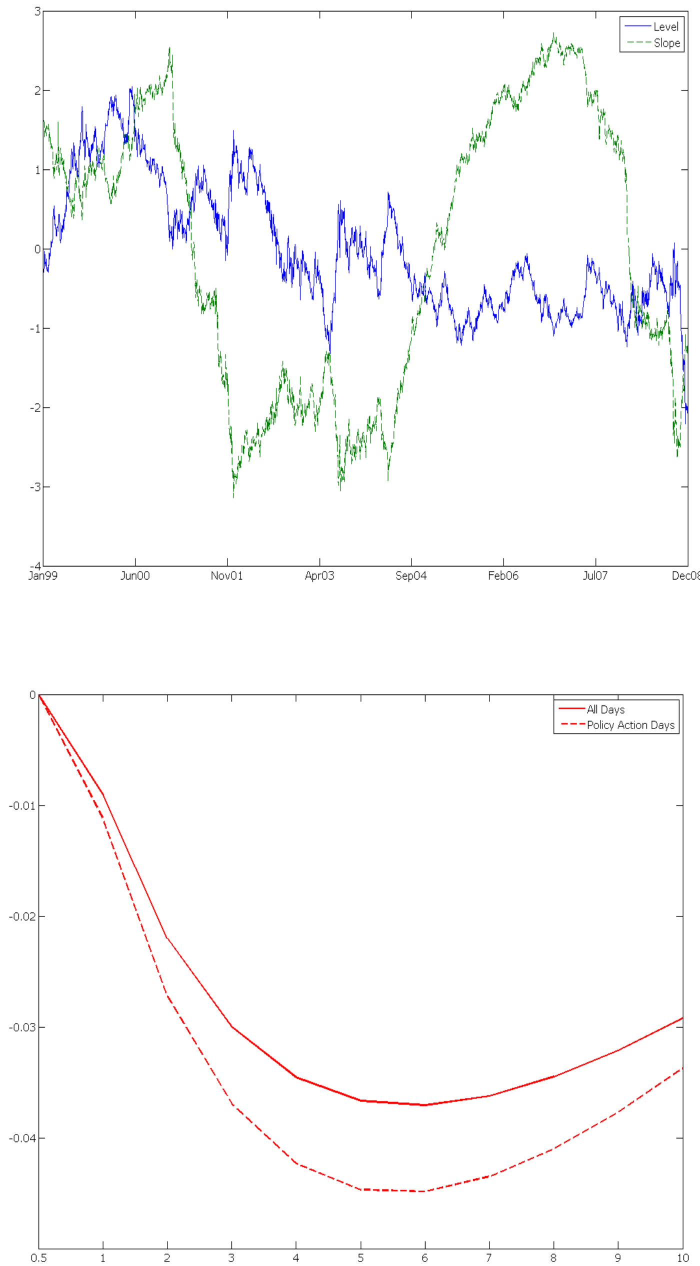


Figure 4: All the panels report the posteriors for the parameters defining the risk neutral part of the model. The algorithm is ran for 100,000 times and the first 40,000 sweeps are considered as the "burn-in" period.

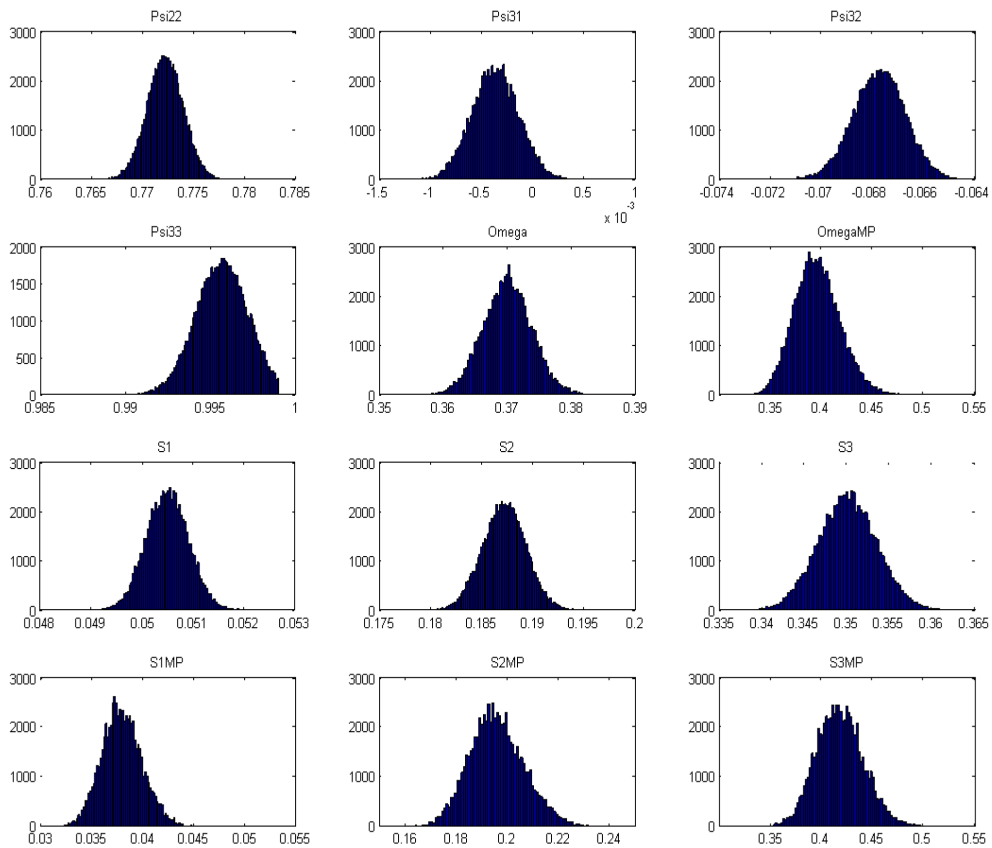


Figure 5: All the panels report the posteriors for the parameters defining the risk neutral part of the model. The algorithm is ran for 100,000 times and the first 40,000 sweeps are considered as the "burn-in" period.

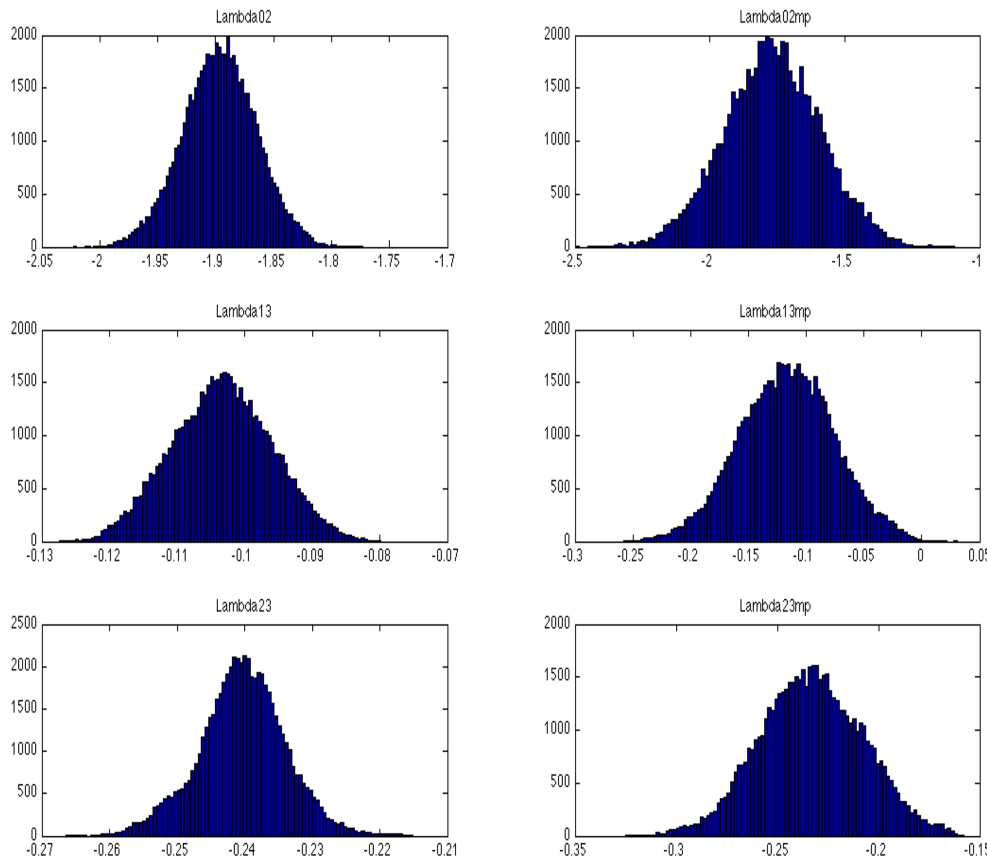


Figure 6: Two-parameter-set model output. The four panels report the modelled reaction of the forward term premia to all decisions in the sample (upper left), all decisions to hike Fed funds rate (upper right), anticipated interest rate cuts (lower left) and surprise interest rate cuts (lower right) together with the 90 percent credible interval.

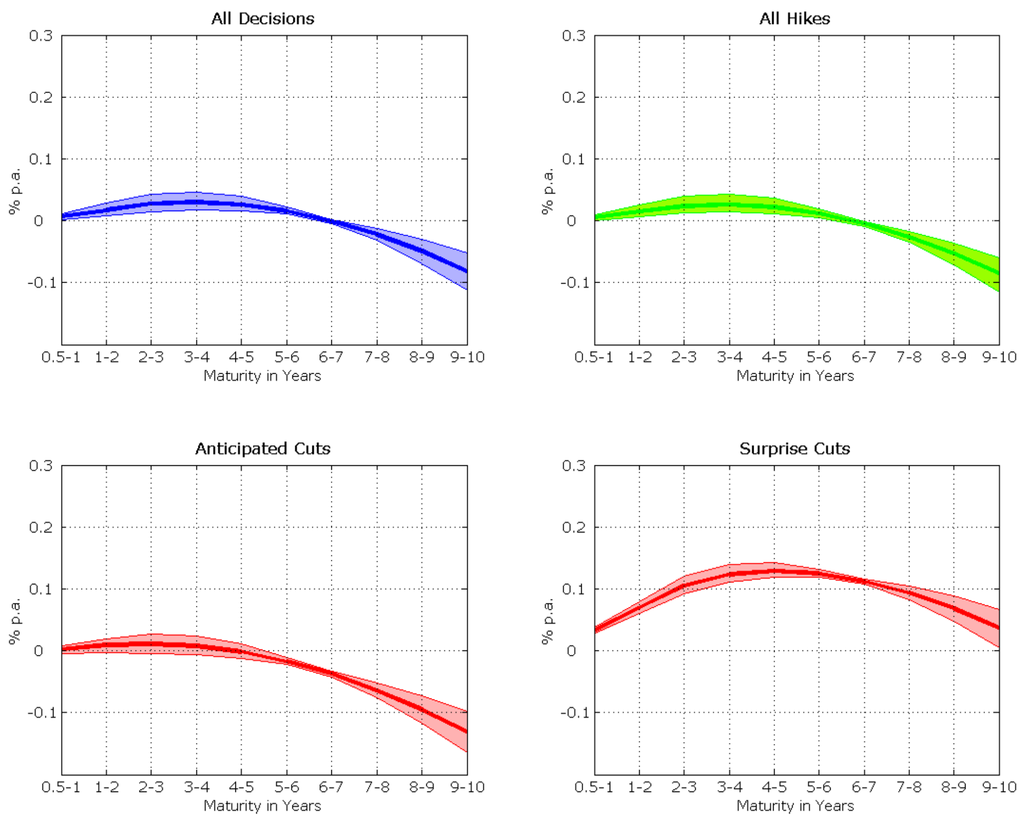


Figure 7: Single-set model output. The four panels report the modelled reaction of the forward term premia to all decisions in the sample (upper left), all decisions to hike Fed funds rate (upper right), anticipated interest rate cuts (lower left) and surprise interest rate cuts (lower right) together with the 90 percent credible interval.

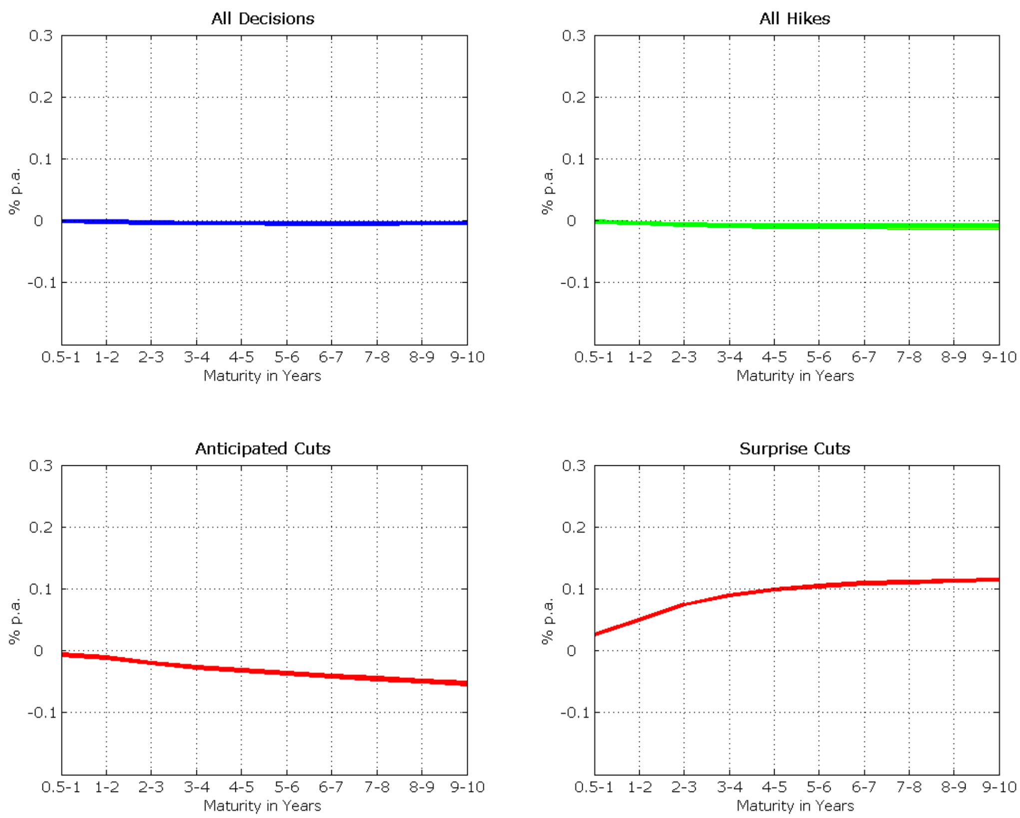


Figure 8: The four panels report the modelled reaction of the expected future short-term interest rate to all decisions in the sample (upper left), all decisions to hike Fed funds rate (upper right), anticipated interest rate cuts (lower left) and surprise interest rate cuts (lower right) together with the 90 percent credible interval. The credible interval is calculated by using every 100-th sweep from one of the Markov chains after burn-in, i.e. once the parameters converged in distribution.