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Abstract

In this paper we show how the degree of central bank credibility influences the level, slope and curvature of the term structure of interest rates. In an estimated structural model, we find that historical yield curve data are best matched by the Federal Reserve conducting policy in a loose commitment framework, rather than the commonly used discretion and full commitment assumptions. The structural impulse responses indicate that the past history of realized shocks play a crucial role in determining the dynamic effects of monetary policy on the yield curve. Finally, the regime-switching framework allows us to estimate likely re-optimization episodes which are found to impact the middle of the yield curve more than the short and long end.

Keywords: Term Structure, Commitment, Regime-Switching Bayesian Estimation, Optimal Monetary Policy, DSGE models

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1 Introduction

How does monetary policy impact the term structure of interest rates? The answer to this question is of interest to central bankers who want to understand how their actions affect long-term interest rates and consequently the economy. This topic is also relevant for bond market participants so that they can make informed investment decisions. Thus it is no surprise that there is a growing literature that tries to analyze this issue.[1] As is common in the monetary policy literature most of these analyses use a simple Taylor rule to model monetary policy. But as macroeconomic models become more sophisticated, increasing attention is being paid to the modeling of optimal monetary policy. However, an optimal policy framework with forward looking agents gives rise to the time-inconsistency issue, which is well known since the work of Kydland and Prescott (1977) and Barro and Gordon (1983). The policy maker can reap the benefits of shaping agents' expectations by announcing a plan and credibly committing to it. But this policy is not time-consistent as the policy maker has an ex-post incentive to deviate from the promised plan. The optimal monetary policy literature has dealt with this issue by assuming either that the central bank has access to a commitment technology (full commitment case) or that they re-optimize every period (discretion case). Yet neither of the two dichotomous cases of discretion or full commitment seems reasonable in practice.[2] Moreover, recent theoretical and descriptive evidence suggests that assumptions about central bank credibility may have a key effect on the term structure.[3] In this paper we use the general framework of loose commitment (this nests both the full commitment and discretion cases) and explore both theoretical and empirical implications for the term structure of interest rates.

We begin by considering a simple theoretical model to shed light on the effects of optimal monetary policy on the term structure. This analysis generalizes the work of Palomino (2012) where only discretion and commitment are considered. We use the framework of loose commitment, following the work of Roberds (1987), Schaumburg and Tambalotti (2007) and Debortoli and Nunes (2010). This is a flexible setting in which the central bank has the ability to commit to its future plans, but it may occasionally give in to the temptation to re-optimize plans. These re-optimization episodes are modeled using a regime-switching

[1]See recent papers by Campbell et al. (2014), Ang et al. (2011) and Bikbov and Chernov (2013) and references therein.

[2]In an empirical study with a medium scale DSGE model, Debortoli and Lakdawala (2016) show that both full commitment and discretion are rejected by the data.

[3]See the analyses of Palomino (2012) and Campolmi et al. (2012) for a detailed discussion.

process where both the policy maker and the agents are aware of the possibility and take it into account when forming expectations. We embed optimal monetary policy within the loose commitment framework in a simple New-Keynesian model where a cost-push shock drives the dynamics. The degree of credibility has a key effect on the covariance between the agents' stochastic discount factor and bond returns. This in turn determines whether long-term bonds are viewed by investors as acting as a hedge or increasing their risk. The typical assumption of full commitment or discretion can have stark implications for yield curve. In contrast, the loose commitment setting provides a more flexible framework where different values for the degree of credibility can generate a wide variety of properties for the yield curve. The loose commitment framework also affects the dynamic behavior of the yield curve through the effects of re-optimization shocks. The response of the economy and bond prices to re-optimization shocks is history dependent and this setting can help generate rich and complicated dynamics for the entire yield curve.

Having highlighted the main mechanisms in the simple model, we then estimate a fully specified medium scale DSGE model using US data on both macroeconomic variables and bond yields. The analysis is conducted in the model based on the work of Smets and Wouters (2007). We depart from that model in two important ways. First, monetary policy is conducted by a central bank operating under loose commitment, rather than being described by a simple interest rate rule. Second, we augment the model with yield data and derive bond prices that are consistent with the stochastic discount factor of the agents. The degree of credibility affects the agents' expectations for both macro variables and bond prices, and is a parameter of the model that is estimated. The presence of re-optimization shocks generates regime-switching dynamics in the state variables. We derive bond prices in this framework using a log-linear approximation as in Bansal and Zhou (2002) and Ang et al. (2008) among others. Additionally, for estimation purposes this requires the use of regime-switching techniques. We use a Bayesian Markov Chain Monte Carlo procedure following Debortoli and Lakdawala (2016).

The degree of credibility of the Federal Reserve is estimated to be 0.6, which is a little lower than the estimate of Debortoli and Lakdawala (2016) where they do not use term structure data. The use of quarterly data implies that re-optimizations are expected to occur roughly once every 2.5 quarters. An advantage of the estimation framework is that it allows for the identification of historical episodes when the Federal Reserve likely abandoned its commitments, as measured by the (smoothed) probability of re-optimization. We find that policy re-optimizations likely occurred throughout the sample with the exception of the period from late 1980s to early 1990s. Using impulse responses we emphasize the history dependence in the effects of re-optimization shocks. The effect of a re-optimization that is preceded by a markup shock makes yields lower relative to the case where no re-optimization occurs, while a re-optimization preceded by a technology shock has the opposite effect. An analysis of the historical effects in U.S. data reveals that the contemporaneous effect of re-optimizations is larger for medium maturities than at the short and long end of the yield curve. To understand the effects on the entire yield curve we construct simple measures representing three factors that are commonly used in the literature: level, slope and curvature. The biggest effects of the re-optimization shock occur with a lag of about two years. Comparing the model implied effects of re-optimization shocks to the data, we notice that while the re-optimizations have a non-negligible effect on the level and slope of the yield curve, they have a relatively bigger effect on the curvature.

With the rich DSGE model, we can perform a structural decomposition of the shocks contributing to the yield curve. We find that demand and markup shocks are the main drivers of bond yields, while technology shocks have a limited influence. Finally, we conduct a counterfactual analysis to explore how yields would have behaved under different credibility scenarios. We find that neither full commitment or discretion can satisfactorily characterize the yield dynamics captured by the loose commitment setting and that under discretion bond yields would have been much lower than the data. We conclude that the flexibility of the loose commitment framework helps significantly in explaining term structure data from the perspective of a structural macro model.

Our work is related to a growing macro-finance literature that tries to combine structural macro models with the term structure of interest rates. Early work, like Hordahl et al (2006), Rudebusch and Wu (2008) combined simple New-Keynesian models with an ad hoc stochastic discount factor to price long-term bonds. In contrast, here we derive the stochastic discount factor and the implied bond price dynamics that are consistent with the inter-temporal marginal rate of substitution. Starting with Bekaert et al. (2010), there are several empirical studies that use this approach, with more recent work that generates a time-varying term premium in a DSGE framework. Rudebusch and Swanson (2012) and Van Binsbergen et al. (2012) use a third order approximation, Chib et al. (2010) use regime-switching in the monetary policy rule and shock volatility, Dew-Becker (2014) uses time variation in the risk aversion parameter, while Song (2014) considers regime-switching covariance between inflation and consumption growth. In our empirical setup we do allow for regime switching in the variance of the shocks. However the re-optimization shock is assumed to be i.i.d. and thus monetary policy does not contribute to any time variation in the term-premium. The i.i.d. assumption is necessary to keep the model tractable for estimation. While we recognize this limitation of our framework, the focus of the paper is to study the effects of optimal monetary policy setting on the term structure. Ours is the first paper to empirically estimate a DSGE model with optimal monetary policy and the term structure, while all the papers mentioned above specify a simple reduced from Taylor-type rule to model monetary policy. Moreover, we use the flexible loose commitment framework to explore the role of credibility on the term structure.

The remainder of the paper is divided in two main parts. In the next section we describe the loose commitment framework and use a simple model to explain the basic conceptual issues involved in optimal monetary policy setting in this framework and its implications for the yield curve. In Section 3 we start with a brief overview of the DSGE model and the estimation algorithm. Next we present the results from the estimation and the key term structure results. Finally, we offer some concluding remarks in section 4.

2 Loose Commitment and the Yield Curve

In this section, we first explain the intuition behind loose commitment in a simple macro model. Then we add bond yields and show how term structure properties are related to the degree of credibility and how bond yields respond to re-optimization shocks.

2.1 The Loose Commitment Setting

The working assumption is that the central bank has access to a commitment technology, but it occasionally succumbs to the temptation to revise its plans, termed as policy re-optimizations. This is similar to the assumption in Schaumburg and Tambalotti (2007) and Debortoli and Nunes (2010). Private agents are aware of the possibility of policy re-optimizations and take it into account when forming expectations. More formally, at any point in time, monetary policy can switch between two alternative scenarios, captured by the unobserved state variable $s_t \in \{0, 1\}$. If $s_t = 1$, previous commitments are honored.

Instead, if $s_t = 0$, the central bank makes a new (state-contingent) plan over the infinite future, disregarding all the commitments made in the past. The variable s_t evolves according to a two-state stochastic process

$$s_t = \begin{cases} 1 \text{ with prob. } \gamma \\ 0 \text{ with prob. } 1 - \gamma \end{cases}$$

In the limiting case where the probability $\gamma = 1$, the central bank always honors its promises and this formulation coincides with the canonical full commitment case. Instead if $\gamma = 0$, the central bank always re-optimizes, as in the approach commonly referred to as discretion. The main advantage of this setup is that γ can take on any value in $[0, 1]$ and can be estimated from the data. Note that the switching is i.i.d. in nature. This means that the probability of a re-optimization occurring next period is the same, regardless of a re-optimization having occurred in the current period or not. Debortoli and Lakdawala (2016) provide a discussion and some suggestive evidence in support of this assumption. From the perspective of asset pricing, this assumption has important implications that are discussed below.

In the case of the Federal Reserve these re-optimizations could represent a change in the composition of the Federal Open Market Committee (the Fed's main policy making arm) due to appointment of a new chairman or a change in the voting members. Additionally pressure from the political system or the financial markets may cause a re-optimization. The results in Debortoli and Lakdawala (2016) suggest that the Federal Reserve does not have full credibility but that it can be viewed as being close with γ estimated to be around 0.8. The empirical results from section 3.2 confirm this finding of imperfect credibility but with an estimate of γ closer to 0.6.

2.2 Loose Commitment in a Simple Model

The main conceptual issues behind the loose commitment framework are illustrated using a simple model similar to Clarida et al. (1999) and also used by Palomino (2012). Consider a quadratic loss function for the central bank, where the aim is to minimize deviations of inflation (π_t) and output gap (y_t) from their target levels. Without loss of generality, the targets for both are assumed to be equal to zero.

$$\min \frac{1}{2} E_0 \sum_{t=0}^{\infty} \beta^t \left[\kappa y_t^2 + \theta \pi_t^2 \right] \tag{1}$$

This loss function is minimized subject to constraints that govern the dynamics of inflation and output gap.

$$\pi_t = \beta E_t \pi_{t+1} + \kappa y_t + u_t \tag{2}$$

$$y_t = E_t y_{t+1} - \frac{1}{\sigma} \left(i_t - E_t \pi_{t+1} \right) \tag{3}$$

The first equation is commonly referred to as the New-Keynesian Phillips Curve and can be derived from optimal firm pricing behavior. u_t is a cost-push shock (also known as markup shock) that is modeled as an i.i.d. process without loss of generality. The second equation is called the dynamic IS curve and can be derived from the household optimization problem, where i_t is the nominal short interest rate. This equation can be appended with a shock that could be interpreted as a demand shock. However, this demand shock does not create a tradeoff for the policymaker and would contribute nothing to the analysis at hand. In this setup, it is the cost-push shock that creates a tradeoff between inflation and output gap stabilization. In other words, without the presence of u_t optimal policy can be achieved by setting both π_t and y_t to zero for each time period. While in the presence of this shock, the central bank is not always able to simultaneously set both π_t and y_t to zero. It must choose the relevant tradeoff which depends on the state of the economy and the central bank preference parameters. The first order condition for optimal policy under discretion can be represented by

$$\pi_t^d = -\frac{1}{\theta} y_t^d \tag{4}$$

This equation depicts the classic principle of "leaning against the wind" and adjusting inflation in the opposite direction to the deviation of output gap from its target.[4] The relationship under full commitment is given by

$$\pi_t^c = -\frac{1}{\theta} \left[y_t^c - y_{t-1}^c \right] \tag{5}$$

[4]The d superscript denotes the dynamics of the variables when policy is conducted under discretion. Similarly we will use the superscripts c and lc for full commitment and loose commitment respectively.

This equation is similar to the discretion case but now inflation responds to the change in the output gap rather than the level of the output gap. When formulating optimal policy under commitment, the central bank takes into account the effects of their policy on agents' expectations. This effect is ignored in the discretion case. To get a better understanding, figure 1 shows the impulse responses to an i.i.d. cost-push shock using the following calibration: $\kappa = .25$, $\beta = 0.99$, $\theta = 1$ and $\sigma = 2$. Under both discretionary and commitment regimes, inflation rises on impact and the output gap falls. Under the discretionary case inflation is high just on impact (period 0) and falls back to zero (the target value) from the next period. In the commitment case, the central bank promises to lower inflation in the future and thus the rise in inflation on impact is not as high relative to the discretionary case. Under discretion the short rate has to be raised enough to completely absorb the effects of the cost-push shock, while under commitment the short rate does not have to be raised as much on impact and then it is gradually moved back to zero.

The key point is that agents should trust the central bank to be credible and follow through with the promise of low inflation from period 2 onwards, after the central bank has reaped the reward of lower relative inflation in period 1. This is the crux of the time-inconsistency issue and creates the incentive for the policy maker to re-optimize. If the central bank is not perfectly credible then we are in the loose commitment setting and agents assign a positive probability of the central bank reneging on its promises in any period in the future. Under loose-commitment, the dynamics are affected by a re-optimization shock s_t in addition to the cost-push shock. The relations implied by the first order conditions are now given by

$$\pi_t^{lc} = \begin{cases} -\frac{1}{\theta} y_t^{lc}, & \text{if } s_t = 0 \\ -\frac{1}{\theta}(y_t^{lc} - y_{t-1}^{lc}), & \text{if } s_t = 1 \end{cases} \tag{6}$$

Figure 2 shows the effect of an i.i.d cost-push shock under the loose commitment setting with probability of commitment $\gamma = 0.5$. This means that agents expect that a re-optimization will occur in any period with probability 0.5. The thin blue line shows the response of the variables in the case that no re-optimization shock occurs. While the blue line with the crosses shows the behavior when a re-optimization shock occurs in period 3. The thin blue line shows that the central bank promised to keep inflation low for a few periods after the cost-push shock but with a re-optimization this promise is not kept and inflation is set to 0, which minimizes the central bank's current period loss. The inflation response under loose commitment lies in between the discretion and full commitment cases for the first few periods. However the dynamic behavior of the variables under loose commitment do not have to lie in between discretion and full commitment as can be seen more clearly from the response of the output gap and the short rate. The crucial determinants of the effects of re-optimization shocks are the timing of the re-optimization shock and the history of all other shocks preceding the re-optimization shock.[5]

Before we derive bond prices in the simple model, we setup the general formulation of optimal policy in the loose commitment framework. Gathering all the state variables $[y_t, \pi_t, i_t, u_t]$ in x_t and the exogenous shock $[e_{u,t}]$ in v_t, the system of equations can be written as

$$A_{-1}x_{t-1} + A_0 x_t + A_1 E_t x_{t+1} + B v_t = 0 \tag{7}$$

We can write the optimization problem for the central bank in the following format.

$$x'_{-1} V x_{-1} + d = \min_{\{x_t\}_{t=0}^{\infty}} E_{-1} \sum_{t=0}^{\infty} (\beta\gamma)^t [x'_t W x_t + \beta(1-\gamma)(x'_t V x_t + d)] \tag{8}$$

$$s.t.\;\; A_{-1}x_{t-1} + A_0 x_t + \gamma A_1 E_t x_{t+1} + (1-\gamma) A_1 E_t x_{t+1}^{reop} + B v_t = 0 \;\; \forall t \tag{9}$$

The terms $x'_{t-1} V x_{t-1} + d$ summarize the value function at time t. Since the problem is linear quadratic, the value function is given by a quadratic term in the state variables x_{t-1}, and a constant term d reflecting the stochastic nature of the problem. The objective function is given by an infinite sum discounted at the rate $\beta\gamma$ summarizing the history in which re-optimizations never occur. The first part is the period loss function. The second part indicates the value the policymaker obtains if a re-optimization occurs in the next period. The sequence of constraints (9) corresponds to the structural equations (7), with the only exception that expectations of future variables are expressed as the weighted average between two terms: the allocations prevailing when previous plans are honored (x_{t+1}), and those prevailing when a re-optimization occurs (x_{t+1}^{reop}). This reflects the fact that private agents are aware of the possibility of policy re-optimizations, and take this possibility into account when forming their expectations. The solution uses the concept of a Markov-Perfect equilibrium and can be shown to be of the form[6]

$$\xi_t = F_{s_t} \xi_{t-1} + G v_t \tag{10}$$

[5]An implication of this is that if a re-optimization shock occurs in the steady-state (when $u_t = 0$) it will have no effect.

[6]See Debortoli and Nunes (2010) and Debortoli et al. (2014) for a detailed discussion.

where $\xi_t = [x_t, \lambda_t]'$ and λ_t is a vector of Lagrange multipliers attached to the constraints (9). In particular, the Lagrange multipliers λ_{t-1} contain a linear combination of past shocks $\{v_{t-1}, v_{t-2}, \ldots, v_{-1}\}$, summarizing the commitments made by the central bank before period t. Therefore, the effects of policy re-optimizations can be described by the state dependent matrices where a re-optimization involves setting to zero the column of F corresponding to the Lagrange multipliers

$$F_{(s_t=1)} = \begin{bmatrix} F^{xx} & F^{x\lambda} \\ F^{\lambda x} & F^{\lambda\lambda} \end{bmatrix} \qquad F_{(s_t=0)} = \begin{bmatrix} F^{xx} & 0 \\ F^{\lambda x} & 0 \end{bmatrix}. \tag{11}$$

2.3 Bond pricing

We now derive bond prices in a framework where the term structure of interest rates reflects the dynamic properties of the representative consumer's elasticity of inter-temporal substitution (or stochastic discount factor), M_{t+1}. In particular, let $i_{n,t}$ denote the (continuously compounded) interest rate at time t of a n-period zero-coupon bond, and $m_{t+1} = \ln(M_{t+1})$. We have from the first order condition of inter-temporal utility maximization,

$$e^{-ni_{n,t}} = E_t\left(e^{\sum_{\tau=1}^{n} m_{t+\tau}}\right) \tag{12}$$

Under the assumption of a stationary joint log-normal distribution, it then follows:

$$i_{1,t} = -E_t(m_{t+1}) - \frac{1}{2}Var_t(m_{t+1}) \tag{13}$$

$$ni_{n,t} = -E_t\left(\sum_{\tau=1}^{n} m_{t+\tau}\right) - \frac{1}{2}Var_t\left(\sum_{\tau=1}^{n} m_{t+\tau}\right) \tag{14}$$

We can use the above equations to decompose the yield spread, $i_{n,t} - i_{1,t}$ into three parts,

$$\begin{aligned} i_{n,t} - i_{1,t} = {} & \frac{\sum_\tau E_t(-m_{t+\tau})}{n} - E_t(-m_{t+1}) \\ & - \frac{1}{2}\left[\frac{\sum_\tau Var_t(m_{t+\tau})}{n} - Var_t(m_{t+1})\right] \\ & - \frac{1}{2}\frac{\sum_{\tau_1 \neq \tau_2} Cov_t(m_{t+\tau_1}, m_{t+\tau_2})}{n} \end{aligned} \tag{15}$$

The first term in the expression above captures the expectation component which implies that part of of the long-term interest rate, $i_{n,t}$ is determined by the expectation of the short-term interest rate that will prevail over the life of the long-term bond. The second term is due to Jensen's inequality. The third term is risk compensation (or term premium) for holding the long-term bond. The term premium depends critically on auto-correlations of the stochastic discount factor. A positively (negatively) auto-correlated stochastic discount factor implies a negative (positive) term premium and hence a downward-sloping (upward sloping) yield curve. The intuition is as follows. If today's bad news about growth is expected to be followed by further bad news in the future, a bond that promises a fixed payoff in the future will see its value increase today (as interest rate decreases). This create a positive co-variance between bond return and investor's marginal utility today and hence a negative risk premium. On the contrary, if today's bad news about growth is expected to be followed by good news in the future, a bond that promises a fixed payoff in the future will see its value decreases today (as interest rate increases). This creates a negative co-variance between bond return and investor's marginal utility and hence a positive risk premium.

We will use this intuition to explain how the degree of monetary policy credibility affects the term structure of interest rates below. We start by considering the same simple model laid out in Section 2.2 above. We assume a power utility function that is consistent with the dynamic IS curve in (3). The stochastic discount factor for bond pricing can be written as (ignoring any constant term):

$$m_{t+1} = -\sigma(y_{t+1} - y_t) - \pi_{t+1} \tag{16}$$

where $\sigma > 0$ is the coefficient of relative risk aversion. Given the solution to the optimal policy problem in (10), we can express the stochastic discount factor in general as:

$$m_{t+1} = -\lambda_0 - \lambda_1' \xi_{t+1} - \lambda_2' \xi_t \tag{17}$$

where λ_1 and λ_2 load up relevant state variables respectively according to the specification of the utility function in (16) and the optimal policy solution in (10). Notice that in (10), ξ_t has regime-switching dynamics governed by the variable s_t. We will assume that the structural shocks in (10) are normally distributed ($v_t \sim N(0, Q)$) and uncorrelated with each other. We obtain an analytical solution for the term structure of interest rates under regime switching. This allows us to solve for the term structure of interest rates in closed form. Let $P_{n,t}$ denote the price of a n-period zero-coupon bond at time t. It then follows that, for $n \geq 0$,

$$P_{n,t} = e^{-A_n - B_n' \xi_t} \tag{18}$$

The detailed derivation of the coefficients A_n and B_n is provided in the online appendix and they are given recursively by the following equations

$$A_n = A_{n-1} + \lambda_0 - \frac{1}{2}(\lambda_1 + B_{n-1})' GQG' (\lambda_1 + B_{n-1}) \tag{19}$$

$$B_n = \bar{F}' B_{n-1} + (\lambda_2 + \bar{F}' \lambda_1) \tag{20}$$

where

$$\bar{F} = \gamma F_{(s_t=1)} + (1-\gamma) F_{(s_t=0)} \tag{21}$$

and $A_0 = B_0 = 0$.

For $n \geq 1$, interest rate, $i_{n,t}$, is given by

$$i_{n,t} = \frac{A_n}{n} + \frac{B_n'}{n} \xi_t \tag{22}$$

Notice that, because s_t is i.i.d., the coefficients A_n and B_n don't depend on the policy regime s_t even though s_t affects the persistence of state variable ξ_t. To predict $F(s_{t+1})$ at time t investors simply use the average value of $F(s_{t+1})$. This has an important implication for the bond risk premium. We define bond risk premium as the expected excess holding period return of a long-term bond.

$$\begin{aligned} rp_{n,t} &= E_t(\log P_{n-1,t+1} - \log P_{n,t}) - i_{1,t} \\ &= \frac{1}{2}\lambda_1' GQG' \lambda_1 - \frac{1}{2}(\lambda_1 + B_{n-1})' GQG' (\lambda_1 + B_{n-1}) \\ &= -\lambda_1' GQG' B_{n-1} - \frac{1}{2} B_{n-1}' GQG' B_{n-1} \end{aligned} \tag{23}$$

The second term in the risk premium expression is simply due to Jensen's inequality. The first-term is the negative covariance of bond returns and the stochastic discount factor (under the macroeconomic shocks v_{t+1}). Since both λ_1 and B_n are constant in our model, the covariance is constant and so is the risk premium. Relaxing the i.i.d. assumption about the transition matrix governing the re-optimization shock will generate time-varying risk premia. However this approach makes the estimation strategy intractable and we leave it for future research.

In the empirical part of this paper (section 3) we estimate the probability of commitment γ in a fully specified DSGE model. There we allow the variance matrix of the shocks

Q to be regime switching. This introduces time variation in the risk premia which is helpful for the model to generate volatility for long term bonds that can match the observed data. This is a popular method in the DSGE term structure literature and is used by Chib et al. (2010) among others. Since our focus in this part of the paper is to understand the effect of central bank credibility and re-optimization shocks, we abstract from this complication for now.

2.4 Degree of Credibility and the Yield Curve

In this section we explore the effect of the degree of credibility on the term structure in the simple model outlined above.

First, consider the case of discretionary policy (i.e. $\gamma = 0$). Recall that the first order condition implies that inflation responds to the level of the output gap,

$$\pi_t^d = -\frac{1}{\theta} y_t^d$$

Plugging this into the the stochastic discount factor (equation 16), we have:

$$m_{t+1}^d = -\sigma(y_{t+1} - y_t) - \pi_{t+1} = -\left(\sigma - \frac{1}{\theta}\right) y_{t+1}^d + \sigma y_t^d \tag{24}$$

where $y_{t+1}^d = -\frac{\theta}{1+\kappa\theta} u_{t+1} \equiv \chi_u^d u_{t+1}$. In the online appendix we show that this implies

$$Cov(m_{t+1}^d, m_{t+n}^d) = \begin{cases} \frac{(1-\sigma\theta)\sigma\theta}{(1+\kappa\theta)^2}\sigma_u^2, & \text{if } n = 2 \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

Thus the sign of the autocorrelation of the stochastic discount factor and hence the sign of the risk-premium depends on the weight on inflation in the loss function and the risk aversion parameter. As long as $\sigma\theta > 1$, m_{t+1}^d is serially negatively correlated and the yield curve slopes upward on average (ignoring the Jensen's inequality term). The intuition is as follows. Under discretion, in response to a cost-push shock, output declines and inflation increases.[7] Since the shock is i.i.d., expected *output growth* increases as the level of output moves back to its steady state level.[8] Higher expected growth leads to a higher interest rate and hence

[7] We will assume that the natural rate of output is constant so that changes in output are the same as changes in the output gap.

[8] Recall from figure 1 that under discretion inflation is an i.i.d. process and expected inflation is zero.

lower bond price (and thus lower bond return). The sign of the risk-premium depends on the covariance between the bond return and the nominal stochastic discount factor. The direction of the movement in the nominal stochastic discount factor depends on the relative magnitude of σ and θ. If both σ and θ are large ($\sigma\theta > 1$), investors are very concerned with decreases in output (or consumption) and policy makers are very concerned with increases in inflation. As a result, in response to a cost-push shock, there will be relatively small increase in inflation and relatively large decrease in output, and given a large value of the risk-aversion coefficient, the nominal stochastic discount factor (or inflation-adjusted marginal utility) increases. On the other hand, if both σ and θ are small ($\sigma\theta < 1$), the opposite is true, the nominal stochastic discount factor (or inflation-adjusted marginal utility) decreases in response to a cost-push shock.

In contrast, under a full-commitment policy, inflation responds to *changes* in output,

$$\pi_t^c = -\frac{1}{\theta}(y_t^c - y_{t-1}^c) \tag{26}$$

and hence,

$$m_{t+1}^c = -\left(\sigma - \frac{1}{\theta}\right)(y_{t+1}^c - y_t^c) \tag{27}$$

where $y_{t+1}^c = \chi_y^c y_t^c + \chi_u^c u_{t+1}$ and $\chi_y^c < 1$. In the online appendix we show that this implies

$$Cov(m_{t+1}^c, m_{t+n}^c) = -\left(\sigma - \frac{1}{\theta}\right)^2 \left(\chi_y^c\right)^{n-2} (\chi_u^c)^2 \sigma_u^2 \frac{\left(1 - \chi_y^c\right)^2}{1 - (\chi_y^c)^2} \tag{28}$$

Thus regardless of the value of θ and σ, the stochastic discount factor is serially negatively correlated. Bond risk premium is always positive under a full-commitment policy in this simple model and the yield curve slopes upward. The reason is that, under full commitment, the nominal interest rate can either increase or decrease, but it always moves in the same direction as the nominal stochastic discount factor in response to a cost-push shock regardless of the relative values of σ and θ. With a full commitment technology, the policy maker can promise negative inflation (or deflation) in the future at the impact of a cost push shock. If the nominal stochastic discount increases as in the case of $\sigma\theta > 1$, the expected deflation will be smaller than expected output growth, the nominal interest rate also increases. If the nominal stochastic discount factor decreases as in the case of $\sigma\theta < 1$, the expected deflation will be larger than the expected output growth, the nominal interest rate decreases as well.

Finally, as pointed out by Palomino (2012), y_{t+1} has a bigger exposure to the cost-push shock in the discretionary-policy regime than in the full-commitment policy regime. From (24) and (27), we have:

$$m^i_{t+1} - E_t(m^i_{t+1}) = -(\sigma - 1/\theta)\chi^i_u u_{t+1}$$

where $i = d, c$. The absolute value of market price of risk under a discretionary policy, $|(\sigma - 1/\theta)\chi^d_u|$, will be larger than that under a full-commitment policy, $|(\sigma - 1/\theta)\chi^c_u|$. This has a direct impact on the magnitude of bond risk premiums.

Under loose-commitment, the first order condition implies

$$\pi^{lc}_t = \begin{cases} -\frac{1}{\theta}y^{lc}_t, & \text{if } s_t = 0 \\ -\frac{1}{\theta}(y^{lc}_t - y^{lc}_{t-1}), & \text{if } s_t = 1 \end{cases}$$

In this case the auto-covariance of the stochastic discount factor has a complicated analytical solution (it is included in the online appendix). To better understand the effect of the degree of credibility (γ), in figure 3 we plot the model implied yield curve for different values of γ. In panel (a) we consider a calibration where $\sigma\theta < 1$. As pointed above, under such a calibration the yield curve slope is negative under discretion (blue line) and it is positive under full commitment (yellow line). In the loose commitment setting, the slope is negative for low values of γ and it becomes less negative as γ is increased before finally becoming positive. In panel (b) we show the yield curve with a calibration where $\sigma\theta > 1$. In this case the slope is non-negative for all values of γ and we see the same pattern that the slope increases with γ.[9] The degree of monetary policy's credibility shapes expectation about future inflation, and hence has a key effect on the co-movement between the nominal interest rate and the stochastic discount factor. This effect is reflected in the shape of the term structure of interest rates. In particular, as γ increases, the monetary policy is more likely to remain on its promised course. Expected inflation then tends to move in the direction that produces a positive (negative) co-variance between interest rate (bond return) and the stochastic factor, and hence an upward sloping yield curve as explained above. The next figure shows how the unconditional standard deviation of the yield curve depends on γ. Again, panel (a) shows the case where $\sigma\theta < 1$ and panel (b) shows $\sigma\theta > 1$. The short end of the yield curve is always more volatile under discretion relative to full commitment regardless of the preference and policy parameters. This is because, by promising lower (or negative) inflation in the future

[9] Notice that when $\sigma\theta > 1$ the yield curve is flat instead of sloping upward under discretion ($\gamma = 0$) because a negative Jensen's inequality term offsets a positive bond risk premium at each maturity.

with full commitment, the central bank doesn't need to raise interest rate as much as it does under discretion in response to a cost push shock. We notice that as γ increases agents have a higher confidence that the central bank will continue proposed plans and thus they adjust their current inflation expectations accordingly. Thus the volatility of the short end of the yield curve decreases with γ. For the second calibration this relationship is true for yields of all maturities. But in the calibration in panel (a) we see a non-monotonic relationship where the volatility of long-term rates is the highest for $\gamma = 1$.

Overall figures 3 and 4 show that the loose commitment framework is quite flexible and depending on the probability of commitment (γ) can generate a variety of different properties for slope and standard deviation of the term structure. In addition to the effect of γ the loose commitment framework also has important implications for the dynamic behavior of yields as governed by re-optimization shocks.

2.5 Re-optimization Shocks and the Yield Curve

In this section we analyze the effect of a re-optimization shock on the term structure in the simple model. As mentioned above, the impulse response to a re-optimization shock is history dependent. The re-optimization shock involves reneging on past promises which are captured by the Lagrange multipliers. Thus the effect of the re-optimization shock is to set the lagged Lagrange multipliers to zero. As a special case, if a re-optimization shock occurs in the steady state, it will have no effect as the Lagrange multipliers are already zero. While a re-optimization occurring immediately after a cost-push shock that creates a tradeoff for the central bank, can have big effects.

In the same vein as figures 1 and 2, figure 5 shows the effect of a cost-push shock happening at time period 1, followed by a re-optimization shock occurring in period 3. γ is set to 0.5. The discretion and full commitment paths (which are not affected by the re-optimization shock) are plotted for comparison. The solid thin blue line shows that in response to a cost-push shock the central bank raises the short rate and promises to gradually decrease it to zero over time. When the re-optimization occurs, the central bank sets the short rate to zero to bring inflation back to zero immediately. Since the cost-push shock is i.i.d. all the long-term yields move to zero instantly as well. One way to gauge the effect of the re-optimization shock is to compare the value of the yields under a re-optimization with the value if no re-optimization shock had occurred. In figure 5, this is the difference between the thin blue line and the thick blue line with the crosses. To better understand the effect on the yield curve, we construct three term structure factors that are commonly studied in the literature: level, slope and curvature. The level is defined as just the 3 month rate, the slope as (10 year - 3 month) and the curvature as (10 year + 3 month - 2*3 year). Figure 6 plots the effect of the re-optimization shock on these three factors. We see that a re-optimization shock in this model increases the slope of the term structure while lowering the level and the curvature. Notice that the x-axis in the graph represents time and starts when the re-optimization shock hits, i.e. period 3. In this simple model, the effect of the cost-push shock monotonically decreases with maturity, thus when a re-optimization causes yields to be set to their steady-state value the fall is biggest at the short end of the yield curve and the effect diminishes with maturity. This causes the yield curve to become more steep and less curved as a result. This simple example illustrates that, depending on the history of past economic shocks, the re-optimization shock can generate rich dynamic responses of interest rates. It not only affects the short-term interest rate, but can also have profound effects on the entire yield curve.

Using a simple New Keynesian model we have shown in sections 2.4 and 2.5 that both the degree of credibility (γ) and the timing of the re-optimization shocks can have important implications for the yield curve. Next we conduct an empirical analysis to quantify these effects for post Great Moderation US data. We expand the simple macro model and use a medium scale DSGE model that is known to fit the US macro data well.

3 Medium-Scale DSGE Model

The DSGE model we use is from Smets and Wouters (2007) (SW henceforth) and is based on earlier work by Christiano et al. (2005) among others. This model has shown to fit the macro data well and is competitive with reduced form Vector Autoregressions in terms of forecasting performance. The model includes monopolistic competition in the goods and labor market, nominal frictions in the form of sticky price and wage settings, allowing for dynamic inflation indexation. It also features several real rigidities – habit formation in consumption, investment adjustment costs, variable capital utilization, and fixed costs in production. For further details of the model we refer the reader to SW.[10]

[10] In the online appendix accompanying the SW paper, available at `https://www.aeaweb.org/aer/data/june07/20041254_app.pdf`, a detailed derivation of the model's equations is provided.

We depart from the SW formulation in the specification of monetary policy. In SW, monetary policy is described by an interest rate policy rule, while in this paper the central bank is modeled as minimizing a loss function under the loose commitment framework as described in section 2.2. The period loss function that we use for the empirical results is the following:

$$x_t' W x_t \equiv \pi_t^2 + w_y \widetilde{y}_t^2 + w_r (r_t - r_{t-1})^2 \tag{29}$$

The weight on inflation (π_t) is normalized to one so that w_y and w_r represent the weights on output gap ($\widetilde{y}_t$) and the nominal interest rate (r_t), relative to inflation. π_t represents the deviation of inflation from the steady state, implying that the inflation target is the steady state level of inflation $\bar{\pi}$, which will be estimated. The target for output is the "natural" counterpart, defined as the level of output that would prevail in the absence of nominal rigidities and markup shocks. This formulation is consistent with the natural rate hypothesis, i.e. that monetary policy cannot systematically affect average output. The last term in the loss function ($w_r(r_t - r_{t-1})^2$) indicates the central bank's preference for interest rate smoothing, see Coibion and Gorodnichenko (2012) for a detailed discussion.

3.1 Estimation

The estimation setup is similar to SW with some key differences. We use the same quarterly US time series as SW, except we replace the fed funds rate with the 3 month Treasury bill. The macro series are as follows: the log difference of real GDP, real consumption, real investment, the real wage, log hours worked and the log difference of the GDP deflator. In addition to the 3 month rate, we use 5 more yields: 6 month, 1 year, 3 year, 6 year and 10 year. For the yields we use the data from Gürkaynak et al. (2007). As discussed above the dynamics of the short rate are governed according to optimal policy under loose commitment. To avoid the stochastic singularity issue in evaluating the likelihood function, we add an i.i.d measurement error to the short rate equation.

$$r_t^{obs} = r_t + \eta_t^r \tag{30}$$

with the assumption that $\eta_t^r \sim N(0, \sigma_r^2)$. We also account for changes in the volatility of the exogenous shocks in the regime-switching framework. A large macroeconomic literature has showed that exogenous shocks have displayed a high degree of heteroskedasticity in the recent US data. Here, we would like to avoid issues of inaccurate inference by explicitly accounting for this heteroskedasticity. The regime switching in the volatility also helps in fitting the long end of the yield curve as we discuss below. The error terms are assumed to be normal

$$v_t \sim N(0, Q_{s_t^v}),$$

where the variance-covariance matrix $Q_{s_t^v}$ depends on an unobservable state $s_t^v \in \{1, 2\}$, that differentiates between the two alternative volatility regimes. The Markov-switching process (s_t^v) evolves independently from the regime-switching process that governs re-optimizations (s_t). The transition matrix for s_t^v is given by

$$P^v = \begin{bmatrix} Pr(s_t = 1|s_{t-1} = 1) & Pr(s_t = 2|s_{t-1} = 1) \\ Pr(s_t = 1|s_{t-1} = 2) & Pr(s_t = 2|s_{t-1} = 2) \end{bmatrix} = \begin{bmatrix} p_1 & (1 - p_1) \\ (1 - p_2) & p_2 \end{bmatrix} \tag{31}$$

Recall that the transition matrix for the re-optimization switching is given by

$$P = \begin{bmatrix} Pr(s_t = 1|s_{t-1} = 1) & Pr(s_t = 0|s_{t-1} = 1) \\ Pr(s_t = 1|s_{t-1} = 0) & Pr(s_t = 0|s_{t-1} = 0) \end{bmatrix} = \begin{bmatrix} \gamma & 1 - \gamma \\ \gamma & 1 - \gamma \end{bmatrix} \tag{32}$$

For convenience we define $\widetilde{s}_t$ as a composite regime indicator with 4 regimes with the transition matrix $\widetilde{P} = P \otimes P^v$. Then for estimation we can write the system as the following state space model.

$$\xi_t = F_{\widetilde{s}_t} \xi_{t-1} + G v_t \tag{33}$$

$$Y_t^{obs} = A_{\widetilde{s}_t} + H \xi_t + w_t \tag{34}$$

$$v_t \sim N(0, Q_{\widetilde{s}_t}) \tag{35}$$

$$w_t \sim N(0, R) \tag{36}$$

The state equation (33) corresponds to the macro dynamics governed by optimal policy under loose commitment (described earlier in equation (10)). The parameter matrix $F_{\widetilde{s}_t}$ is regime dependent as certain elements of the matrix are set to zero in a re-optimization state. The observed macro variables and the yield data are stacked in Y_t^{obs} and the observation equation (34) relates them to the state variables ξ_t. For the macro variables the relevant part of the matrix H just picks out the corresponding variables from the state vector ξ_t, while the elements in $A_{\widetilde{s}_t}$ capture the steady state constants. For the yield data in Y_t^{obs}, the corresponding elements of $A_{\widetilde{s}_t}$ and H capture the bond pricing equations which govern how yields depend on the model's state variables. The detailed derivation of the bond pricing equations under regime-switching is provided in an online appendix. The regime dependence arises from the presence of the Markov switching volatility process s_t^v. The errors v_t include all the structural shocks from the SW model. Finally, we add an i.i.d. measurement error to each of the yields in the observation equation, given by w_t.

With regards to the yields, our empirical specification has two more points worth emphasizing. In the model, the central bank sets the short rate, here the 3 month T-bill rate, as dictated by minimization of the loss function. Thus in our initialization of the bond pricing recursion (equations (19) and (20)) we start with $n = 1$ instead of $n = 0$ and set $An(1)$ equal to the constant in the 3 month T-bill rate equation in the observation equation and we set the corresponding element of $B_n(1) = 1$ which picks out the short rate from the state vector ξ_t. Additionally, to help the model fit the average level of the term structure we treat λ_0 in equation (19) as a free parameter to be estimated. When we tried to let λ_0 be consistent with the utility function, we found that the model underestimated the level of the yield curve but the model's implied slope and dynamics for the yield curve were similar to our baseline results.

The estimation algorithm used here is similar to the one outlined in Debortoli and Lakdawala (2016). To summarize, the regime-switching model requires using the Kim (1994) approximation that combines the Hamilton (1989) filter and the Kalman filter to evaluate the likelihood function, see Kim and Nelson (1999) for details. This likelihood function is combined with the prior to form the posterior distribution. A Metropolis-Hastings algorithm is used to sample from the posterior distribution.

3.2 Estimates from DSGE Model

We follow SW in assigning priors for the model's structural parameters and parameters governing the shock processes. For the the probability of commitment γ we choose a non-informative uniform prior over the unit interval. For the transition matrix parameters of the regime-switching volatility process we use fairly standard Beta priors. Finally for λ_0 we choose a normal prior centered at zero with a large prior variance. The details of the priors are presented next to the posterior estimates. Table 1 shows the posterior mean of the estimates of the structural parameters, along with the 5th and 95th percentile values. In Table 2 the estimates of the parameters of the shock processes are shown. Overall the parameter estimates are similar to SW with a few exceptions.[11] The elasticity estimates of the utility function are somewhat different here relative to SW. The inverse of the elasticity of intertemporal substitution ($\sigma_c = 2.89$ here compared to $\sigma_c = 1.47$ in SW) and the labor elasticity ($\sigma_l = 4.82$ here vs. 2.30 in SW) are higher in our estimates. On the other hand, the habit persistence parameter is lower in our estimates ($h = 0.18$ here vs. 0.68 in SW). The persistence of the risk-preference shock (referred to by SW as the "risk-premium" shock) is higher in our estimates ($\rho_b = 0.98$ here vs. 0.39 in SW). This shock can be broadly thought of as a demand shock and has effects which are similar to a net-worth shock in models that have an external finance premium. Overall, the utility function parameters are closely tied to the stochastic discount factor and bond pricing and thus it is not surprising that this creates the biggest differences in the parameter estimates. Our estimates of the capital capacity utilization parameter and capital adjustment costs are also slightly higher relative to SW. The weight on interest rate smoothing (w_r) and output gap stabilization (w_y) are similar to Debortoli and Lakdawala (2016) and the general empirical literature on optimal monetary policy. Finally there are some differences in the parameters of the price-markup shock. See Debortoli and Lakdawala (2016) and Justiniano and Primiceri (2008) for a detailed discussion.

The bottom two rows of table 1 show the unconditional regime parameters of the volatility process p_1 and p_2. Both these parameters are close to one, signifying a high degree of persistence for each regime. The standard deviation estimates (table 2) for the two regimes do not allow for a clean identification of either regime as the high (or low) volatility regime. The standard deviation of the technology, investment and price markup shocks is higher in regime 2 while the standard deviation of the other 4 shocks is higher in regime 1. The smoothed volatility regime probabilities shown in the bottom panel of figure 7 indicate that regime 1 was likely to have prevailed for most of the 2000s, in the mid to late 1990s and around the mid 1980s.

The probability of commitment (γ) is estimated to be 0.58 with narrow credibility intervals. This is lower than the estimate of Debortoli and Lakdawala (2016) of 0.8 where they do not include term structure data in the estimation. This suggests that adding yield data to the empirical optimal policy DSGE model drives the model's estimates of optimal policy closer to discretion. On the $[0, 1]$ continuum, the value of $\gamma = 0.58$ appears slightly closer to commitment ($\gamma = 1$) than discretion ($\gamma = 0$). However, depending on the metric used,

[11]Given our data sample, we compare our estimates to the second sub-sample of the results reported in Table 5 of SW.

it could also be interpreted as being closer to discretion. For example, the use of quarterly data implies that the Federal Reserve is expected to re-optimize plans roughly once every two and a half quarters (in other words more than once a year). From this perspective it would be reasonable to conclude that the results are closer to discretion (re-optimizations every period) relative to full commitment (no re-optimizations at all). In section 3.3 we discuss this issue in more detail.

In the loose commitment theoretical setting, both the agents and the central bank have full information, including which regime is prevalent at any given time. This information about the prevailing regime is not observable to the econometrician. Nevertheless, we can back out an estimate of this by looking at the smoothed probability of re-optimization. This can be interpreted as the probability of a re-optimization having occurred on any given date conditional on observing all the data. We can use this probability to try to characterize when the re-optimization episodes were likely to have occurred in the historical data. To this end, the top panel in figure 7 we plot the smoothed probability of re-optimization. If the there was no estimation uncertainty, γ close to 0.6 would mean that the smoothed probability of re-optimization should be close to 1, 60% of the time and close to 0, 40% of the time. However the figure shows that this is not quite the case and the probability is close to 0 or 1 for only a handful of periods. For most of the other periods, it hovers around 0.6 which is the unconditional probability. If we consider a smoothed probability greater than 0.5 as a likely re-optimization episode then we find 42 such episodes that are spread throughout the sample. This is in line with the number of re-optimizations one would expect in the data spanning 101 quarters with our estimate of γ close to 0.6. Given the uncertainty involved in the estimation, if we choose a stricter cutoff point of 0.8 then it is narrowed down to 13 re-optimization episodes.[12] These episodes are clustered in the mid 1980s, early 1990s and early 2000s. Intuitively, our model identifies re-optimization episodes when there are large differences in the path of variables with or without re-optimizations. When such differences are small, it is more difficult to distinguish re-optimizations from continuations of past plans, so that the smoothed probability remains near the unconditional average. One possible interpretation of our results is that during prolonged periods with moderate fluctuations, commitment plays a minor role, and it is therefore hard to find overwhelming evidence in favor or against central bank's deviations from commitment.

To evaluate how well our model fits the term structure, we start by plotting the yield

[12]The list is as follows 1)1983:Q3, 2)1985:Q2, 3)1985:Q4, 4)1986:Q2, 5)1986:Q4, 6)1991:Q3, 7)1991:Q4, 8)1992:Q4, 9)1996:Q3, 10)2000:Q2, 11)2001:Q2, 12)2003:Q4 and 13)2008:Q2.

data with the corresponding model implied fit in figure 8. Overall, the model does a good job of fitting the yield data. The estimated standard deviations of the measurement errors range from 42 to 54 basis points at an annualized rate. In comparison, the unconditional standard deviation of the yields in our sample is over 200 basis points for all the yields. The model's fit at the long end of the yield curve (10 year) does suffer slightly from the model not being able to generate enough volatility. To get a sense of the loose commitment framework's ability to fit the yields, we have also estimated the DSGE model with no regime switching in the volatility of the shocks. In this homoskedastic case, the fit of the model for short-term yields was very similar to the results presented here but the fit of the long term yields was significantly worse, with measurement error standard deviation of around 80 basis points for the 10 year yield.

In addition to the regime-switching volatility in the variances of the shocks modeled here, we believe that there are a few natural extensions that can help improve the fit in our setting. First, De Graeve et al. (2009) use the SW model (with an interest rate rule) and find that a time-varying inflation target significantly improves the fit of the longer yields. For example, the shock to the inflation target in their paper explains more than 90% of the variation in the 10 year yield. Rudebusch and Swanson (2012) also acknowledge the importance of the time-varying inflation target in matching yield data. Second, time-varying term premia could be induced by allowing parameters of the utility function to change. Dew-Becker (2014) uses this approach by modeling time variation in the risk-aversion parameter. Finally, rather than assuming an i.i.d. re-optimization shock, we can introduce a Markov structure in the transition matrix governing the re-optimization shocks. With this state-dependence in the re-optimizations, the factor loading of bond prices in the term structure solution will be dependent on the monetary policy regime and contribute to time-variation in bond risk premia. These approaches could be adopted in our current framework. However, since our paper represents the first effort to study the empirical effects on the term structure of Federal Reserve credibility and re-optimization shocks, we leave these extensions for future research.[13]

Next, we discuss the contribution of the various macroeconomic shocks in explaining the variation in the yield curve. In table 3 we present the forecast error variance decomposition, where we weight the the coefficients under each regime by the steady state regime

[13] Additionally, Rudebusch and Swanson (2012) show that using Epstein-Zin preferences in a DSGE model can help drastically improve the fit of the model. But that would require a higher-order approximation to solve the model which would make the computation of optimal policy and estimation intractable.

probabilities. We consider short (1 quarter), medium (5 quarters) and long (20 quarters) forecast horizons. For the purpose of this exercise, following SW we lump together government spending, investment and risk preference shocks into a unified demand shock. Additionally we lump together the price markup and wage markup shocks into a unified markup shock. A few interesting results stand out. Markup and demand shocks are important drivers of yield curve while technology and monetary policy shocks contribute very little. Demand shocks explain a significant variation of the yield curve fluctuation at all maturities but for the short and medium term forecast horizons, the effect is hump shaped in maturity. At these forecast horizons, demand shocks have the maximum effect on yields at the medium end of the curve. For example, demand shocks explain almost three-quarters of the variation in the 3 year yield in the medium term. On the other hand, markup shocks have the biggest effect on longer maturity yields at all forecast horizons. At the short end of the yield curve, the monetary policy shock contributes a significant share to the variance but its contribution diminishes to essentially zero with the forecast horizon. The contribution of structural shocks to historical U.S. data will be important in determining the effects of re-optimization shocks, as we will discuss in section 3.4.

3.3 Comparison with Discretion and Full Commitment

In this section we start by asking the following question: How would the historical path of yields have been different if the Federal Reserve had acted under full commitment or discretion? To answer this question we perform a counterfactual simulation. We first back out the structural shocks for our model from the benchmark estimates. Next, fixing these shocks we simulate the path of interest rates while changing the probability of commitment to 0 (for discretion) and 1 (for full commitment). These simulations are presented in figure 9, where the red, blue and black lines represent the data, full commitment and discretion cases respectively. This graph shows that neither full commitment nor discretion can capture the term structure dynamics satisfactorily. The longer end of the yield curve (6 and 10 year yields) is closer to full commitment (especially in the 1980s and 1990s). Whereas for the medium end of the yield curve there are certain periods (mid 1990s) where the data is closer to discretion. We also notice a pattern that holds for most of the simulation periods that the yields would have been lower on average under discretion relative to full commitment. In section 2.5 analysis of impulse responses we discussed how the path of yields under loose commitment do not necessarily have to lie in between the discretion and full commitment cases. The two key components that matter are the timing of the re-optimization shocks and the history of structural shocks. This point can be seen clearly from the counterfactual simulation and will be discussed again using impulse response analysis in section 3.4.

The loose commitment setting nests both the cases of commitment ($\gamma = 1$) and discretion ($\gamma = 0$). The empirical estimates imply a higher weight for the posterior distribution at $\gamma = 0.6$ as compared to $\gamma = 0$ or $\gamma = 1$. Thus the data prefer a model with loose commitment over discretion or commitment. However a potentially different way to estimate the model at the end points is to use a strategy that fixes the parameter $\gamma = 0$ or $\gamma = 1$. Such a strategy has two potential advantages to our baseline loose commitment model. First, one less parameter needs to be estimated and second the estimation uncertainty involved with the regime-switching due to re-optimizations is avoided. To explore whether this alternative empirical strategy has any material advantage we separately estimate the commitment and discretion versions of the model and compare them to the baseline model. To keep the comparison fair, for all specifications we model regime-switching in the variance of the shocks.

With a Bayesian estimation framework, a natural way to perform model comparison is to calculate the posterior odds. With a priori equal weight associated to each model the Bayesian posterior odds ratio boils down to comparing the marginal likelihood. We use the modified harmonic mean estimator with the truncated normal weighting function suggested by Geweke (1999). Let $y^{1:t} = [Y_1^{obs}, Y_2^{obs}, ...Y_t^{obs}]$ denote a vector of data from period 1 up to t. Gathering all the parameters in Θ, the marginal likelihood is given by

$$p\left(y^{1:T}\right) = \int p(y^{1:T}|\Theta)\pi(\Theta)d\Theta \tag{37}$$

Table 4 shows the log marginal likelihood for the three different specifications of the models. The marginal likelihood is highest for our baseline estimate of $\gamma = 0.58$. The difference with the next best case is almost 50 log points pointing to strong evidence for the loose commitment framework, in line with the results in Debortoli and Lakdawala (2016). Interestingly, the model fit for discretion is considerably better than the full commitment case. Thus our model with yield curve data also confirms the optimal monetary policy literature that focuses solely on discretion vs full commitment (see for example Givens (2012) that discretion fits the data better than full commitment.

3.4 Effect of Re-optimization Shocks

What is the effect of a re-optimization shock on the yield curve? In the loose commitment framework, the effects of a re-optimization depend on the history of past shocks, as discussed in section 2. Figures 10, 11, and 12 illustrate this phenomenon showing the impulse responses to a technology, price-markup shock and demand (risk-preference) shock respectively. The solid blue line shows the path under the assumption that a re-optimization never occurs (even though agents expect it to occur with probability 0.6). The line with dots refers to the scenario where a re-optimization occurs once after 5 quarters, but not after that. The difference between the two lines thus measures the effects of a policy re-optimization that occurs after period 5. The figure also shows the impulse responses under discretion and commitment which are obtained by just setting $\gamma = 0$ and $\gamma = 1$ but keeping the rest of the parameters fixed at the estimated values for the baseline model. The effect of a re-optimization that is preceded by a price-markup shock (figure 11) or risk-preference shock (figure 12), is to make yields lower relative to the case where no re-optimization occurs. The intuition is similar to the one in the simple model of section 2, where the central bank would like to bring inflation and interest rates to their steady-state levels sooner. On the other hand, a re-optimization shock that occurs after a technology shock, makes the central bank want to set interest rates higher than promised, as can be seen in figure 10. The sign of the effect is similar for yields of all maturities but the magnitude varies. To better understand the differential effects on the yield curve, in figure 13 we plot the effects of a re-optimization shock on the three factors: level, slope and curvature. We define these in the same way as in section 2.5. The level factor as just the 3 month rate, the slope factor as 10 year - 3 month and the curvature factor as 10 year + 6 month - 2*(3 year). Specifically, we plot the difference between the thin blue line and the thick blue line with the dots (from figures 11-12). Notice that the x-axis in the graph represents time and starts when the re-optimization shock hits, i.e. period 5. Each row shows the effect after a specific structural shock. There emerges an interesting pattern in the dynamics responses of the three factors. The sign of the response of the level and curvature factors to a re-optimization is the same regardless of the type of structural shock we consider, while the slope response has the opposite sign. Moreover, the effect on the factors peaks a few quarters after the re-optimization. It is important to note that in addition to the effects of a re-optimization depending on which shocks have preceded it, the timing of those shocks matter as well. As an extreme example, when the economy is in the steady state, a re-optimization will have no effect. On the other hand if a structural shock has hit the economy, and a few quarters have passed (which allow the effects of the shock to peak), then a re-optimization shock can have big effects.

Next, using our model and estimated structural shocks, we try to quantify the effects of re-optimization shocks in the historical U.S. data. We answer the following hypothetical question: Given the past history of shocks in the U.S. data (implied by our model), what would be the effect if a re-optimization occurred in every period? To this end, we plot the difference between the reaction of yields if a re-optimization occurs relative to the case where one does not occur, conditional on the estimated structural shocks. Using the model's equations, this can be written as $[i_{n,t}|s_t = 0, \xi_{t-1}] - [i_{n,t}|s_t = 1, \xi_{t-1}]$, where $i_{n,t}$ refers to the yield of maturity n. ξ_{t-1} represent the smoothed state variables that capture the full history of shocks up to time $t-1$. Figure 14 shows this difference for the 6 yields. The dashed black vertical lines represent time periods when re-optimization periods are most likely, as discussed in section 3.2. As observed in the impulse response figures, we notice that re-optimizations can act as both contractionary and expansionary shocks. However the contractionary effect of re-optimization shocks appears to dominate in magnitude and frequency, with the biggest effects in the early 1990s and early 2000s and just before the financial crisis. This reinforces the notion that the quantitative effect of a re-optimization is crucially dependent on past historical shocks. The effect on the yield curve is also non-monotonic in the maturity. The biggest effect is felt by the 1 year yield followed closely by the 6 month yield. The effect on the long end is much smaller, with negligible effects on the 10 year yield.

To explore this non-monotonic effect of re-optimizations in more detail, we also consider the the response of the constructed term structure factors. Additionally, note that figure 14 plots only the contemporaneous response of yields to a re-optimization shock. But the analysis in figure 13 suggests that there can be lags in the effects. Thus in figure 15 we consider the "medium-term" and "long-term" effects in addition to the contemporaneous effect. Specifically, we plot $[f_{k,t+j}|s_t = 0, \xi_{t-1}] - [f_{k,t+j}|s_t = 1, \xi_{t-1}]$ where $f_{k,t+j}$ is the response of the kth term structure factor in time period $t+j$. The blue line is the contemporaneous response ($j = 1$ quarter), the green line is the "medium-term" response ($j = 8$ quarters) and the red line is the "long-run" response ($j = 40$) quarters.[14] Again, the dashed black verti-

[14]To clarify, the medium and long term response is calculated in the following way. We assume a re-optimization occurs only once in time period t and then trace out the response of the yields. From this response we subtract the behavior of the yields in the scenario where a re-optimization does not occur. The other shocks are set to zero from period t onwards.

cal lines represent time periods when re-optimization periods are most likely, as discussed in section 3.2. Similar to figure 14, the graph shows that the re-optimization episodes in the early 1990s and 2000s have had the biggest effect on the yield curve while the other re-optimization episodes have had smaller effects.

Additionally, the biggest effects of the re-optimization shock occur in the medium term. The contemporaneous effects are smaller and the long-term effects are almost negligible. Finally for comparison, the standard deviation of the level, slope and curvature factors calculated from the data is 2.22, 1.23 and 0.80 respectively. This suggests that relative to the overall movement in the factors, re-optimization shocks have accounted for a bigger proportion of the variation in the curvature of the yield curve. This can be explained by the non-monotonic relationship shown in figure 14. Re-optimization shocks have the biggest effect on the medium term bonds while having a smaller effect on short term and long term bonds.

4 Conclusion

The Federal Reserve is keenly interested in understanding how changes in its policy instruments (typically the short interest rate) translate into changes in the economy. This transmission mechanism works through the effect of the policy instrument on the long rates. Instead of using the standard Taylor rule setup, this paper focuses on optimal monetary policy and central bank credibility to get a deeper structural understanding of the effects of central bank actions on the term structure. In a simple model we explain the intuition behind how our flexible loose commitment framework affects the yield curve by comparing it to the commonly used discretion and full commitment cases. We highlight two features that can have important implications for the yield curve: the existing degree of credibility and the timing and frequency of re-optimization shocks.

We quantify these effects by estimating a medium-scale DSGE model where the central bank conducts optimal policy under loose commitment. This structural macro model is augmented with bond prices that are consistent with agents' optimization decision and the resulting system is jointly estimated using regime-switching Bayesian techniques. Consistent with earlier work, we find that the Federal Reserve is credible to some extent, but that credibility is not perfect. Moreover, neither full commitment nor discretion can do a satisfactory job of explaining term structure dynamics. Additionally, we find that re-optimization shocks affect the middle of the yield curve more as compared to the short and long end. This creates a relatively bigger impact of the re-optimization shocks on the curvature of the yield curve.

A natural extension is to allow the probability of re-optimization to be regime-dependent rather than the i.i.d. case that is used this in paper. While this would make the computation of optimal policy under loose commitment more complicated, it would have the advantage of generating a time-varying term premium where the underlying model can still be linear. Such a setup would make it feasible to conduct an empirical study where re-optimization shocks could provide a structural explanation for the change in the term premium over time.

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		Prior			Posterior		
		Distr.	Mean	Std. Dev	Mean	5%	95%
$\bar{l}$	St. State Labor	Normal	0	2	-3.963	-5.971	-1.846
$\bar{\pi}$	St. State Inflation	Gamma	0.62	0.1	0.996	0.948	1.069
$\bar{\gamma}$	Growth Rate	Normal	0.4	0.1	0.300	0.270	0.328
$\bar{\beta}$	Discount Factor	Gamma	0.25	0.1	0.378	0.177	0.632
α	Capital Income Share	Beta	0.3	0.05	0.155	0.136	0.175
ψ	Capital Cap. Utilization	Normal	0.5	0.15	0.917	0.858	0.963
φ	Capital Adj. Cost	Normal	4	1.5	7.539	5.652	9.467
σ_c	Risk Aversion	Normal	1.5	0.37	2.887	2.640	3.148
h	Habit Persistence	Beta	0.7	0.1	0.175	0.129	0.223
σ_l	Wage Elasticity	Normal	2	0.75	4.820	3.982	5.732
Φ	Fixed Cost	Normal	1.25	0.12	1.039	0.982	1.109
ι_w	Wage Indexation	Beta	0.5	0.15	0.472	0.233	0.717
ι_p	Price Indexation	Beta	0.5	0.15	0.195	0.096	0.312
ξ_p	Price Stickiness	Beta	0.5	0.1	0.883	0.849	0.913
ξ_w	Wage Stickiness	Beta	0.5	0.1	0.400	0.330	0.473
w_y	Output Gap Weight	Gamma	1	1	0.010	0.006	0.015
w_r	Interest Rate Weight	Gamma	1	1	1.781	1.313	2.364
γ	Prob. of Commitment	Uniform	0.5	0.29	0.582	0.518	0.645
λ_0	Const in SDF	Normal	0.0	2.0	3.224	2.912	3.577
p_1	Vol. prob 1	Beta	0.8	0.16	0.988	0.979	0.995
p_2	Vol. prob 2	Beta	0.8	0.16	0.982	0.968	0.993

Table 1: The table reports the prior distribution (mean and standard deviation) and the estimated posterior mean, fifth, and ninety-fifth percentiles for the baseline model's structural parameters.

		Prior				Posterior	
	Distr.	Mean	Std. Dev		Mean	5%	95%
Standard deviations							
$\sigma_a^{(1)}$	Inv Gamma	0.1	2		0.429	0.369	0.494
$\sigma_b^{(1)}$	Inv Gamma	0.1	2		0.067	0.053	0.082
$\sigma_g^{(1)}$	Inv Gamma	0.1	2		0.440	0.382	0.503
$\sigma_I^{(1)}$	Inv Gamma	0.1	2		0.375	0.315	0.444
$\sigma_p^{(1)}$	Inv Gamma	0.1	2		0.127	0.104	0.154
$\sigma_w^{(1)}$	Inv Gamma	0.1	2		0.510	0.398	0.647
$\sigma_r^{(1)}$	Inv Gamma	0.1	2		0.137	0.101	0.182
$\sigma_a^{(2)}$	Inv Gamma	0.1	2		0.701	0.620	0.786
$\sigma_b^{(2)}$	Inv Gamma	0.1	2		0.055	0.044	0.066
$\sigma_g^{(2)}$	Inv Gamma	0.1	2		0.269	0.240	0.306
$\sigma_I^{(2)}$	Inv Gamma	0.1	2		0.389	0.325	0.463
$\sigma_p^{(2)}$	Inv Gamma	0.1	2		0.151	0.125	0.180
$\sigma_w^{(2)}$	Inv Gamma	0.1	2		0.408	0.321	0.513
$\sigma_r^{(2)}$	Inv Gamma	0.1	2		0.078	0.062	0.097
$\sigma_{i^{6m}}$	Inv Gamma	0.5	0.5		0.108	0.093	0.123
$\sigma_{i^{1yr}}$	Inv Gamma	0.5	0.5		0.137	0.120	0.156
$\sigma_{i^{3yr}}$	Inv Gamma	0.5	0.5		0.127	0.111	0.144
$\sigma_{i^{6yr}}$	Inv Gamma	0.5	0.5		0.120	0.107	0.136
$\sigma_{i^{10yr}}$	Inv Gamma	0.5	0.5		0.121	0.106	0.138
MA parameters (μ) and AR parameters (ρ)							
μ_w	Beta	0.5	0.2	1	0.410	0.222	0.594
μ_p	Beta	0.5	0.2	1	0.793	0.705	0.869
ρ_{ga}	Beta	0.5	0.2	1	0.240	0.146	0.334
ρ_a	Beta	0.5	0.2	1	0.979	0.975	0.983
ρ_b	Beta	0.5	0.2	1	0.982	0.968	0.993
ρ_g	Beta	0.5	0.2	1	0.964	0.950	0.976
ρ_I	Beta	0.5	0.2	1	0.715	0.655	0.773
ρ_p	Beta	0.5	0.2	1	0.996	0.992	0.999
ρ_w	Beta	0.1	0.2	1	0.984	0.974	0.994

Table 2: The table reports the prior distribution (mean and standard deviation) and the estimated posterior mean, fifth, and ninety-fifth percentiles for the baseline model's parameters describing the shock processes.

Horizon	Technology	Demand	Markup	Monetary
6 month				
1 Q	0.03	0.37	0.32	0.28
5 Q	0.04	0.57	0.36	0.03
20 Q	0.02	0.80	0.17	0.01
1 year				
1 Q	0.04	0.54	0.37	0.05
5 Q	0.05	0.58	0.37	0.01
20 Q	0.03	0.70	0.27	0.00
3 year				
1 Q	0.04	0.68	0.27	0.01
5 Q	0.04	0.72	0.23	0.00
20 Q	0.03	0.68	0.29	0.00
6 year				
1 Q	0.04	0.69	0.26	0.01
5 Q	0.04	0.66	0.29	0.00
20 Q	0.04	0.51	0.45	0.00
10 year				
1 Q	0.07	0.48	0.44	0.00
5 Q	0.07	0.42	0.50	0.00
20 Q	0.07	0.30	0.62	0.00

Table 3: This table shows the contribution of the structural shocks in explaining the forecast error variance of the yield curve. See section 3.2 for more details.

Model	Log Marginal Likelihood
Loose Commitment ($\gamma = 0.58$)	-209.85
Discretion ($\gamma = 0$)	-258.19
Full Commitment ($\gamma = 1$)	-369.3

Table 4: The table shows the marginal likelihood calculations for three different models. The first row shows the baseline model where γ is estimated. The discretion and full commitment model estimation fixes γ to 0 and 1 respectively.

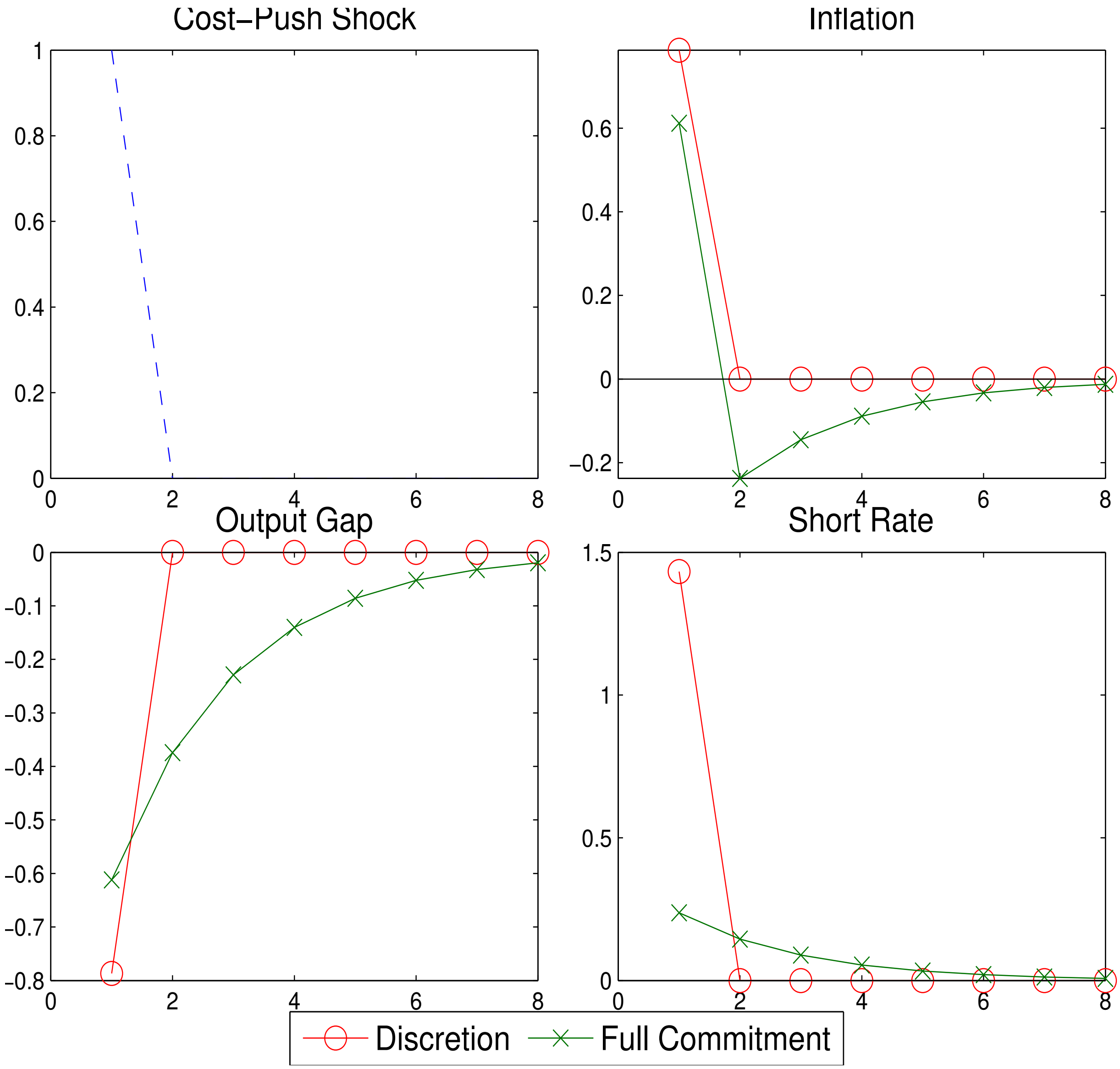

Figure 1: Impulse-response to i.i.d. cost-push shock. The green line shows the response of macro variables under full commitment while the red line shows the response under discretion.

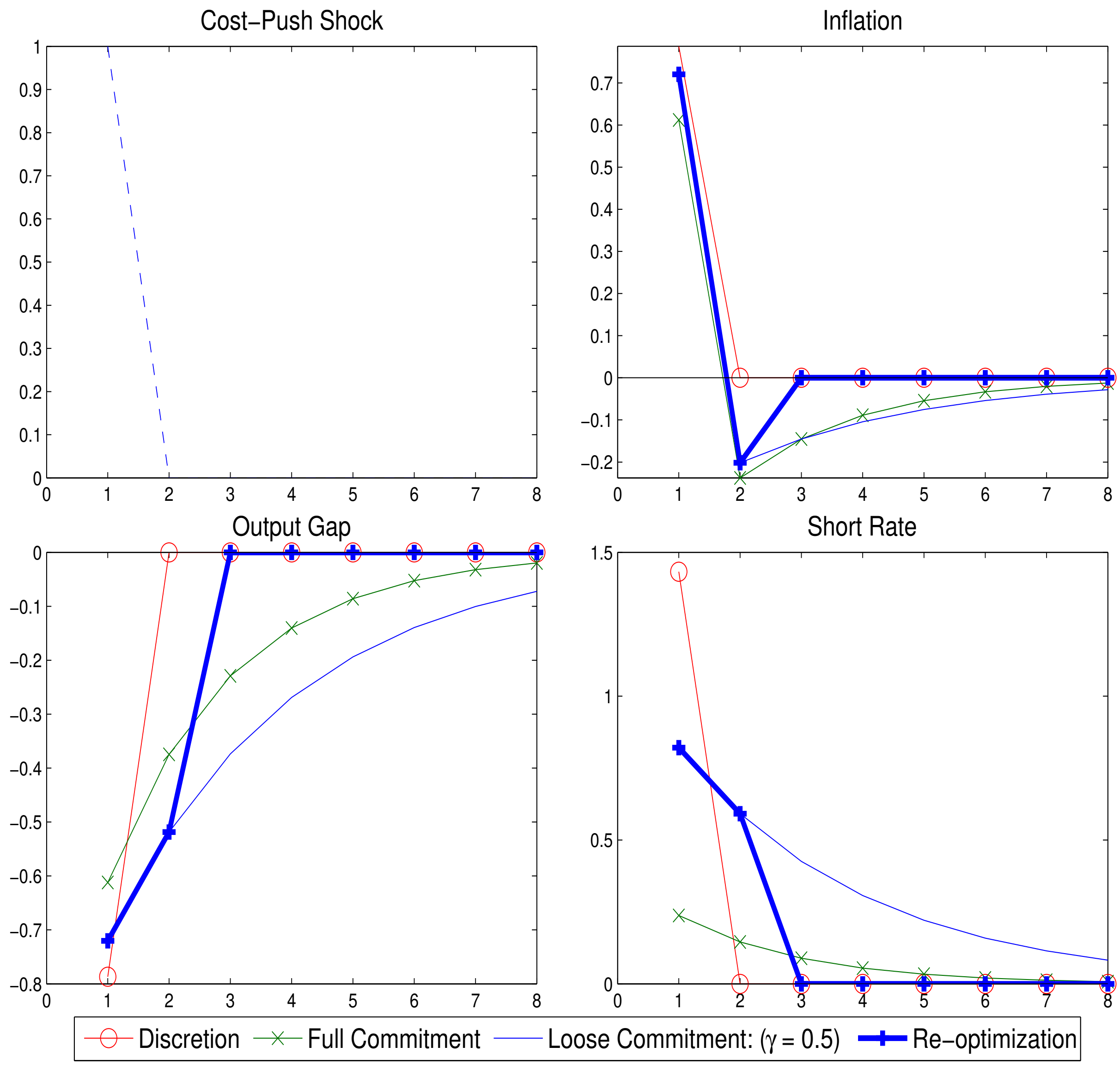

Figure 2: Impulse-response to i.i.d. cost-push shock. The green line shows the response of macro variables under full commitment while the red line shows the response under discretion. The blue lines show the responses under loose commitment: the solid blue line assumes that no re-optimizations occur while the blue line with dots shows responses where a re-optimization occurs only in the third period.

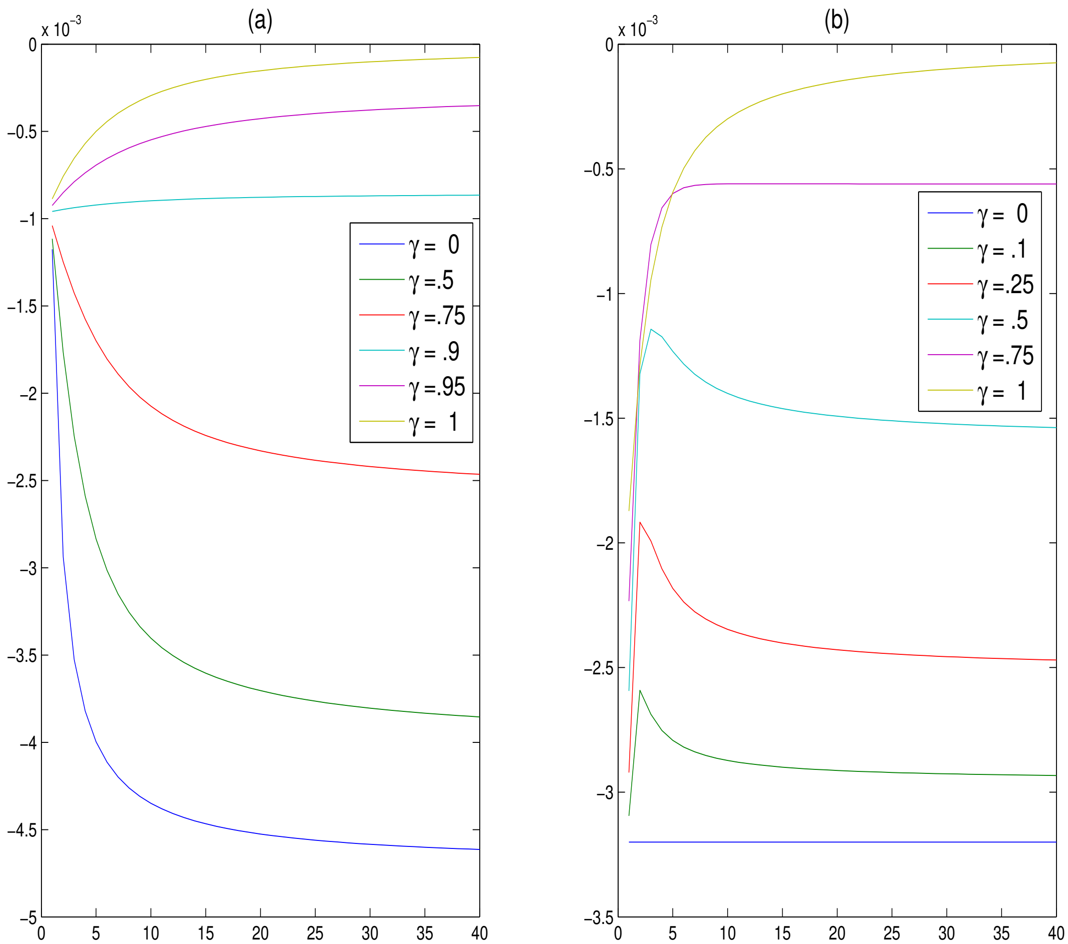

Figure 3: The figure shows the average slope of the yield curve as a function of the probability of commitment (γ). Panel (a) uses the calibration with $\sigma\theta < 1$, while panel (b) uses a calibration with $\sigma\theta > 1$

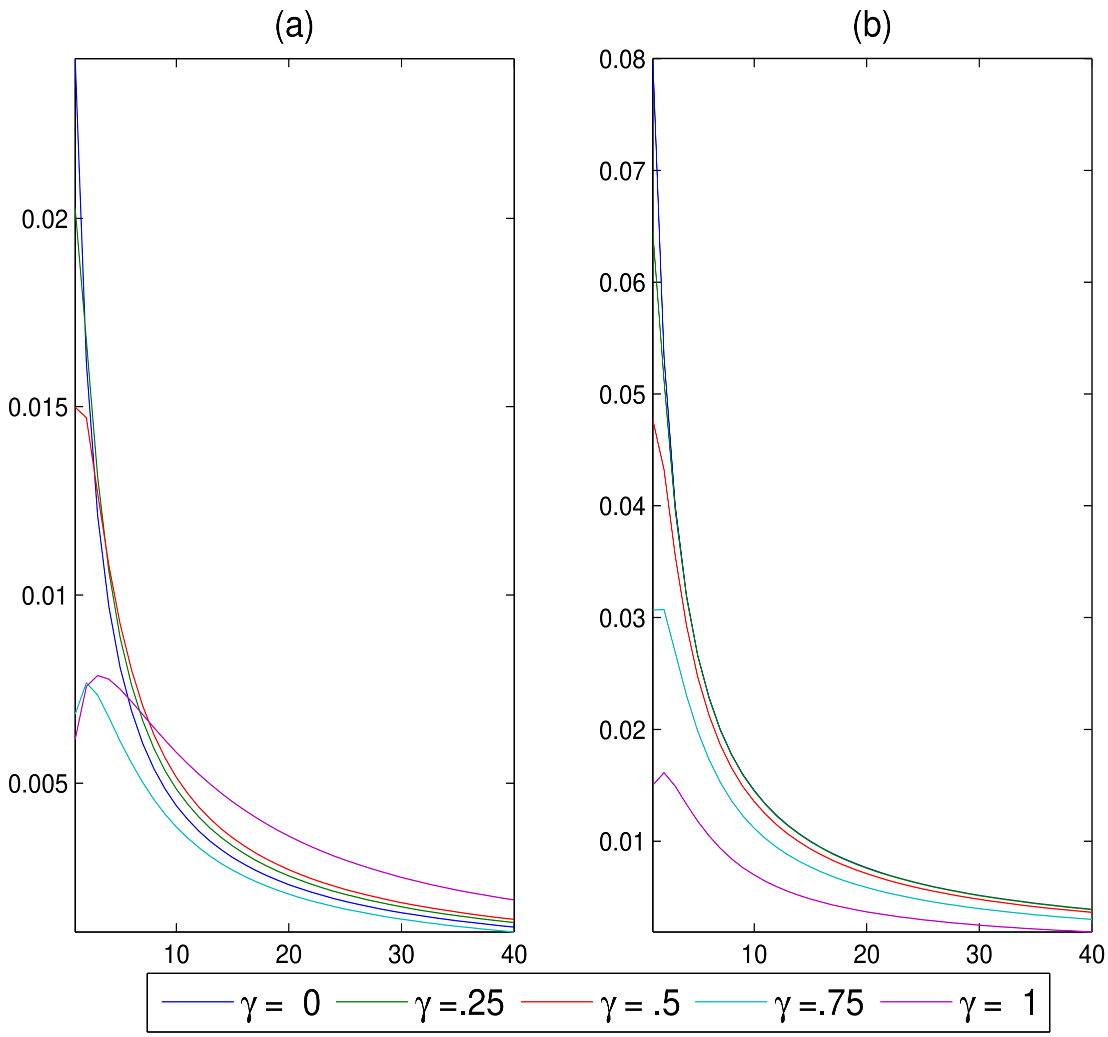

Figure 4: The figure shows the unconditional standard deviation of the yield curve as a function of the probability of commitment (γ). Panel (a) uses the calibration with $\sigma\theta < 1$, while panel (b) uses a calibration with $\sigma\theta > 1$

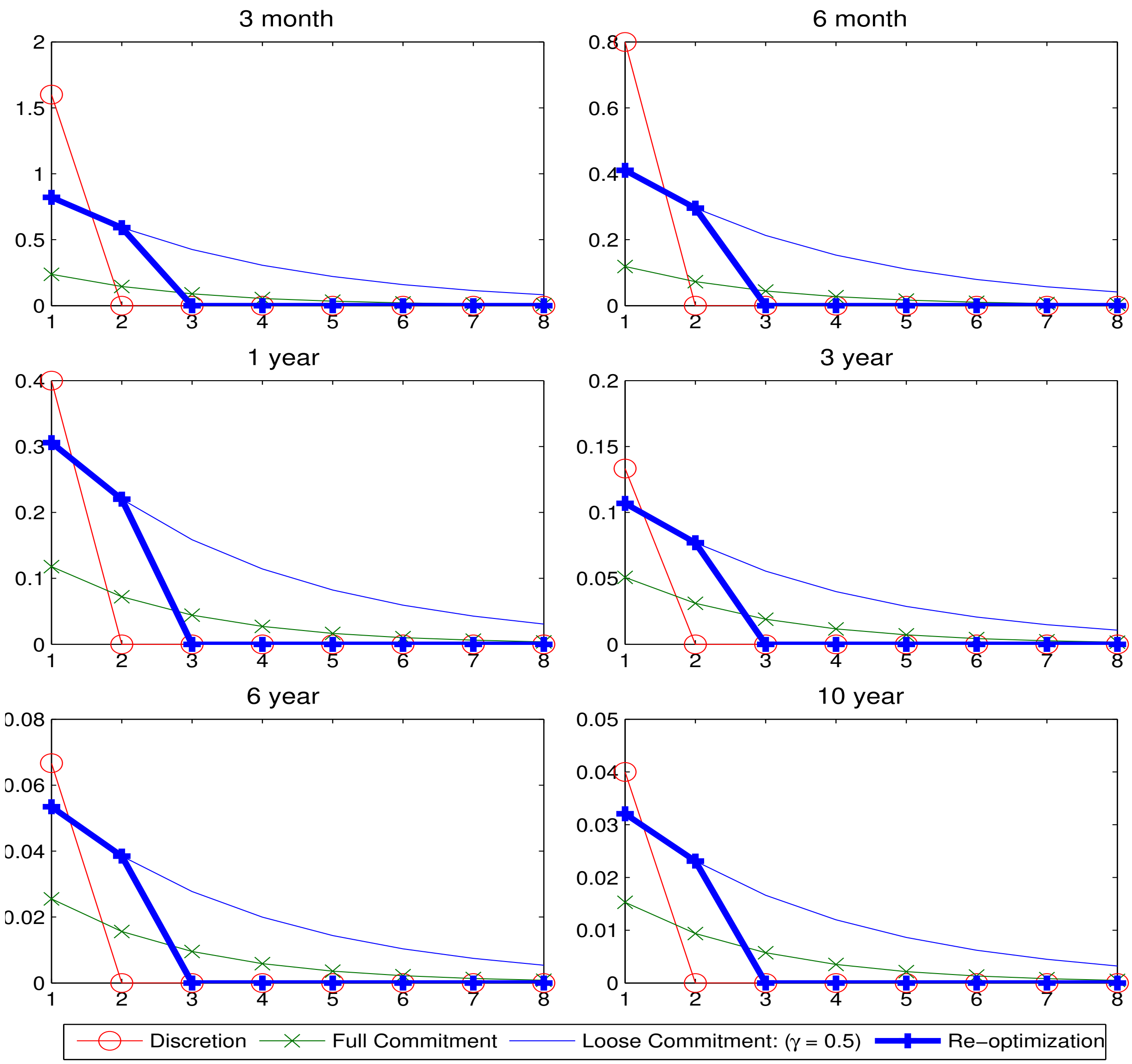

Figure 5: Impulse-response of yields to i.i.d. cost-push shock. The green line shows the response under full commitment while the red line shows the response under discretion. The blue lines show the responses under loose commitment: the solid blue line assumes that no re-optimizations occur while the blue line with dots shows responses where a re-optimization occurs only in the third period.

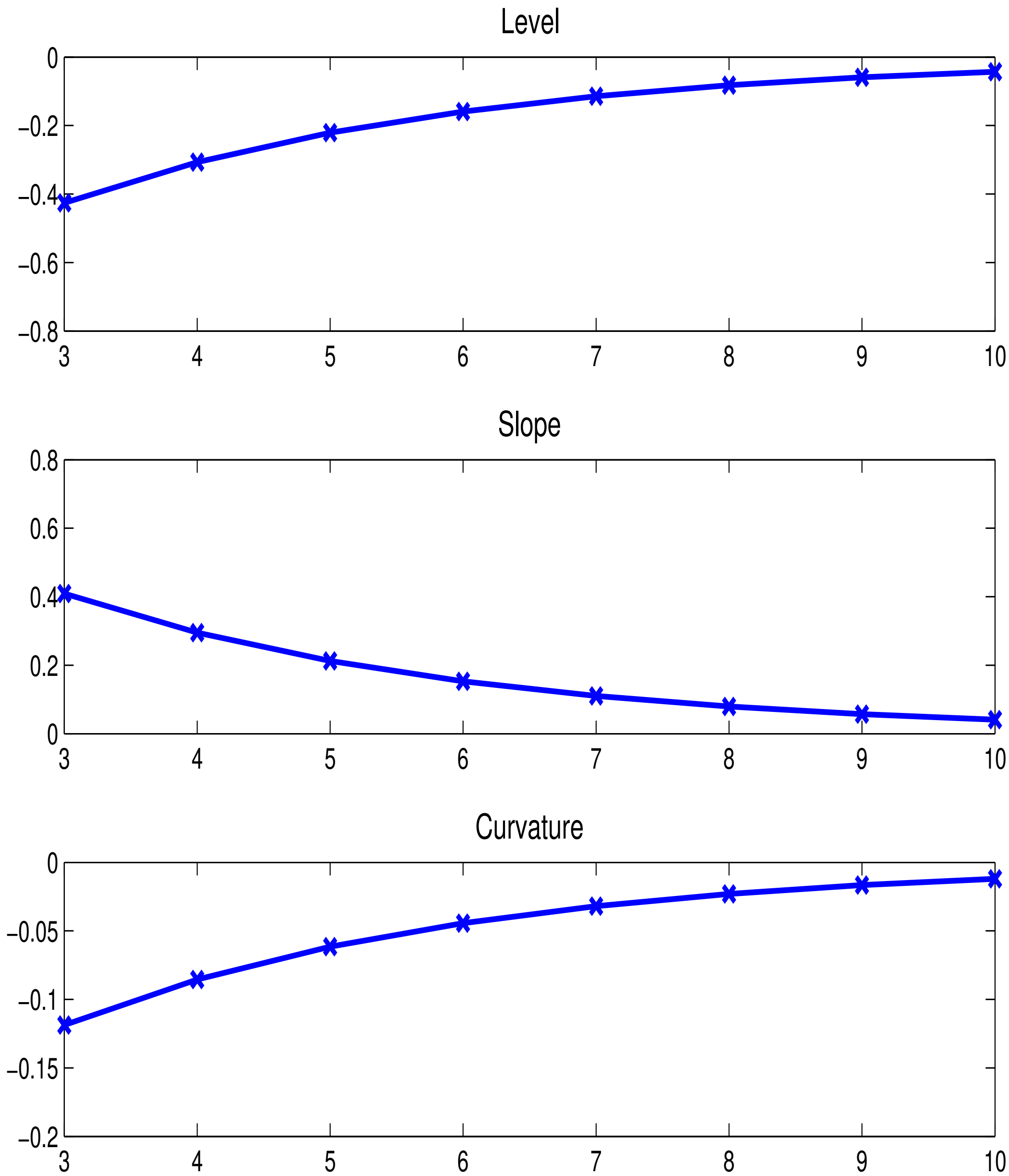

Figure 6: This figure shows the effects of re-optimization shock on the term structure factors following a cost-push shock. The cost-push shock occurs in period 1, followed by a re-optimization shock in period 3. The graph shows the path after the re-optimization shock relative to a case where no re-optimization shock occurs. The level factor is defined as just the 3 month yield, the slope factor as (10 year - 3 month) and the curvature factor as (10 year + 3 month - 2*3 year) yields. See section 2.5 for more details.

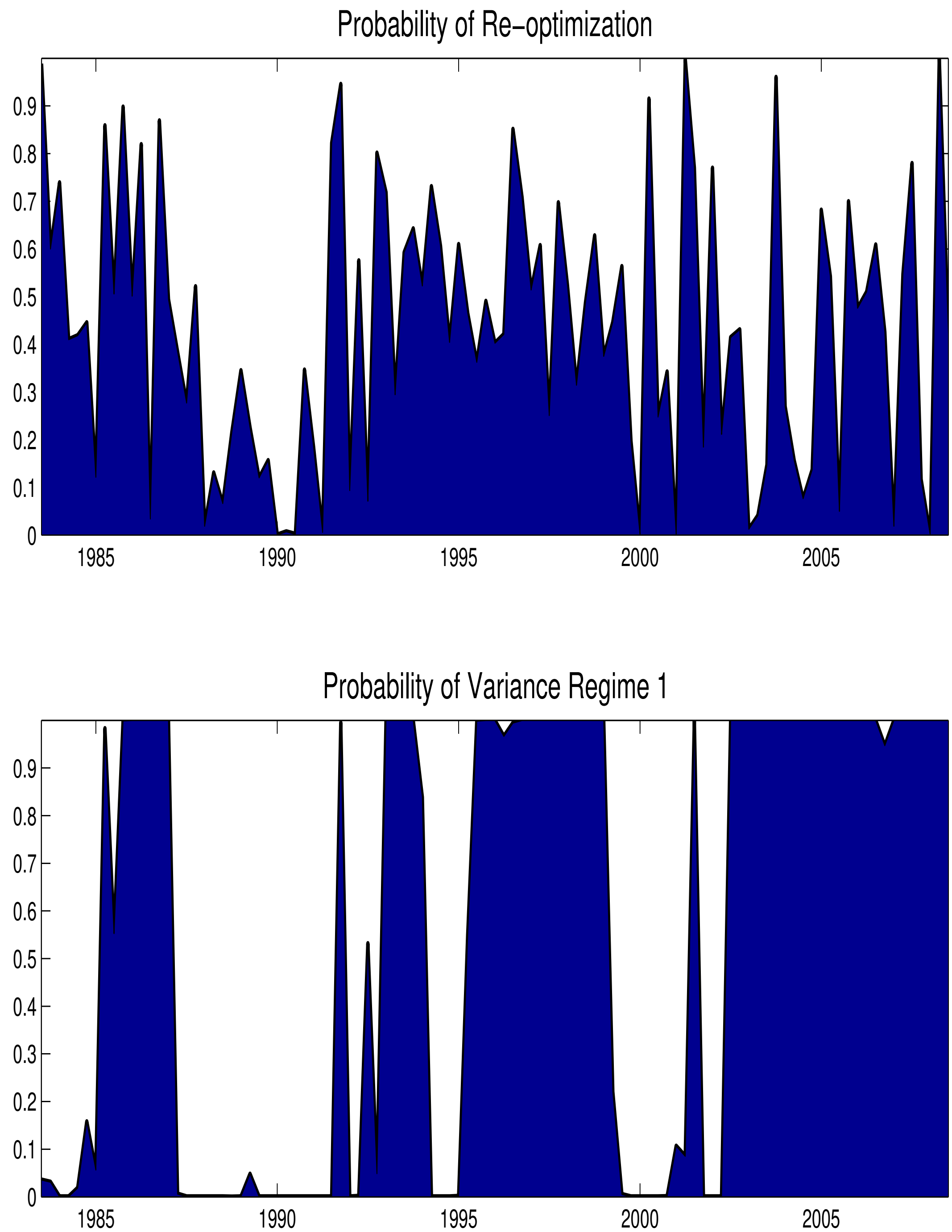

Figure 7: The figure shows the smoothed probability of being in a re-optimization state (upper panel), and of being in variance regime 1 (lower panel) for the posterior mean estimates from the medium-scale DSGE model.

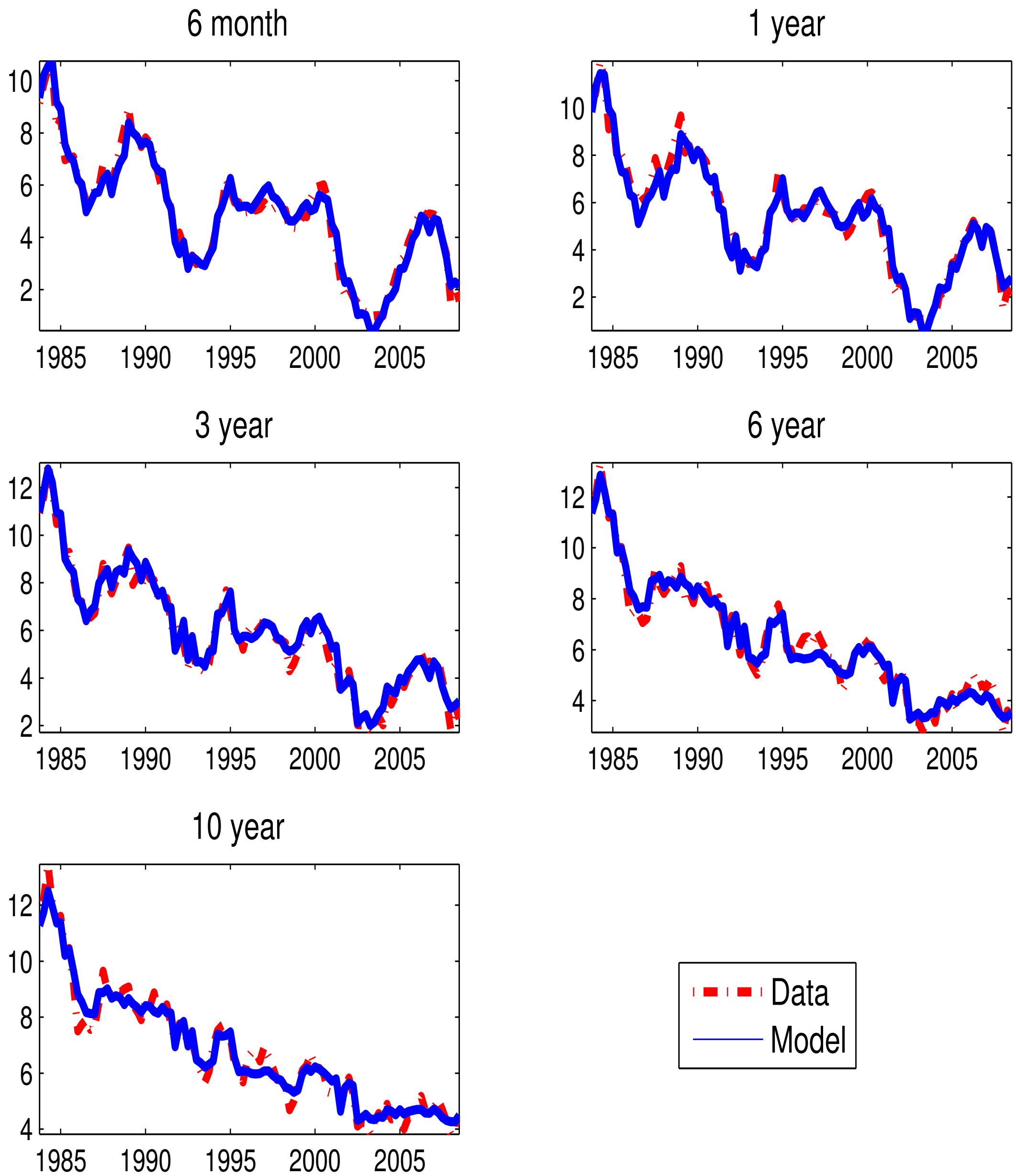

Figure 8: The dashed red lines in the figure show the actual yield data. The solid blue lines show the model's fit.

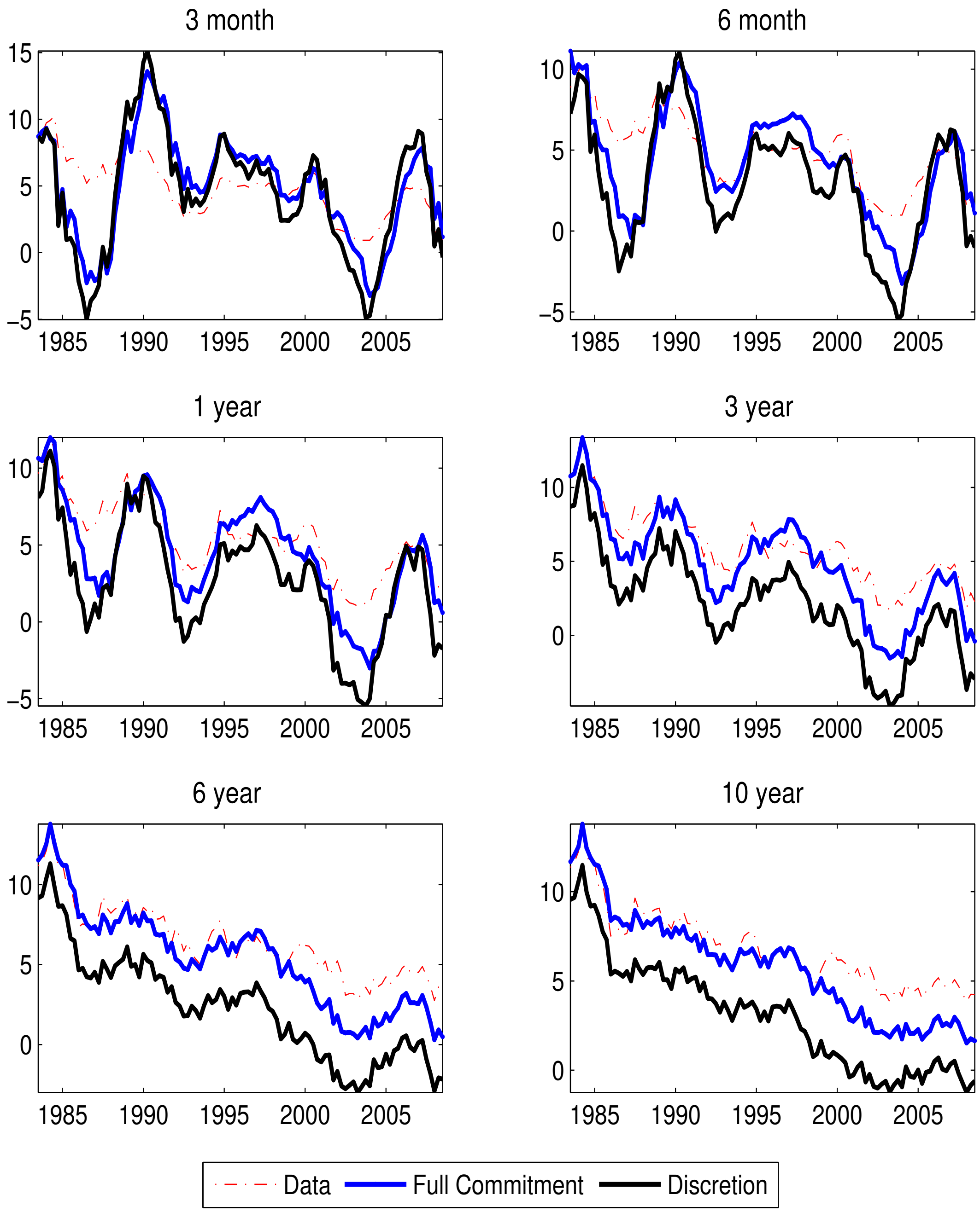

Figure 9: The figure reports counterfactual simulations under full commitment (blue line) and discretion (black line), keeping the structural shocks fixed at their estimated values.

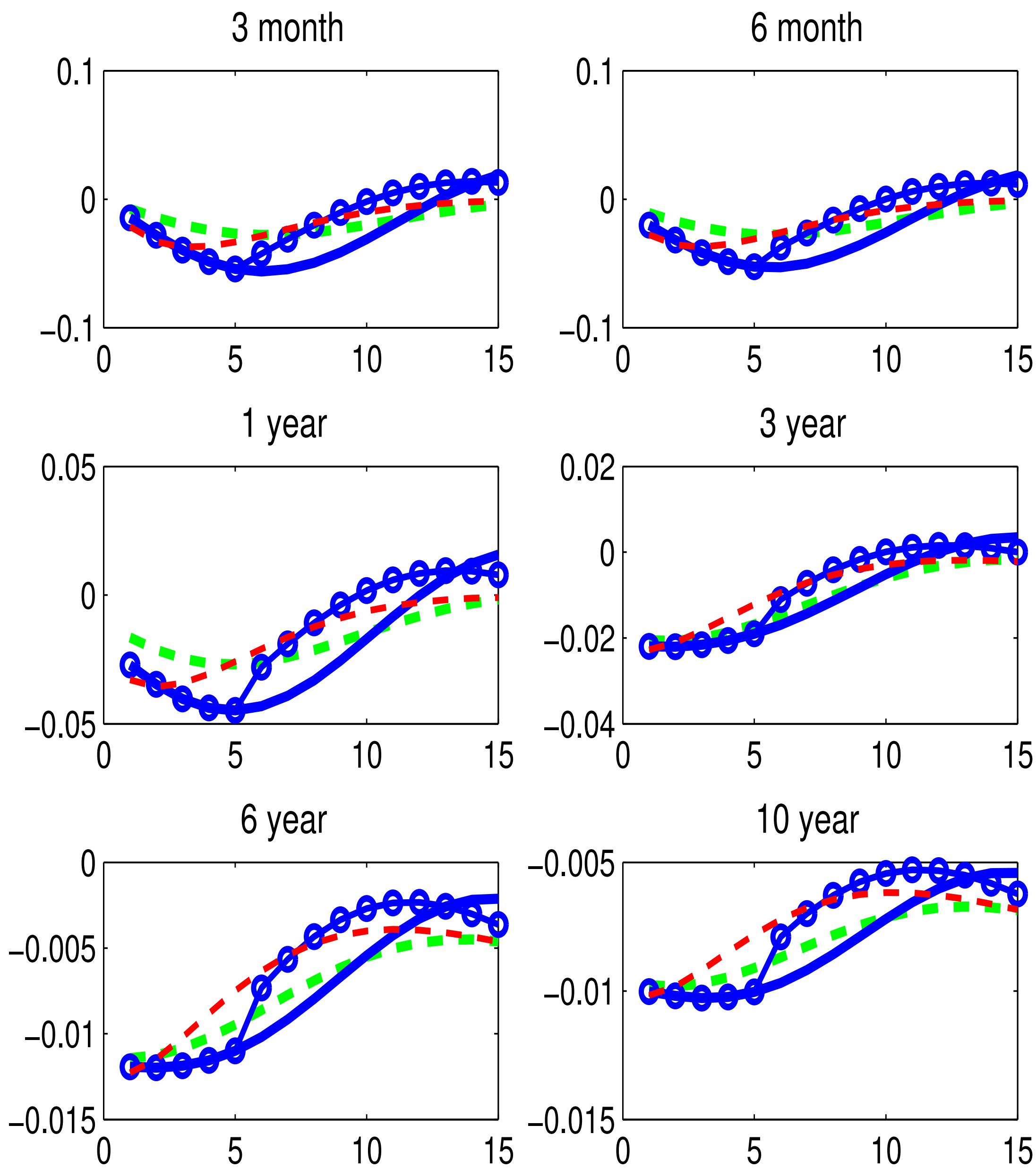

Figure 10: Impulse responses to a 1 standard deviation technology shock under alternative commitment settings. The blue lines indicate the responses under loose commitment; the solid one assumes that no re-optimizations occur and dashed blue line displays a re-optimization occurring after the 5th quarter, but not afterwards. The green and red line show the responses under full commitment and discretion respectively.

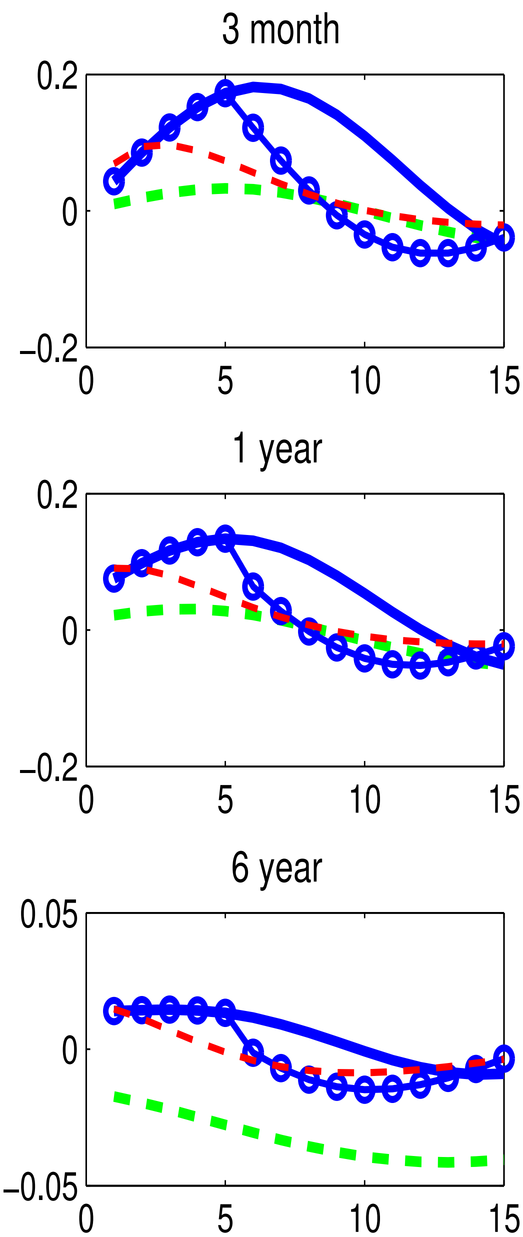

Figure 11: Impulse responses to a 1 standard deviation price markup shock under alternative commitment settings. The blue lines indicate the responses under loose commitment; the solid one assumes that no re-optimizations occur and dashed blue line displays a re-optimization occurring after the 5th quarter, but not afterwards. The green and red line show the responses under full commitment and discretion respectively.

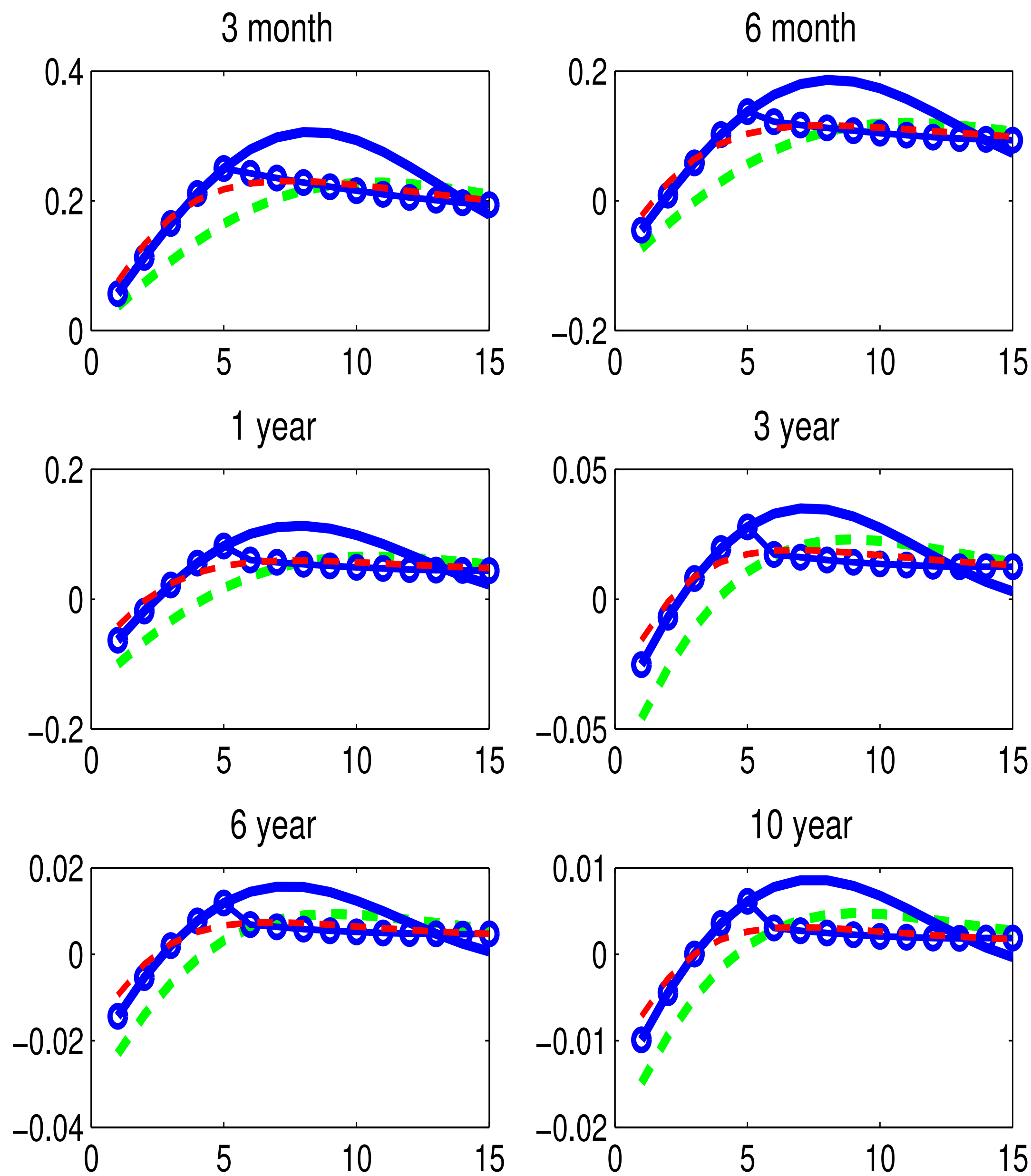

Figure 12: Impulse responses to a 1 standard deviation demand (risk-preference) shock under alternative commitment settings. The blue lines indicate the responses under loose commitment; the solid one assumes that no re-optimizations occur and dashed blue line displays a re-optimization occurring after the 5th period, but not afterwards. The green and red line show the responses under full commitment and discretion respectively.

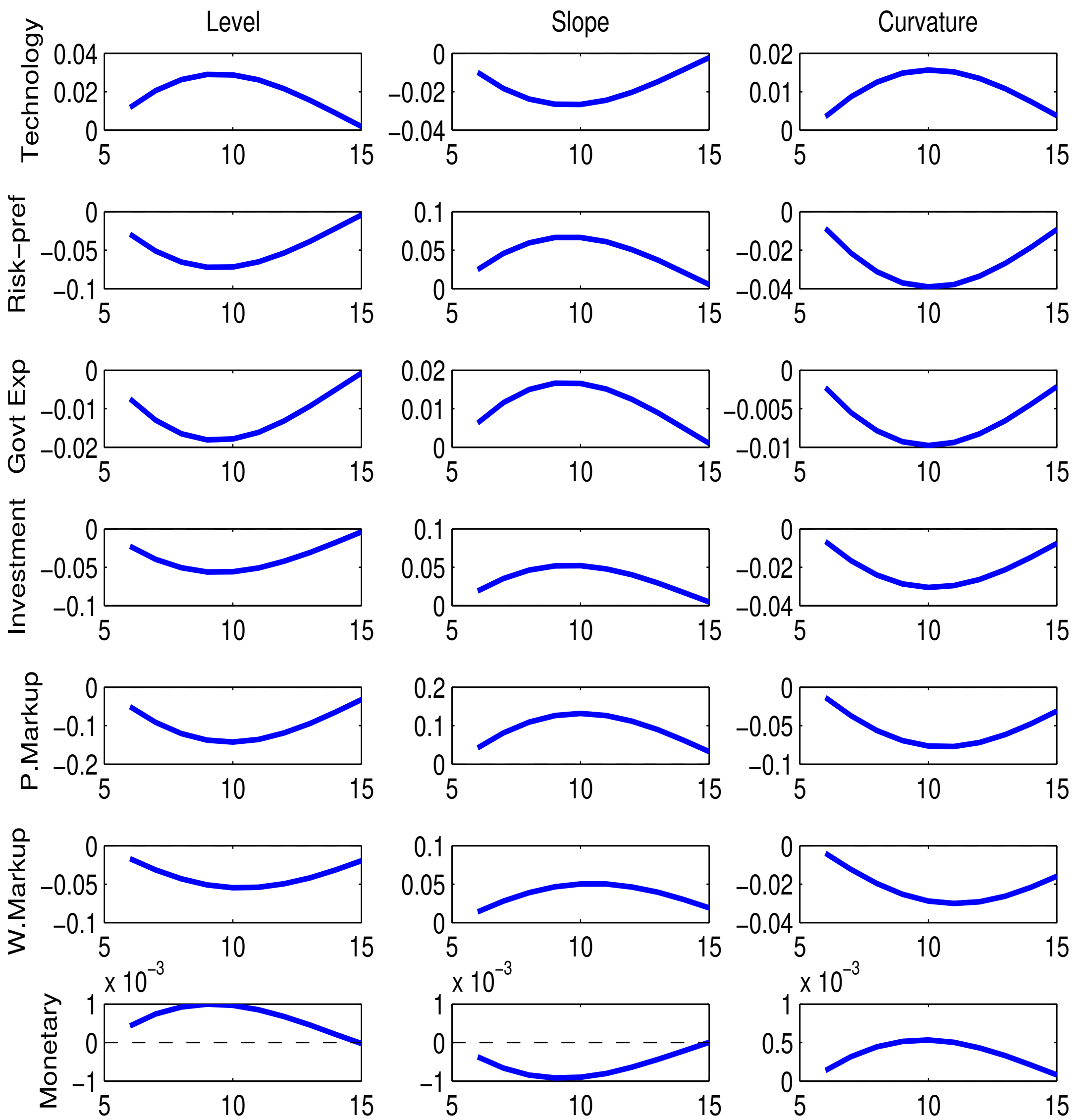

Figure 13: This figure shows the effects of re-optimization shock on the term structure factors following the structural shocks. The structural shock occurs in period 1, followed by a re-optimization shock after period 5. The graph shows the path after the re-optimization shock relative to a case where no re-optimization shock occurs. The level factor is defined as just the 3 month yield, the slope factor as (10 year - 3 month) and the curvature factor as (10 year + 3 month - 2*3 year) yields. See section 3.4 for more details.

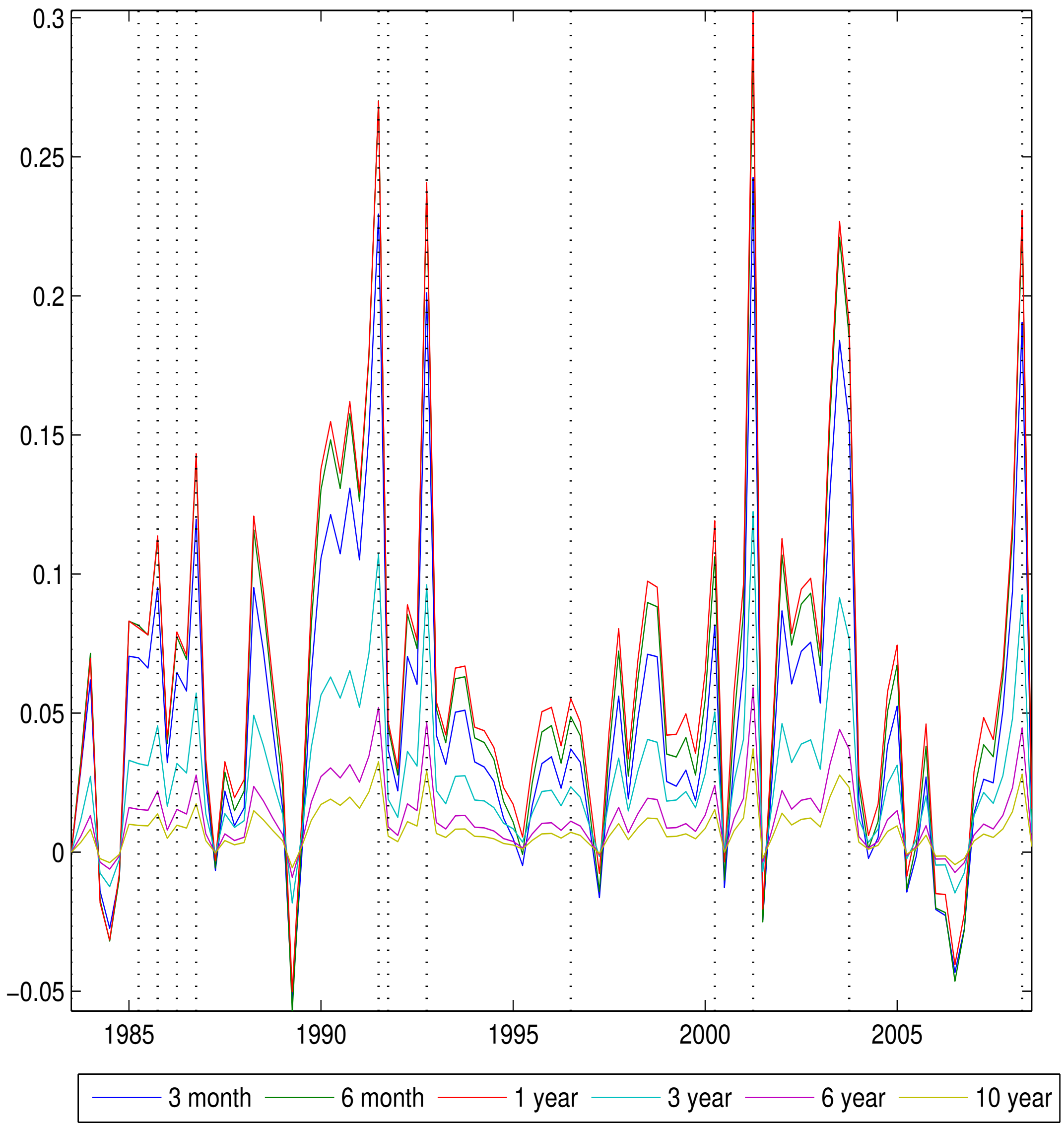

Figure 14: The figure shows the effects of re-optimizations on yields over time, measured as the difference between the value conditional on re-optimization and the value conditional on continuation of previous commitment.

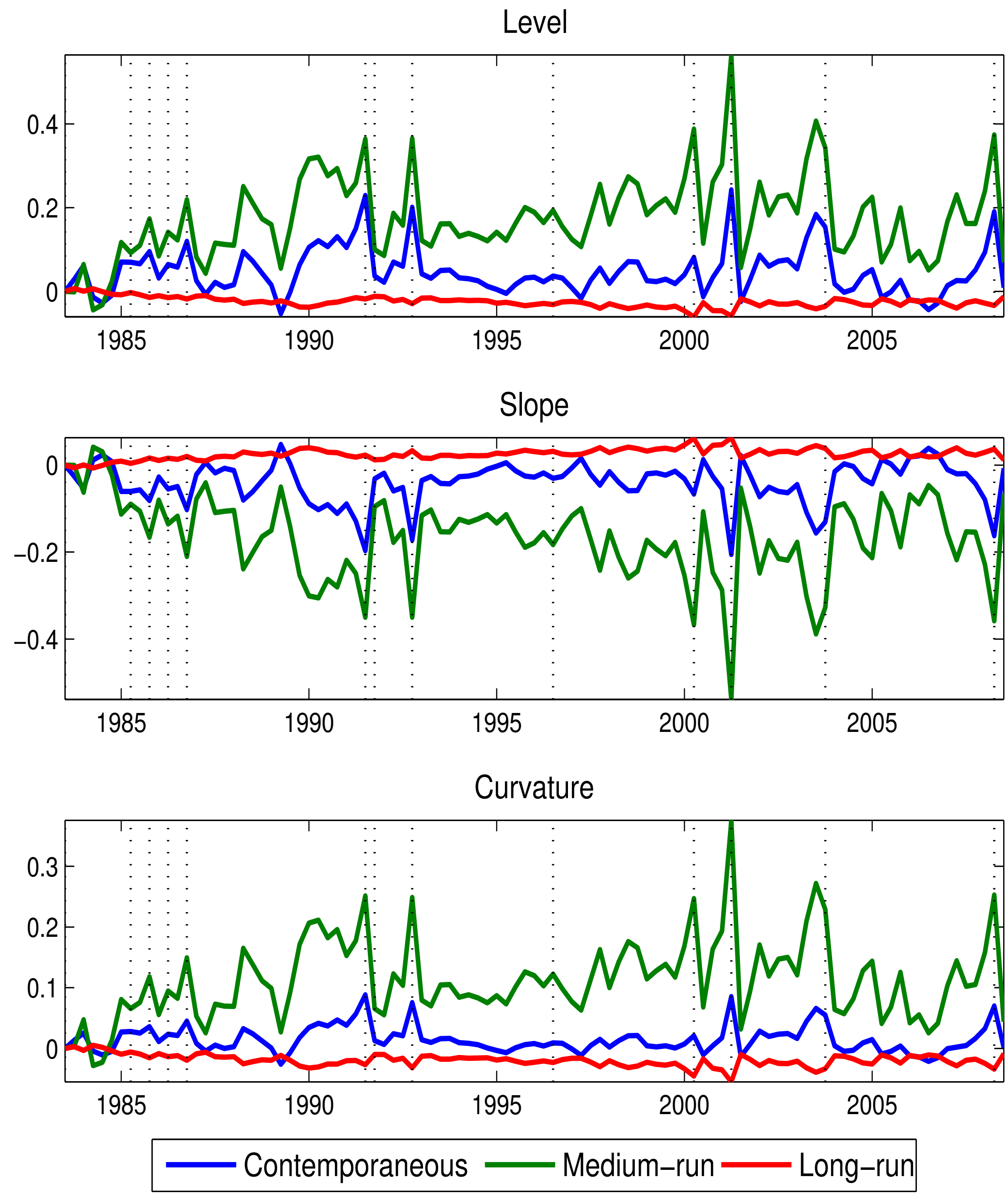

Figure 15: The figure shows the effects of re-optimizations on terms structure factors over time, measured as the difference between the value conditional on re-optimization and the value conditional on continuation of previous commitment. The level factor is defined as just the 3 month yield, the slope factor as (10 year - 3 month) and the curvature factor as (10 year + 3 month - 2*3 year) yields.