How credible is the Federal Reserve? A structural estimation of policy re-optimizations *

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Abstract

Using a Markov-switching Bayesian likelihood approach, the paper proposes a new measure of the degree of credibility of the Federal Reserve over the post WWII period. We estimate a medium-scale macroeconomic model, where the central bank is endowed with a commitment technology, and where a regime-switching process governs occasional re-optimizations of announced plans. Our estimates reject the conventional full-commitment and discretion cases, and show that deviations from commitment plans were rather infrequent, and at dates consistent with conventional accounts of the US monetary history. Our framework is used to discuss the role of policy re-optimizations as sources of monetary policy shocks, and to assess the importance of central bank credibility through counterfactual analysis.

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1 Introduction

Both in academia and in policy circles there is a widespread consensus on the importance of central bank credibility for the conduct of monetary policy. However, very few studies have attempted to assess empirically whether central banks are indeed credible. Such an empirical assessment incurs in two main obstacles. First of all, the term "credibility" is used in practice to refer to very different concepts, like those of "accountability", "predictability", "independence", 'transparency" just to name a few examples.[1]. Thus, the objective to be measured is ambigous by nature. Second, even upon agreeing on a particular definition, measures of credibility would depend on factors – like agent's expectations, policy announcements, economic shocks – that are not directly observable, and need to be proxied with alternative and sometimes subjective measures.[2]

This paper proposes a novel measure of credibility that deals with these two problems. First, our measure is based on a precise theoretical definition of credibility. Following the large literature on time-inconsistency of macroeconomic policies (see e.g. Kydland and Prescott (1977) and Barro and Gordon (1983)), we define credibility as the ability to commit to previously announced plans. In the presence of forward looking agents, central banks can reap the benefits of shaping agents' expectations by announcing a plan and credibly committing to it. However, there is an ex-post temptation to deviate from such a plan. Credibility is defined as the ability to resist to such a temptation. This is consistent with the central bank having "a history of doing what it says it will do", which both academics and policy makers selected as the most important factor in building central bank credibility in Blinder (2000)'s survey. Second, our measure is obtained from a likelihood-based structural estimation of a micro-founded Dynamic Stochastic General Equilibrium model, and relies only on widely available aggregate macroeconomic series.

The monetary policy literature has dealt with the time-inconsistency problem either assuming that the central bank always follow their announced plans (full commitment case) or that it always deviates (discretion case). But it is not obvious that either of the two dichotomous cases is reasonable in practice. In this paper we use a general framework, which we refer to as *loose commitment*, that nests the extreme cases of full commitment and

[1]See Blinder (2000) for a survey of different uses of the term credibility among academics and policymakers.

[2]For instance, Faust and Svensson (2001) proposed using the deviation of survey-based inflation expectations from the central bank's inflation target as a measure of credibility. Cukierman (1992)) develops some indicators of independence and transparency, through an index-based aggregation of information contained in bylaws and questionnaires, among other data sources.

discretion while allowing for a continuum of intermediate cases. The theoretical setting is based on the works developed by Roberds (1987), Schaumburg and Tambalotti (2007) and Debortoli and Nunes (2010). Here the central bank has access to a commitment technology, but it occasionally gives in to the temptation to revise its plans.[3] In the case of the Federal Reserve a re-optimization could occur if policy makers succumb to outside pressure from the political or the financial system. Additionally, as the composition of the Federal Open Market Committee (the Fed's main monetary policy making arm) changes over time there may arise situations where past policy promises are abandoned.

In the model, re-optimizations are governed by a two-state stochastic process (s_t). When $s_t = 1$ past promises are honored with probability γ, while $s_t = 0$ implies a re-optimization with probability $1 - \gamma$. A value of $\gamma = 1$ means there are no re-optimizations (the case of full commitment) while $\gamma = 0$ means there is a re-optimization every period (the case of discretion). Importantly, this setting allows for any intermediate value of γ between 0 and 1. We estimate this unconditional probability of honoring past promises, and interpret it as a measure of the Federal Reserve's level of credibility. Alternatively, that probability can be thought of as a continuous variable measuring the durability of the Federal Reserve's promises, where longer durability corresponds to higher levels of credibility.

The empirical analysis is conducted within the medium-scale model of Smets and Wouters (2007) (henceforth SW). This model does a good job of fitting the data and has become the benchmark in the monetary policy literature. Additionally, models similar to this are commonly being used for policy analysis at central banks. We depart from that model in two important ways. First, instead of considering a simple monetary policy rule, monetary choices are the outcome of the central bank's optimal decision problem, within a *loose commitment* framework. The central bank and the private agents are both aware of the possibility of future re-optimizations and explicitly take it into account. Second, and since we are dealing with a version of the SW model with regime-switching, we allow the variance of the shock processes to shift over time to control for potential sources of time variation, other than policy re-optimizations. Estimation is carried out using a Bayesian Markov Chain Monte Carlo (MCMC) estimation.

The posterior mode of the unconditional probability of commitment is estimated to be 0.81 with fairly small confidence intervals. This implies that the data reject the commonly used assumptions of full commitment ($\gamma = 1$) and discretion ($\gamma = 0$). Note that the empirical

[3]Roberds (1987) used the term "stochastic replanning" while Schaumburg and Tambalotti (2007) used the term "quasi-commitment".

literature on optimal monetary policy has abstracted from assessing the empirical plausibility of alternative commitment settings, by assuming either commitment or discretion.[4] As the only exceptions, the recent works of Givens (2012), Coroneo et al. (2013) and Chen et al. (2013) contain estimates under both commitment and discretion (concluding that the data favor the specification with discretionary policy) but not allowing for intermediate cases.[5].

Our estimation also allows us to identify historical episodes when the Federal Reserve has been more likely to have re-optimized policy plans. We find that there is a rise in the smoothed probability of re-optimization (or smoothed probability of not fulfilling past promises) coinciding with the appointment of Arthur Burns, G. William Miller and Paul Volcker but not during the appointments of Alan Greenspan and Ben Bernanke. There is also a rise in this probability around changes in operating procedures of the Federal Reserve; specifically during the reserves targeting experiment conducted under Volcker in the early 1980s and the FOMC policy to start announcing the target for the Federal Funds rate around 1994. Additionally we find a rise in this probability in 2008 around the start of the quantitative easing policy under Ben Bernanke.

The estimated probability of commitment (0.81) and the use of quarterly data implies that the Federal Reserve is expected to re-optimize plans once every 5 quarters. Since 0.81 is closer to 1, it is tempting to deduce that Federal Reserve policy is closer to commitment. However, that conclusion would be unwarranted, as it clearly depends on the specific metric being considered. In fact, we show that most second moments of the estimated model are closer to their counterparts under discretion (i.e. $\gamma = 0$). But on the other hand the counterfactual analysis paints a somewhat different picture. For the important case of inflation, the counterfactual path of inflation under full commitment is much closer to actual data, and furthermore it suggests that if the Federal Reserve had followed policy under discretion, inflation would have stayed at high levels throughout the 1980s. Overall, these issues highlight the importance of using our general framework, where sometimes the dynamics of the economy are better described by the case of full commitment while at other times the case of discretion is better. Lastly, another potential way to view our re-optimization episodes is to view them as a source of monetary policy shocks. From this viewpoint, we find that typically the deviations from commitment during the 70's have

[4]See Dennis (2004), Söderström et al. (2005), Salemi (2006), Ilbas (2010) and Adolfson et al. (2011) among others.

[5]The independent and contemporaneous work of Chen et al. (2013) also contains one specification with "quasi-commitment" setting, similar to the one considered in this paper. That specification is nevertheless rejected in favor of discretion, although it does not nest the cases of discretion and commitment.

implied policies that are more expansionary, while deviations in the '90s and 2000's imply policies that are relatively more contractionary.

The rest of the paper is organized as follows. Section 2 describes the setup of the loose commitment framework and the baseline model. In section 3 we discuss the loose commitment framework and the solution algorithm, and Section 4 presents the estimation details. Section 5 illustrates the results, namely the parameter estimates the impulse response analyses, and counterfactual exercises. Section 6 concludes.

2 The model

As discussed in the introduction, the distinctive feature of our model concerns the way monetary policy is designed. The underlying economy is instead described by a standard system of linearized equations

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

where x_t denotes a vector of endogenous variables, v_t is a vector of zero-mean, serially uncorrelated, exogenous disturbances with variance-covariance matrix Σ_v, and A_{-1}, A_0, A_1 and B are matrices whose entries depend (non-linearly) on the model's structural parameters (Θ). The term E_t denotes rational expectations with respect to those innovations, conditional on the information up to time t. The vast majority of the models used for monetary policy analysis can be mapped into such formulation.[6]

The system of equations (1) implies that current variables (x_t) depend on expectations about future variables ($E_t x_{t+1}$). This gives rise to the time-inconsistency problem at the core of our analysis. The central bank's plans about the future course of policy could indeed have an immediate effect on the economy, as long as those plans are embedded into the private sector expectations. Such plans, however, are typically time-inconsistent. Having reaped the gains from affecting expectations, the central bank has an ex-post incentive to disregard its previous plans, and freely set its policy instruments. For this reason, characterizing monetary policy choices requires a specific assumption regarding the central bank's ability to commit.

Following Schaumburg and Tambalotti (2007) and Debortoli and Nunes (2010), it is assumed that the central bank has access to a *loose commitment* technology. In particular, the central bank is able to commit, but it occasionally succumbs to the temptation to revise

[6]Models with more lags, leads, constants, serially correlated shocks etc. can be cast into eq.(1) by suitably expanding the vector x_t.

its plans. We refer to these occasional events as "policy re-optimizations". 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 accordingly 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 our 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 we will estimate it from the data.

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. Note that s_t is a special case of Markov switching typically known as independent switching. The probability of moving to a commitment (discretion) state next period is the same, γ $(1-\gamma)$, regardless of whether in the current period there has been a re-optimization or not. There are two main reasons for this assumption. First, it's not clear that if a re-optimization has just occurred that another one would be more or less likely in the future. Second, this helps keep the model tractable. The solution algorithm for optimal policy under loose commitment would take significant more computation time with state-dependent switching as it requires a nonlinear solution method with finite sample simulations of a value function. This would render the estimation procedure infeasible as it involves invoking this algorithm a large number of times. Additionally we don't allow for re-optimizations to depend on endogenous state variables. This is potentially a bigger concern as it would invalidate the estimation methods that rely on the re-optimization shocks being exogenous to the state of the economy. In the appendix we address this concern by checking if the endogenous state variables can help predict re-optimization episodes. Granger causality tests show that

in fact the endogenous state variables do not have statistically significant predictive power. Finally Debortoli and Nunes (2010) analyze a simple fiscal policy model where the probability of re-optimization depends on endogenous state variables, and find similar results to the corresponding exogenous probability case. Thus our simplifying assumption made to ensure tractability seems like a reasonable approach. Extensions of this approach are left for future work.

3 The central bank's problem

As is common in the monetary policy literature, the central bank's objectives are characterized by a (period) quadratic-loss function $x_t'Wx_t$. The central bank's objectives may or may not reflect the preferences of the underlying society. For instance, and following Rogoff (1985), appointing a central banker who is more averse towards inflation than the overall public may be desirable in the limited commitment settings considered here. [7] From an empirical viewpoint, simple loss functions without explicit microfoundations have been shown to realistically describe central bank's behavior (see e.g. Rudebusch and Svensson (1999), or more recently Ilbas (2010) and Adolfson et al. (2011)). For comparability with that literature, and given the empirical focus of the present study, our baseline exercises are conducted using a simple loss function.[8].

The problem of central bank when making a new plan can then be written as

$$x'_{-1}Vx_{-1} + d = \min_{\{x_t\}_{t=0}^{\infty}} E_{-1} \sum_{t=0}^{\infty} (\beta\gamma)^t [x_t'Wx_t + \beta(1-\gamma)(x_t'Vx_t + d)] \tag{2}$$

$$s.t.\ A_{-1}x_{t-1} + A_0x_t + \gamma A_1 E_t x_{t+1} + (1-\gamma)A_1 E_t x_{t+1}^{reop} + B(s_t^{vo})v_t = 0\ \ \forall t \tag{3}$$

The terms $x'_{t-1}Vx_{t-1} + d$ 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. Each term in the summation is composed of two parts. The first part is the period loss function. The second part indicates the value the policymaker

[7] Additional theoretical support for describing the central bank's behavior through simple loss functions is provided for instance in Svensson (1999).

[8] As a robustness exercise, we have tried to get estimates obtained with a utility-based welfare criterion, calculated according to the procedures described in Debortoli and Nunes (2006), Levine et al. (2008) and Benigno and Woodford (2012), but the empirical fit is very poor.

obtains if a re-optimization occurs in the next period.

The sequence of constraints (3) correspond to the structural equations (1), 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}).[9] In a Markov-Perfect equilibrium, the choices at the time of re-optimizations only depend on natural state-variables, i.e. $E_t x_{t+1}^{reop} = \tilde{F} x_t$, where the matrix $\tilde{F}$ is taken as given by the central bank.[10] Clearly, a rational expectation equilibrium requires the matrix $\tilde{F}$ to be consistent with the policies actually implemented by the central bank, and can be found as the solution of a fixed point problem.[11]

The solution to the central bank's problem takes the form

$$\begin{bmatrix} x_t \\ \lambda_t \end{bmatrix} = F_{s_t} \begin{bmatrix} x_{t-1} \\ \lambda_{t-1} \end{bmatrix} + G v_t \tag{4}$$

where λ_t is a vector of Lagrange multipliers attached to the constraints (3) and the state dependent matrices

$$F_{(s_t=1)} = \begin{bmatrix} F^{xx} & F^{x\lambda} \\ F^{\lambda x} & F^{\lambda\lambda} \end{bmatrix} \qquad F_{(s_t=0)} = \begin{bmatrix} F^{xx} & 0 \\ F^{\lambda x} & 0 \end{bmatrix}. \tag{5}$$

The above expressions highlight the effects of policy re-optimizations. In particular, notice that the unobservable state s_t only affects the columns of the matrices F_{s_t} describing the responses to λ_{t-1}. This is because a policy re-optimization implies that previous commitments are disregarded. Those commitments are summarized in our framework by the co-state variables λ_{t-1}.[12] Therefore, when policies are re-optimized it is as if the current variables are not affected by λ_{t-1}. On the contrary, the policy responses to the state variables x_{t-1} and to the shocks v_t remain the same, regardless of whether the central bank re-optimizes or not.[13]

[9] To simplify the notation, we have dropped regime dependence and replaced $x_{t+1}(s_t = 0)$ with the more compact term x_{t+1}^{reop}.

[10] A Markov-perfect equilibrium rules out the possibility of reputation and coordination mechanism between different central bank's selves.

[11] The numerical algorithm adopted is an extension of the methods to solve for (Markov-Perfect) equilibria introduced by Backus and Driffill (1985), Söderlind (1999), and Dennis (2007), as described in Debortoli et al. (2012).

[12] More formally, following Kydland and Prescott (1980) and Marcet and Marimon (2011), the central bank problem can be written recursively by expanding the state of the economy to include the Lagrange multiplier vector λ_{t-1}, with initial condition $\lambda_{-1} = 0$.

[13] It follows that $x_t^{reop} = F^{xx} x_{t-1} + G_x v_t$. Moving this equation forward one period and taking expectations,

Our setting bears some similarities to the models recently developed in monetary regime-switching literature (see e.g. Davig and Leeper (2007), Farmer et al. (2009), Liu et al. (2011) and Bianchi (2012)).[14] In those models, an exogenous shock switches the economy from one regime to another where the conduct of policy is different. In our model, the re-optimization shocks are better thought of as starting a new commitment regime, where another re-optimization shock in the future will end it and start yet another. Nevertheless, as it happens in standard rational expectations regime-switching models, what happens under a certain regime depends on what agents expect is going to happen under alternative regimes, and on how likely it is that a regime change will occur. An important difference is that our two policy regimes are described by the same structural parameters. In other words, allowing for occasional re-optimizations does not require introducing any additional parameters, besides the switching probability γ. As indicated by equation (5) policy re-optimizations only impose specific zero-restrictions on the law of motion of the model states. Such restrictions distinguish policy re-optimizations episodes from more generic sources of non-linearities, like switches in structural parameters, or switches in policymakers' preferences.

As mentioned above and is common in the regime-switching literature, considering exogenous stochastic switches is a necessary assumption to maintain tractability. Note that we do show in the appendix that assuming that policy re-optimizations are uncorrelated with endogenous state variables is a reasonable assumption. But we should make it clear that in the model, the structural shocks v_t do not automatically bring about a policy re-optimization. This is because the optimal responses to those shocks is indeed always part of the central bank state-contingent plan. In reality, policy re-optimizations could be the consequence of a variety of factors, not explicitly modeled in our framework. Possible candidates for such events are changes in the dominating views within a central bank due to time-varying composition of its decision-making committee or varying intensity of outside pressures by politicians and the financial industry.[15] In this respect, policy re-optimizations

one obtains $E_t x_{t+1}^{reop} = F_{xx} x_t$. In a rational expectations equilibrium, it must therefore be the case that $F_{xx} = \tilde{F}$.

[14] Note that since the central bank is optimally choosing policy there is no chance of indeterminacy. There would need to be an additional layer of uncertainty or mismeasurement to give rise to the possibility of indeterminacy.

[15] In the case of the United States, the reserve bank presidents serve one-year terms as voting members of the FOMC on a rotating basis, except for the president of the New York Fed. Furthermore, substantial turnover among the reserve bank presidents and the members of the Board of Governors arises due to retirement and outside options. With the (up to) seven members of the Board of Governors being nominated by the U.S. President and confirmed by the U.S. Senate, the composition of views in the FOMC may be affected by the views of the political party in power at the time of the appointment. Chappell et al. (1993) and Berger and Woitek (2005) find evidence of such effects in the U.S. and Germany, respectively.

could be viewed as a particular type of monetary policy shock, say e_t^{reop}, described by

$$e_t^{reop} = x_t^{reop} - x_t = -F^{x\lambda}\lambda_{t-1}. \tag{6}$$

The latter expression makes clear that while the timing of these "re-optimization shocks" is exogenous, their sign and magnitude is instead endogenous, and depends on the model structural parameters and on the history of past shocks summarized by the vector λ_{t-1}. In section 5.3 we describe in more details the implications of these re-optimization shocks.

An alternative approach would be to consider that policy re-optimizations are related to switches in the central bank's preferences, like from a "Hawkish" to a "Dovish" regime. We consider this as a promising area for future research, since such a framework would allow the identification of the deep sources of regime switches in Taylor rule parameters commonly found in the literature.[16] Our setting does not distinguish between re-optimizations within a policy regime, from those happening because of a regime change.

4 Estimation

4.1 Structural equations and parameters

The empirical analysis is conducted within the model of SW, that can be viewed as the backbone of the DSGE models developed at central banks in recent years and used for monetary policy analysis and forecasting. The model includes monopolistic competition in the goods and labor market, nominal frictions in the form of sticky price and wage settings, allowing for backward inflation indexation.[17] It also features several real rigidities – habit formation in consumption, investment adjustment costs, variable capital utilization, and fixed costs in production.

The model describes the behavior of 14 endogenous variables: output (y_t), consumption (c_t), investment (i_t), labor (l_t), the capital stock (k_t), with variable utilization rate (z_t) and associated capital services (k_t^s), the wage rate (w_t), the rental rate of capital (r_t^k), the nominal interest rate (r_t), the value of capital (q_t), price inflation π_t, and measures of price-markups (μ_t^p) and wage-markups (μ_t^w). The model dynamics are driven by six structural shocks: two shocks – a price-markup (e_t^p) and wage-markup (e_t^w) shock – follow an ARMA(1,1)

[16] See for instance the discussion in Debortoli and Nunes (2013), comparing the implications of switches in central banks' preferences with changes in Taylor-rule parameters within a baseline New Keynesian model.

[17] Monopolistic competition is modeled following Kimball (1995), while the formulations of price and wage stickiness follow Yun (1996) and Erceg et al. (2000).

process, while the remaining four shocks – total factor productivity (e_t^a), risk-premium (e_t^b), investment-specific technology shock (e_t^i) and government spending shock (e_t^g) – follow an AR(1) process. All the shocks are uncorrelated, with the exception of a positive correlation between government spending and productivity shocks, i.e. $Corr(e_t^g, e_t^a) = \rho_{ag} > 0$.[18]

We depart from the original SW formulation in two fundamental ways. First, we do not include a (Taylor-type) interest-rate rule, nor the associated monetary policy shock. The central bank behavior is instead modeled according to the *loose commitment* setting described above. Our baseline results are obtained using the following central bank loss function

$$\sum_{t=0}^{\infty} E_0[\pi_t^2 + w_y \widetilde{y}_t^2 + w_r(i_t - i_{t-1})^2] \tag{7}$$

where π_t is inflation, $\widetilde{y}_t$ is the output gap and i_t is the nominal interest rate. π_t is the deviation of inflation from the steady-state level. Thus the implicit inflation target is the steady-state level of inflation ($\bar{\pi}$), which is estimated from the data. Without loss of generality, the weight on inflation is normalized to one so that w_y and w_r represent the weights on output gap and interest rate relative to inflation. The loss function above does not induce an average inflation bias, as the implicit output target is taken to be consistent with the natural-rate hypothesis (i.e. monetary policy cannot systematically affect average output).[19] In other words, within this model the time-inconsistency problem only leads to a stabilization-bias in response to economic shocks, as illustrated in Clarida et al. (1999).

Second, we account for changes in the volatility of the exogenous shocks. Recent studies (see Sims and Zha (2006), Primiceri (2005) and Cogley and Sargent (2006) among others) find that exogenous shocks have displayed a high degree of heteroskedasticity. Ignoring this heteroskedasticity can lead to inaccurate inference as pointed out by Hamilton (2010) and Sims and Zha (2006). Our main concern is that a model without this might attribute time variation in the volatility of the shocks to a re-optimization episode. To mitigate this concern, we assume that the variance-covariance matrix $\Sigma_v(\cdot)$ depends on an unobservable state $s_t^{vo} \in \{h, l\}$, following a two-state Markov-chain with transition probability P^{vo}.

We estimate the same parameters as in the original SW paper, using their same priors,

[18] For a complete description of the model, the reader is referred to the original Smets and Wouters (2007) paper. The model can be cast into (1) defining x_t as a 22x1 vector containing all the variables described above (i.e. endogenous variables, structural shocks and corresponding MA components), and $v_t \sim N(0, \Sigma_v)$ as a 6x1 vector of i.i.d. innovations to the structural shocks.

[19] This is consistent with the original specification of the SW, where because of price and wage indexation, steady state inflation has no real effect.

and the same observable variables.[20] The three additional structural parameters are 1) probability of commitment (γ), 2) the loss function weight on output gap (w_y) and the loss function weight on interest rate smoothing (w_r). For γ we use a uniform prior on the interval [0,1], as we do not want to impose any restrictive prior beliefs about whether the optimal policy is conducted in a setting that is closer to full commitment or discretion. Thus the posterior of γ will be entirely determined by the data. For the weight parameters we set fairly loose gamma priors and the details are in Table 1. Regarding the parameters of the shock processes, two values for the standard deviations of the shocks are estimated using the same priors used by SW. The monetary policy shock that appears in the interest rate rule in SW is replaced by an i.i.d. measurement error. This is required to ensure that we have enough shocks to avoid the stochastic singularity problem in evaluating the likelihood.

We use the same data as in SW but extend the data sample to run from 1965:Q5-2012:Q2. There may be concern about using the data from 2007 onwards that includes the financial crisis and also the zero lower bound. It is important to note that our specification remains agnostic about the specific monetary policy instrument used by the central bank. As a result, one could abstract from considering the zero-bound on the nominal interest rate, and use data that goes through the financial crisis, which would be a challenge if monetary policy were described by a rule for the nominal interest rate. As a robustness check, we estimate the posterior mode of the model where the data sample does not include the financial crisis and find very similar results. Additionally we estimate the model using long-term interest rates (instead of the fed funds rate) which did not face the zero lower bound constraint. All these results are discussed below.

4.2 Estimation procedure

The likelihood function for the DSGE model in SW can be evaluated using the standard Kalman Filter. Given the regime-switching nature of our model, the standard Kalman filter needs to be augmented with the Hamilton (1989) filter, following the procedure described in Kim and Nelson (1999). The likelihood function is combined with the prior to obtain the posterior distribution. We use the Metropolis-Hastings algorithm to sample from the posterior distribution. The detailed steps in evaluating the likelihood function, together with the outline of the Metropolis-Hastings algorithm are provided in the appendix.

The solved equations of the model can be written in the state space notation of Kim and

[20] We also fix the elasticity of labor with respect to the real wage. See section 5.1 and the appendix for a detailed discussion.

Nelson (1999):

$$x_t^{obs} = H\beta_t + Az$$
$$\beta_t = \tilde{\mu} + F_{s_t}\beta_{t-1} + Gv_t$$

with $\beta_t \equiv [x_t, \lambda_t]$ and x_t^{obs} denote the observable variables, which are a subset of x_t. The first equation is the measurement equation that where the matrix H picks out the observables from β_t and the term Az is just a vector of the constant trends in the observables. The errors are assumed to be distributed normally, $v_t \sim N(0, Q_{s_t^{vo}})$, where the variances are allowed to switch over time. The parameters in the matrix F_{s_t} depend on the Markov-switching process s_t and the switching variance parameters in $Q_{s_t^{vo}}$ depend upon the Markov-switching process s_t^{vo}. s_t has two states corresponding to continuing past plans and re-optimizing. We will use two states for s_t^{vo} as well corresponding to high and low variances. A two state Markov switching process governing variance switches has been found to fit the data best in estimated regime-switching DSGE models, see Liu et al. (2011) and Bianchi (2012). The transition probabilities of the Markov process s_t and s_t^{vo} are given by the transition matrices P and P^v

$$P = \begin{bmatrix} \gamma & 1-\gamma \\ \gamma & 1-\gamma \end{bmatrix}$$

$$P^{vo} = \begin{bmatrix} p_1 & (1-p_1) \\ (1-p_2) & p_2 \end{bmatrix}$$

The rows of the transition matrix P are the same, representing the fact that the commitment switching happens independently. This means that next period's probability of a reoptimization (or honoring past promises) is the same regardless whether the central bank has reoptimized this period or not. The variance switching on the other hand is state-dependent. Notice that this setup is different from a standard Markov-switching state-space model, as the probability of commitment,γ, not only enters into the transition matrix P, but it also affects the state-space matrices F_{s_t} and G.

5 Results

5.1 Parameter Estimates

Following SW we fix 5 structural parameters.[21] In addition, we set the wage elasticity of labor supply $\sigma_l = 1$.[22] The different specification of monetary policy introduces three structural parameters, the loss function weight on output-gap (w_y), the loss function weight on interest rate smoothing (w_r) and the probability of commitment (γ). The regime switching variance specification introduces two values for the standard deviation of the shocks as well as two parameters of the transition matrix (P).

Table 1: Prior and Posterior Distribution of Structural Parameters

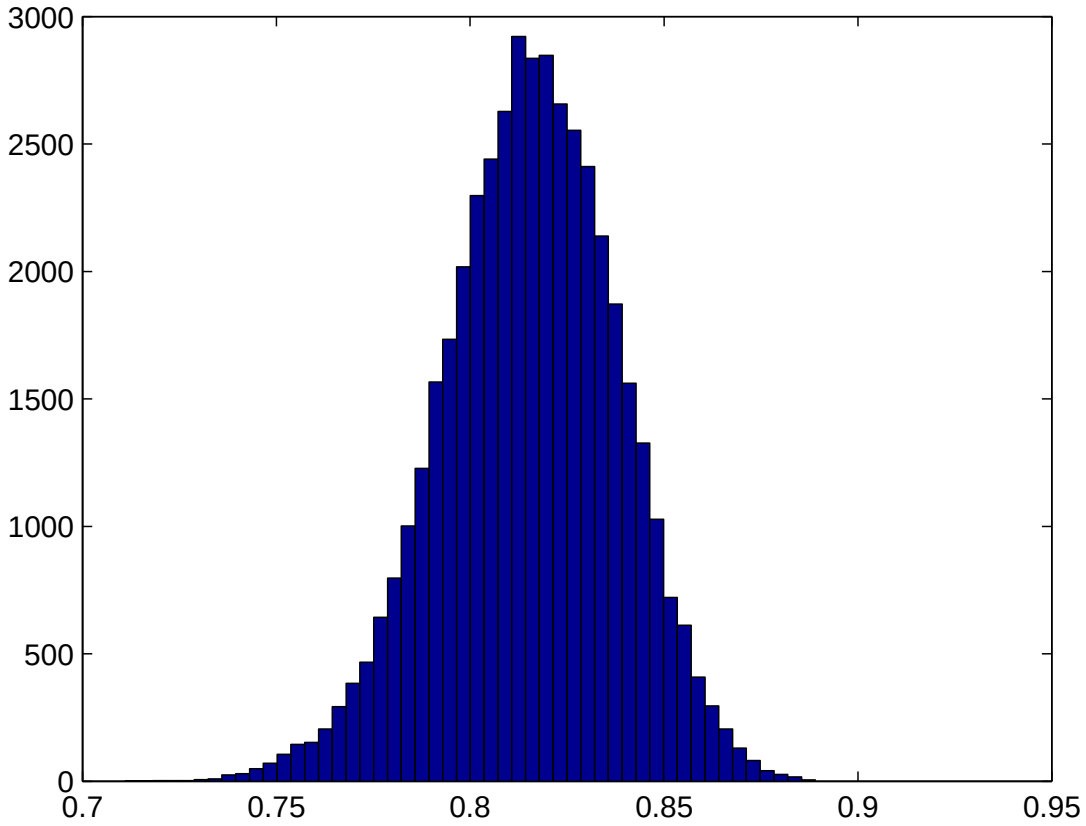
		Prior			Posterior		
		Distr.	Mean	St. Dev	Mode	Mean	5%	95%
$\bar{l}$	St. State Labor	Normal	0.000	2.000	0.243	0.234	0.213	0.253
$\bar{\pi}$	St. State Inflation	Gamma	0.620	0.100	0.742	0.754	0.647	0.874
$\bar{\gamma}$	Growth Rate	Normal	0.400	0.100	0.182	0.184	0.148	0.221
$\bar{\beta}$	Discount Factor	Gamma	0.250	0.100	0.223	0.241	0.129	0.365
α	Capital Income Share	Beta	0.300	0.050	0.192	0.192	0.166	0.219
ψ	Capital Cap. Utilization	Normal	0.500	0.150	0.697	0.686	0.525	0.831
φ	Capital Adj. Cost	Normal	4.000	1.500	6.316	6.532	5.084	8.125
σ_c	Risk Aversion	Normal	1.500	0.370	1.771	1.766	1.488	2.091
h	Habit Persistence	Beta	0.700	0.100	0.765	0.765	0.700	0.821
Φ	Fixed Cost	Normal	1.250	0.120	1.614	1.600	1.490	1.714
ι_w	Wage Indexation	Beta	0.500	0.150	0.500	0.527	0.316	0.734
ι_p	Price Indexation	Beta	0.500	0.150	0.809	0.809	0.689	0.908
ξ_p	Price Stickiness	Beta	0.500	0.100	0.783	0.775	0.727	0.822
ξ_w	Wage Stickiness	Beta	0.500	0.100	0.626	0.619	0.539	0.695
w_y	Output-Gap weight	Gamma	1.000	1.000	0.015	0.017	0.010	0.026
w_r	Interest rate weight	Gamma	1.000	1.000	1.824	2.248	1.403	3.288
γ	Prob. of Commitment	Uniform	0.500	0.290	0.811	0.815	0.777	0.851

The posterior mode of the probability of commitment γ is 0.81 suggesting that the Federal Reserve was expected to reoptimize on average once every 5 quarters. Figure 1 shows the marginal posterior distribution of γ. It is clear that the confidence intervals rule out both

[21] The depreciation rate δ is fixed at .025, spending-GDP ratio g_y at 18%, steady-state markup in the labor market at 1.5 and curvature parameters in the goods and labor markets at 10. See SW for details.

[22] We had difficulty estimating this parameter in the Bayesian MCMC algorithm. In the robustness section in the appendix, we show that changing this value from 1 does not change the results.

Figure 1: Posterior distribution of γ



Note: The figure shows the posterior distribution of γ, which is the probability of commitment.

the commonly used setup of full commitment ($\gamma = 1$) and discretion ($\gamma = 0$). The posterior mode estimates of the structural parameters are reported in 1. The parameter reflecting the weight on interest rate smoothing w_r tends to be sensitive to the model and the data sample. We find a somewhat high estimate of $w_r = 1.82$ but our estimate here falls in the estimated range in the literature, for example from 0.0051 in Favero and Rovelli (2003) to 4.517 in Dennis (2006) and even higher in other papers. Note also that allowing for an additional term in the loss function that involves interest rate variability tends to reduce the estimate of w_r, see Ilbas (2010). The estimated value of 0.015 for w_y also falls in the estimated range from .002 in Favero and Rovelli (2003) to 2.94 in Dennis (2006). The estimates of rest of the structural parameters are reported in 1 and are similar to those reported in SW, despite the

different sample and the differences in the central bank behavior with some differences. The degree of price indexation is estimated to be smaller here pointing towards a bigger role of the forward looking components of the Phillips curve.

Table 2: Prior and Posterior Distribution of shock processes

		Prior		Posterior			
	Distr.	Mean	Std. Dev	Mode	Mean	5%	95%
σ_a^l	Inv Gamma	0.1	2	0.343	0.352	0.307	0.403
σ_b^l	Inv Gamma	0.1	2	0.158	0.158	0.123	0.194
σ_g^l	Inv Gamma	0.1	2	0.356	0.359	0.303	0.418
σ_I^l	Inv Gamma	0.1	2	0.412	0.415	0.350	0.488
σ_p^l	Inv Gamma	0.1	2	0.146	0.149	0.129	0.173
σ_w^l	Inv Gamma	0.1	2	0.274	0.279	0.243	0.318
σ_m^l	Inv Gamma	0.1	2	0.064	0.066	0.055	0.079
σ_a^h	Inv Gamma	0.1	2	0.643	0.652	0.562	0.759
σ_b^h	Inv Gamma	0.1	2	0.292	0.296	0.228	0.372
σ_g^h	Inv Gamma	0.1	2	0.650	0.660	0.568	0.766
σ_I^h	Inv Gamma	0.1	2	0.569	0.573	0.472	0.689
σ_p^h	Inv Gamma	0.1	2	0.221	0.227	0.194	0.264
σ_w^h	Inv Gamma	0.1	2	0.346	0.355	0.293	0.428
σ_m^h	Inv Gamma	0.1	2	0.315	0.322	0.279	0.378
$diag(P^{vo,l})$	Beta	0.8	0.16	0.934	0.916	0.858	0.961
$diag(P^{vo,h})$	Beta	0.8	0.16	0.883	0.857	0.759	0.934
μ_w	Beta	0.5	0.2	0.894	0.874	0.789	0.936
μ_p	Beta	0.5	0.2	0.986	0.977	0.947	0.995
ρ_{ga}	Beta	0.5	0.2	0.425	0.430	0.295	0.567
ρ_a	Beta	0.5	0.2	0.999	0.999	0.997	1.000
ρ_b	Beta	0.5	0.2	0.447	0.456	0.308	0.617
ρ_g	Beta	0.5	0.2	0.940	0.940	0.908	0.968
ρ_I	Beta	0.5	0.2	0.769	0.776	0.710	0.841
ρ_p	Beta	0.5	0.2	0.947	0.927	0.880	0.958
ρ_w	Beta	0.1	0.2	0.996	0.991	0.978	0.999

Note the superscripts l and h refer to the low volatility and high volatility regimes.

Table 2 reports the estimates of the parameters of the shock processes. The standard deviations are not directly comparable to SW since we allow them to switch over time. But the weighted average of our estimated standard deviations across the two regimes is very similar to the SW estimates. The parameters of the shock process of the price-markup shock are somewhat different. Both the autoregressive parameter ρ_p and the μ_p are estimated to be

larger here than in SW. Justiniano and Primiceri (2008) also report having different estimates for the persistence of the price-markup shock and end up using an i.i.d. specification. We estimate the posterior mode of the model using both just an AR(1) specification and an i.i.d. specification of the price-markup process and find that the results are very similar to the benchmark case. These results are presented in the robustness section in the appendix. The rest of the parameters of the shock processes are also very similar to SW.

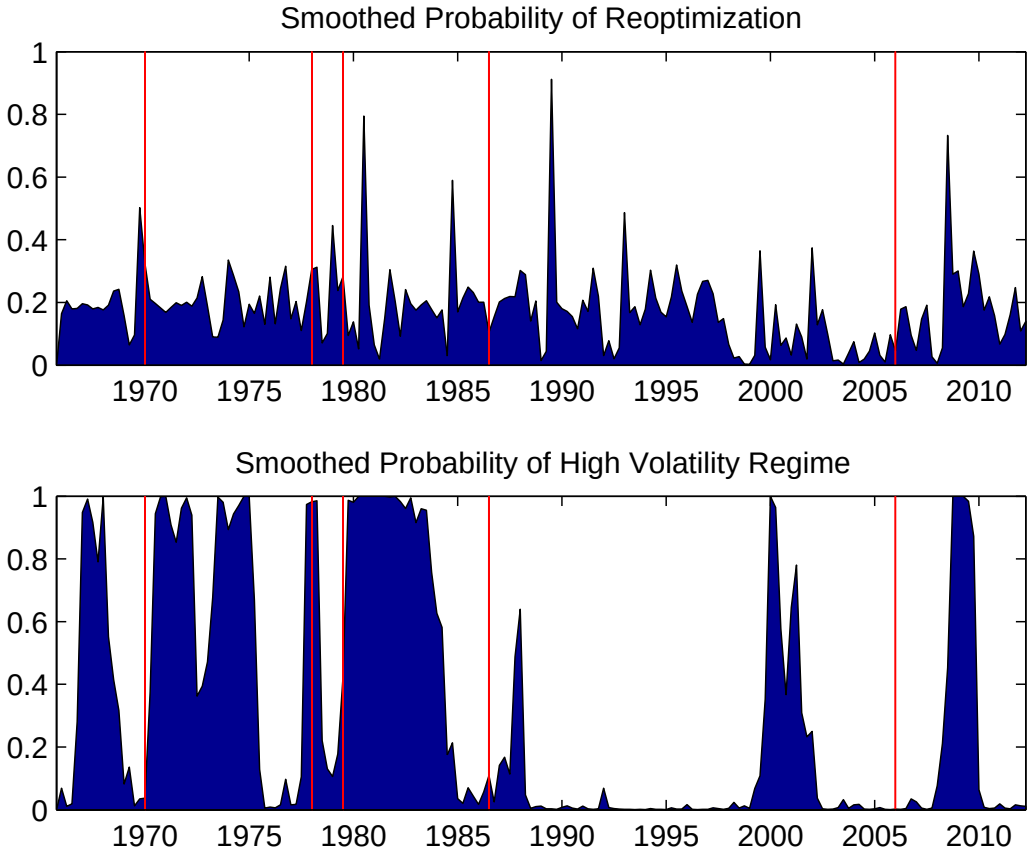
5.2 Policy re-optimizations episodes

The bottom panel of figure 2 shows the (smoothed) probabilities of being in a high volatility regime. Note the term smoothed probability refers to inference about which regime was prevalent based on using all available information. The identified periods of high-volatility are consistent with canonical analyses of US business-cycles. The 70s and the early 80s are characterized by long and recurrent episodes of high-volatility. The probability of high-volatility surges in correspondence with well-known oil shock episodes: the OPEC oil embargo of 1973-1974, the Iranian revolution of 1978-1979 and Iran-Iraq war initiated in 1980.[23] From 1984 onwards, the economy entered a long period with low-volatility – the Great-Moderation – interrupted by the bursting of the dot-com bubble in 2000, and by the events in the aftermath of September 11, 2001. Finally, periods with high-volatility are clearly identified in correspondence with the Great-Recession and financial crisis of 2008-2009.

The top panel shows the smoothed probability of re-optimizations. We can isolate only five dates when re-optimizations were more likely than continuations of previous plans – i.e. the smoothed probability of re-optimization exceeds 50%. Those dates are (i) 1969:Q4, (ii) 1980:Q3, (iii) 1984:Q4, (iv) 1989:3 and (v) 2008:Q3. If we lower the cutoff threshold to 40% then we get two additional dates (vi) 1979:Q1 and (vii) 1993:Q1. A natural test for the validity of our results is to contrast these dates with existing narrative accounts of the US monetary policy history. The first two episodes coincide with the appointment of new Federal Reserve Chairmen: Arthur Burns in early 1970 and Paul Volcker in mid 1979. In late 1980 there is another re-optimization, corresponding to a view that there has been a policy-reversal during 1980, and that the Volcker was credible and effective only from late 1980 or early 1981 (see e.g. Goodfriend and King (2005)). We see another re-optimization in 1984 which could potentially correspond to the end of the experiment of targeting non-borrowed reserves that was undertaken in the first few years under Volcker. Only two episodes are identified over the 20-year long Greenspan tenure. A first re-optimization occurred in 1989, close to

[23] See for example the recent historical survey of Hamilton (2011).

Figure 2: Smoothed Probabilities: Re-optimization and High Volatility Regime



Note: The figure shows the smoothed probability of being in a re-optimization state (upper panel), and of being in the high-volatility regime (lower panel) for the posterior mode estimates. Shaded areas correspond to the NBER recessions, and the vertical solid lines indicate the appointment of a new Federal Reserve Chairman.

the "Romer and Romer" date of December 1988 (see Romer and Romer (1989)). A second re-optimization is identified in 1993. Arguably, this could be related with the major policy change of February 1994 when the Federal Reserve began explicitly releasing its target for the federal funds rate, along with statements of the committee's opinion on the direction of the economy. Those announcements were intended to convey information about future policies, as an additional tool to influence current economic outcomes. The last re-optimization is identified in 2008, when the Federal Reserve started adopting unusual policy decisions like the purchases of mortgage-backed securities and other long-term financial assets. Thus overall it appears that some of our dates align with changes in Federal Reserve chairmen while others correspond to changes in operating procedures of the Federal Reserve. Moreover, there does

not seem to be any systematic correspondence between re-optimizations and recessions, or switches in the volatility regime.

In order to gain some insights about the effects of a policy re-optimization, Figures 3 - 5 illustrate the impulse responses of some variables of interest to a technology, government spending and wage markup shock, respectively. The blue lines show the responses using the estimated value of $\gamma = .81$. The solid blue line shows the path under the assumption that a re-optimization never occurs (even though agents expect it to occur) and the dashed blue line shows the path under the scenario that a re-optimization occurs after 5 quarters – the implied average duration of policy plans. For comparison, the dashed-green line shows the path of the variables when $\gamma = 1$ (full-commitment) – while the dashed red line shows the path when $\gamma = 0$ (discretion). A few interesting observations stand out. First, the effects of a policy re-optimization depend on the history of previous shocks. For instance, if a re-optimization occurs after a technology shock, it involves a reduction in inflation relative to continuing past plans. Whereas if a re-optimization occurs after a markup shock it involves an increase in inflation. The response of the interest rate and output gap to re-optimization shocks display a similar pattern. Second, the responses under loose commitment (blue lines) do not always lie in between the discretion and full commitment cases. This is because there is uncertainty about the timing of future re-optimizations, a feature that is unique to our framework.

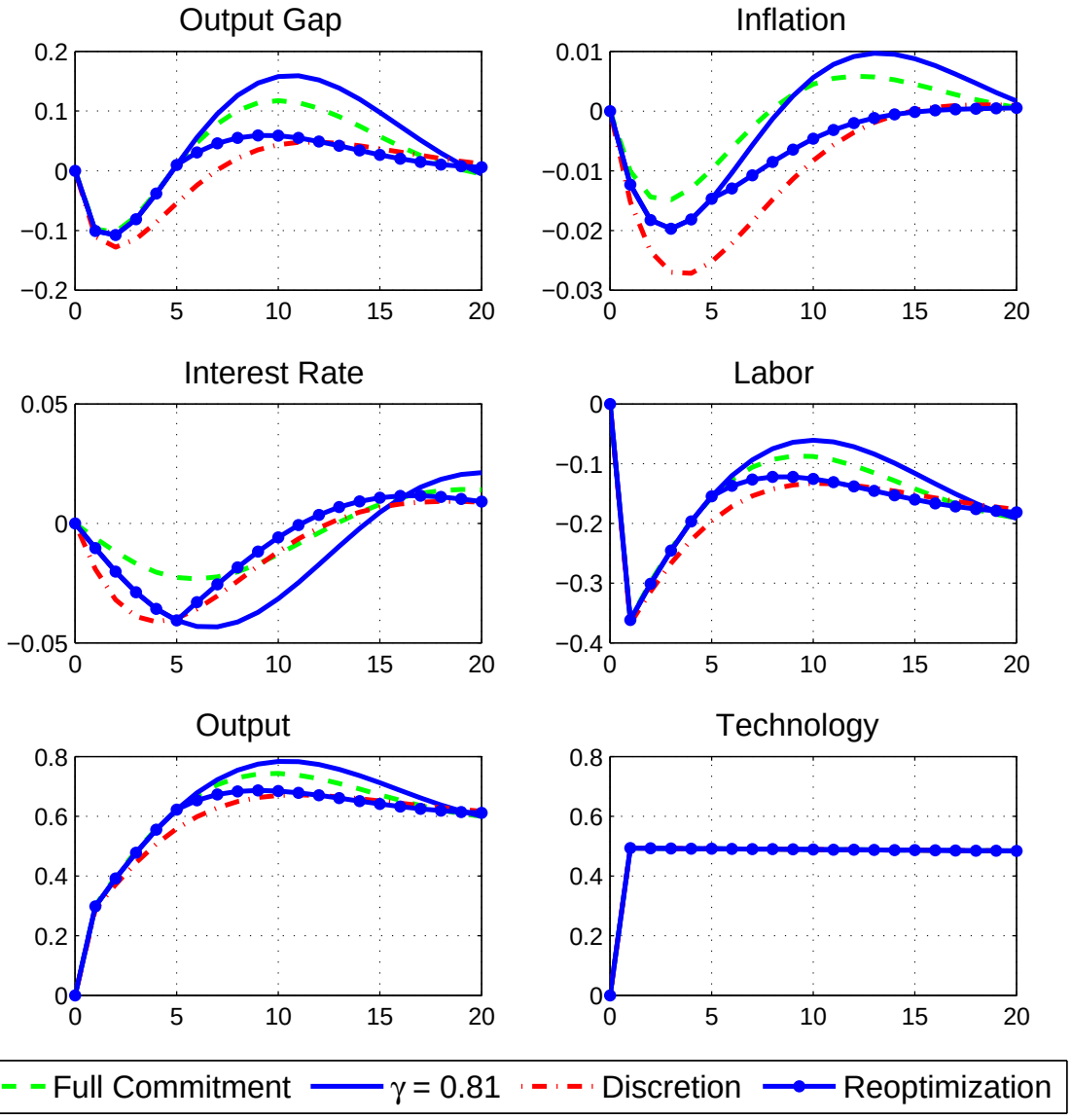
Our re-optimizations could also be interpreted as a particular class of monetary policy shocks. Within our model, a deviation from previous commitment, like a generic monetary policy shock, constitutes an exogenous and unanticipated change in the course of policy. But there is an important difference between policy re-optimizations and generic monetary shocks. For example, suppose the economy was hit by a sequence of increases in oil prices, and that the Federal Reserve had committed to keep the interest rate high over a certain horizon. In that case, a policy re-optimization would bring about a more expansionary policy than expected. On the contrary, in an economy affected by negative demand shocks, the central bank would commit to keep the interest rate low, and and a re-optimization would then be associated with an unanticipated contractionary policy. Thus, whether a re-optimization has a positive or a negative impact on the variable of interest depend on the entire sequence of shocks previously experienced by the economy.

Thus it seems useful to analyze the effects of re-optimizations over our sample period. To that end, Figure 6 illustrates the effects of deviating from a commitment plan on a given date. Specifically it shows the difference, $[x_t|s_t = 0, x_{t-1}] - [x_t|s_t = 1, x_{t-1}]$ for output growth, inflation and the nominal interest rate. The thought experiment is the following: If a re-optimization were to occur at each period in our sample how would the values of output, inflation and interest rates be different relative to the case where the previous commitment is honored? [24] Policy re-optimizations would have made output and inflation higher until the early 1980s, but would have had a negligible effect (or lowered them) during the Great Moderation. This is because in periods with high volatility the central bank needs to make significant commitments to its future actions to stabilize the economy. Those commitments constitute a relevant burden in subsequent periods, and abandoning past commitment would lead to a radically different outcomes. Instead, in a low volatility economy the central bank carries over less relevant commitments, and there is less need to stabilize the economy. As a consequence, the effects of abandoning past commitments are relatively small.

Regarding the specific episodes discussed above, Figure 6 shows that the re-optimizations of the '70s and '80s are all associated with an increase in the level of inflation and output growth. In other words, those re-optimizations implied a "looser" policy than under the commitment plan. The two re-optimizations of 1993 and 2009 are instead associated with a more contractionary policy. This suggests that Quantitative Easing does constitute a deviation from a commitment plan, but in the sense that monetary policy should have been

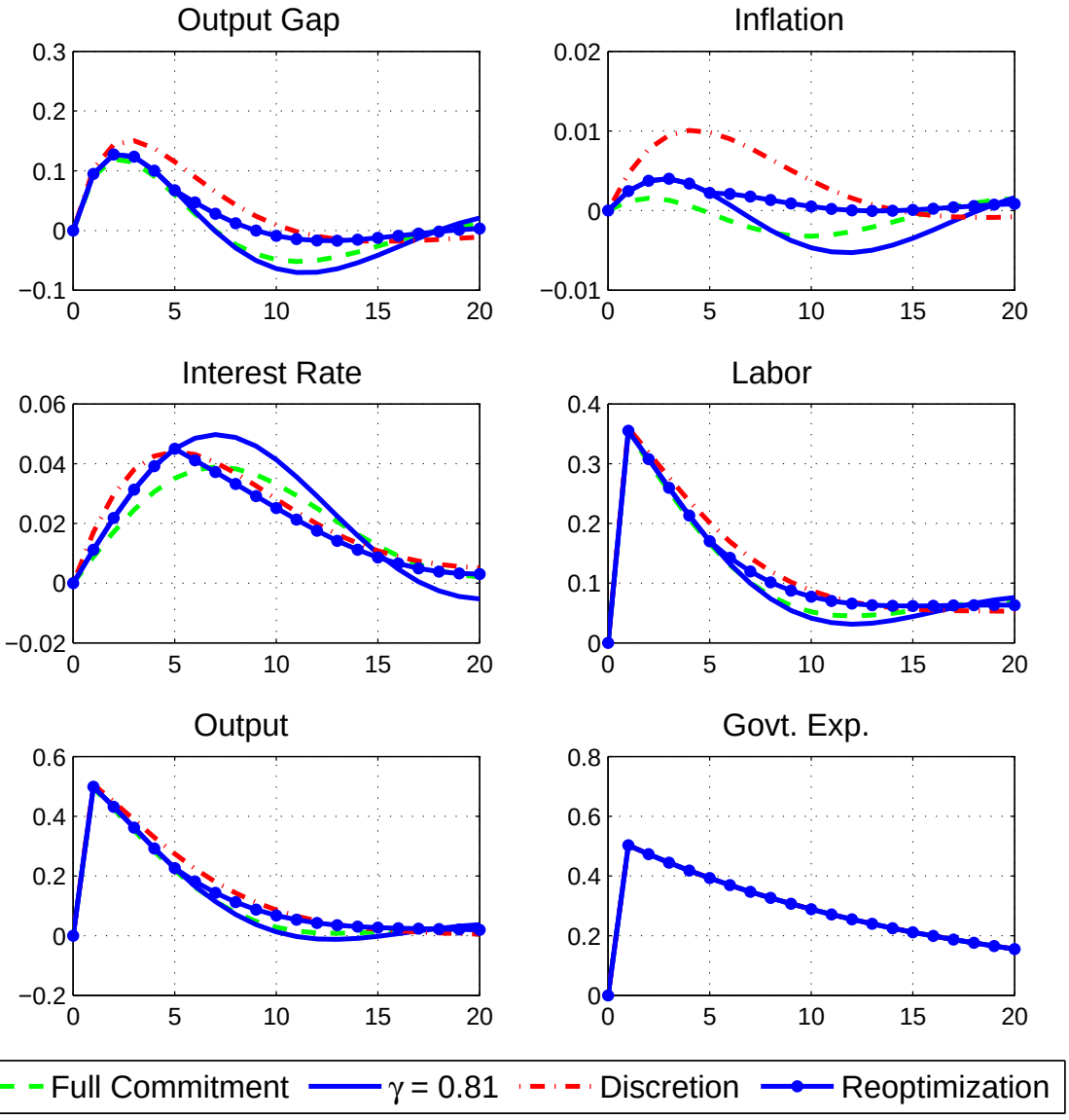
[24] The exercise is conducted conditioning on the estimated parameters being consistent with an unconditional probability of commitment being equal to our estimated value of 0.81.

Figure 3: Impulse responses to a Technology Shock



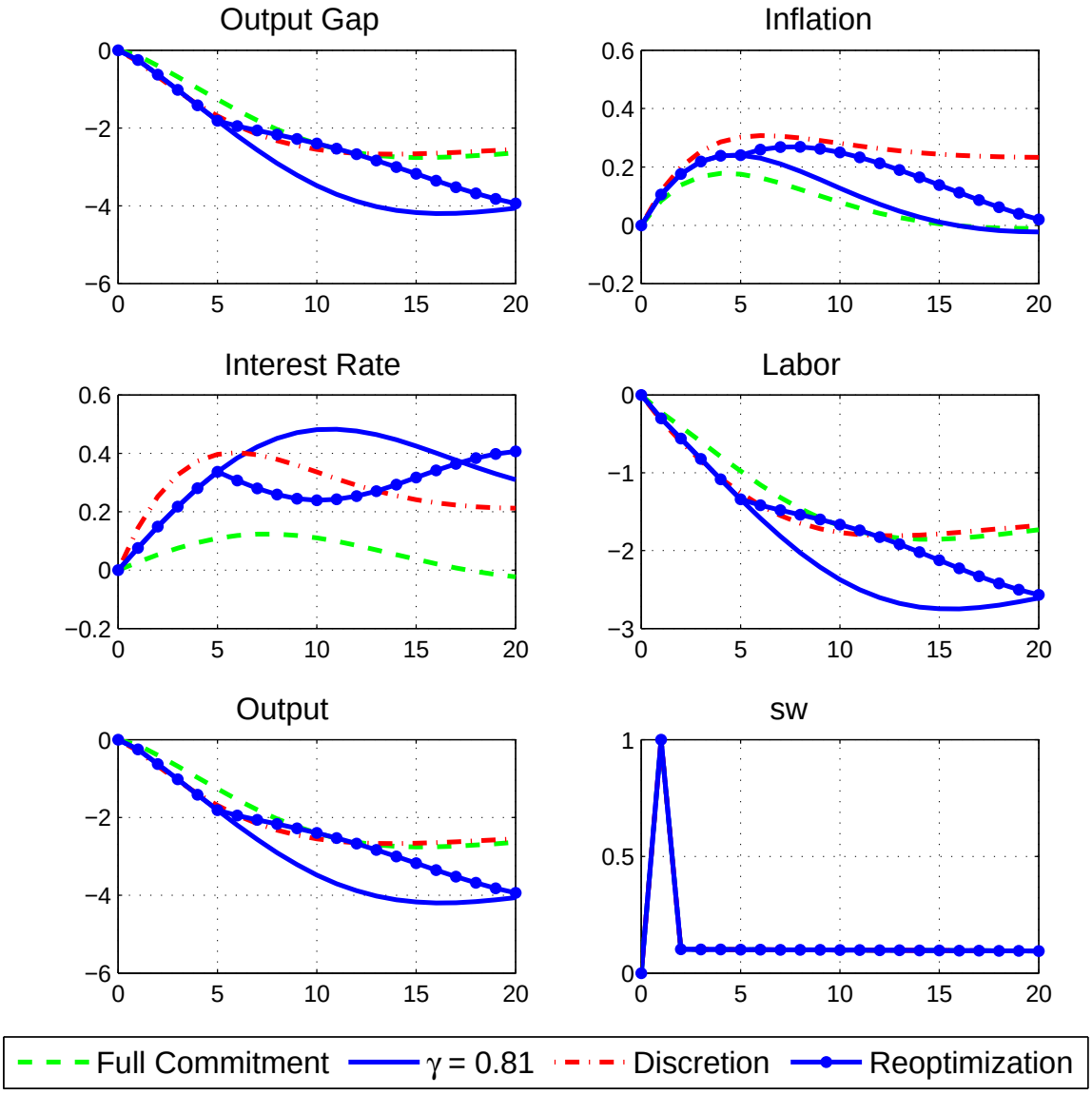
Note: Impulse responses to a 1 standard deviation shock under alternative commitment settings. The line with "dots" indicates the responses under "loose commitment", assuming that a policy re-optimization occurs after 5 quarters, and there is no policy re-optimization thereafter.

Figure 4: Impulse responses to a Demand Shock



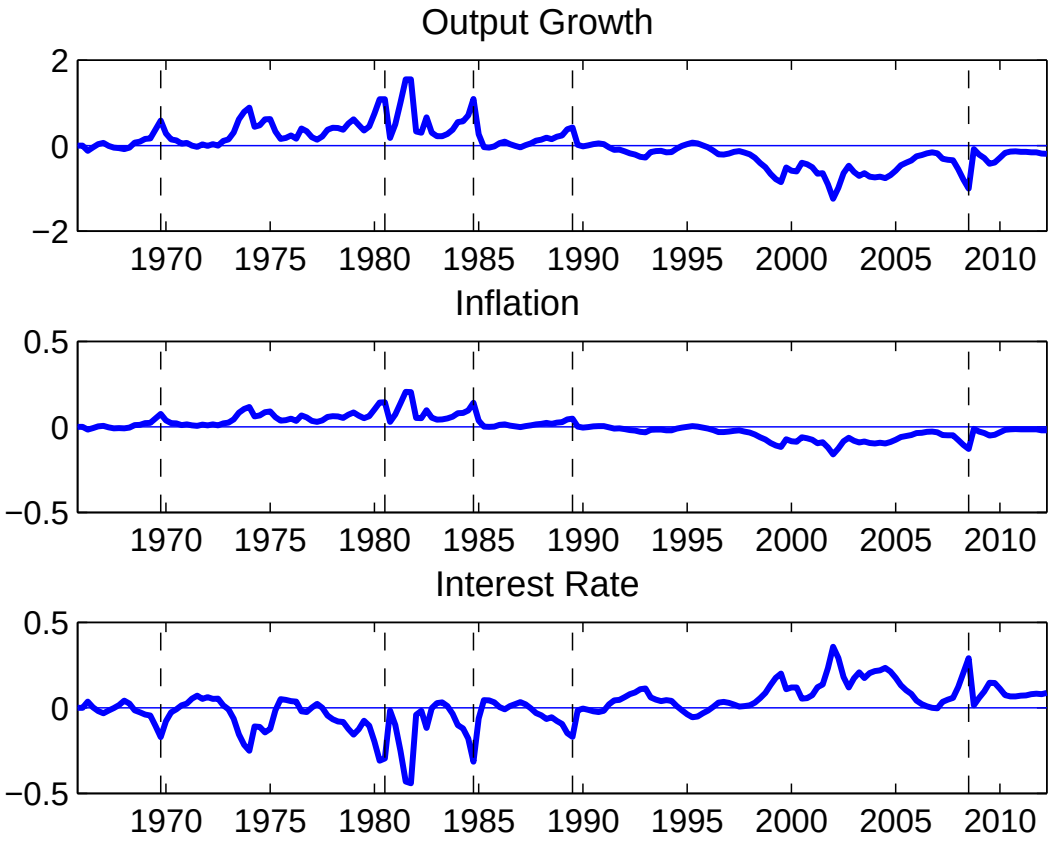
Note: Impulse responses to a 1 standard deviation government expenditure shock under alternative commitment settings. The line with "dots" indicates the responses under "loose commitment", assuming that a policy re-optimization occurs after 5 quarters, and there is no policy re-optimization thereafter.

Figure 5: Impulse responses to a Wage-Markup Shock



Note: Impulse responses to a 1 standard deviation wage markup shock under alternative commitment settings. The line with "dots" indicates the responses under "loose commitment", assuming that a policy re-optimization occurs after 5 quarters, and there is no policy re-optimization thereafter.

Figure 6: Historical Effects of Policy Re-optimizations



Note: The figure shows the effects of re-optimizations over time, measures as the difference between the value conditional on re-optimization and the value conditional on continuation of previous commitment, i.e. $x_t(s_t = 0) - x_t(s_t = 1)$. Vertical lines indicate the episodes where $Prob(s_t = 0) > 50\%$.

more expansionary than it actually was. This conforms to the common view that as the economy hit the zero-lower bound, quantitative easing was a necessary but insufficient tool.

5.3 Is there still a scope for building credibility?

Our estimated value for the probability of commitment of $\gamma = .81$ may induce to think that the Federal Reserve is already sufficiently close to the ideal full-commitment case. That conclusion is unwarranted, as the specific value of γ, *per se*, is not indicative what would be the implications of a further increase in credibility. For this reason, Table 3 shows how commitment affects the (unconditional) second moments for some relevant variables. In general, the relative standard deviations the cross-correlations with output in a model with $\gamma = .81$ are closer to the discretion that to the commitment case. The last line of the table reports the implied welfare losses with respect the full-commitment case, measured in terms of equivalent permanent increase in the inflation rate.[25] According to that measure, the total gains of passing from discretion to commitment are equivalent to a permanent decrease in the inflation rate of 1.2% per year. Most of those gains – corresponding to a 1% permanent reduction in inflation – could still be achieved if increasing credibility from .081 to 1.

Another interesting exercise consists of simulating what would have happened if the Federal Reserve had operated under alternative commitment scenarios. To that end, we re-solve the model assuming that the central bank operates either under full-commitment ($\gamma = 1$) or under discretion ($\gamma = 0$). The remaining parameters of the model, as well as the sequence of disturbances are left unchanged.

Figure 7 displays the actual and the two counterfactual series. Two main messages can be drawn from this exercise. First, credibility seems to play a minor role towards the beginning (late 1960s to late 1970s) and the end (late 1990s onwards). The path of inflation, interest rate and output growth are similar under discretion and full commitment and they are close to actual data. Second there are important differences in the middle of the sample (early 1980s to late 1990s). Crucially, the figure suggests that if the Federal Reserve had pursued policy under discretion in the 1980s then inflation would have stayed high well into the 1990s at the same time that nominal interest rates would have also been high. Put another way, Federal Reserve behavior in this period can be better described as acting under full commitment. The figure also provides a concrete example of the importance of considering a loose commitment framework to fit the behavior of our time series. For instance, the actual

[25] Such a measure is often used to gauge losses for the objective functions employed by central banks and is described, for instance, in Jensen (2002).

Table 3: Second Moments and Welfare

	Model			US Data
	Commitment	$\gamma = .81$	Discretion	1966-2012
Std. of Output	10.80	10.92	10.80	12.05
Relative Standard deviation				
Fed Fund Rate	0.051	0.085	0.095	0.074
Price Inflation	0.035	0.070	0.081	0.049
Wage Inflation	0.068	0.095	0.101	0.065
Hours	0.534	0.541	0.540	0.286
Cross-correlations (w.r.t. output)				
Fed Fund Rate	0.052	-0.478	-0.471	-0.571
Price Inflation	-0.046	-0.551	-0.637	-0.641
Wage Inflation	0.071	-0.319	-0.423	-0.501
Hours	0.397	0.417	0.404	0.102
Welfare Loss (% permanent change in Inflation)	0.000	1.090	1.209	-

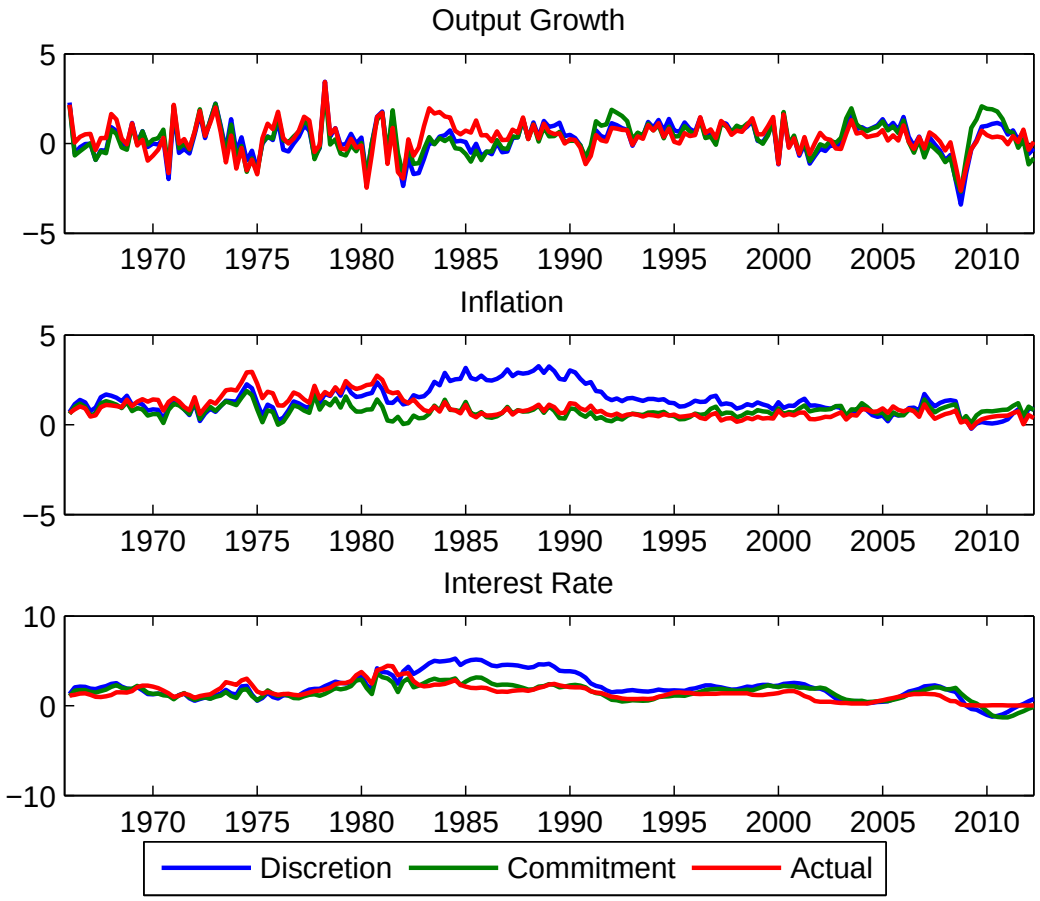
path of the nominal interest rate or inflation is sometimes closer to commitment, sometimes closer to discretion, and does not always lies in between the commitment and discretion extremes.

6 Conclusion

The paper proposes a structural econometric approach to measure the degree of the Federal Reserve's credibility, within a standard medium-scale macroeconomic model. Monetary policy choices are modeled according to a *loose commitment* setting, where deviations from commitment plans are governed by a regime-switching process. The estimated probability of the central bank honoring its promises is used as a measure of credibility. As opposed to previous studies, we find that that the Federal Reserve has a relatively high level of credibility, even though there are significant departures from the full-commitment.

We also identify historical episodes where the Federal Reserve has been more likely to have re-optimized policy plans. Those episodes sometimes line up closely with changes of Fed chairmen and other times with changes in the operational procedures of the Federal

Figure 7: Counterfactual analysis



Reserve. Our policy re-optimizations can be interpreted as a source of monetary policy shocks. In that respect, we find that most deviations from commitment during the 70's have implied too expansionary policies, while deviations in the '90s and 2000's have been more contractionary. Finally, through a counterfactual analysis, we show that the Federal Reserve operating under discretion would not have been able to bring down inflation in the 1980s, while credibility seems to play a minor role during the 1970s and since the 1990s.

Other than the obvious way of honoring its commitments there is another potential way for the Federal Reserve to increase its credibility. It can better communicate with the public about current and future policy actions. Indeed, under the helm of chairman Ben Bernanke, the Federal Reserve has taken several measures to achieve exactly this. In 2012 the Federal Reserve announced an official inflation target of 2%. Additionally they started releasing individual forecasts of the FOMC members' relating to economic activity. Exploring the role of credibility in a dynamic model which has a channel for central bank communication seems a fruitful area for future research.

References

Adolfson, M., S. Laséen, J. Lindé, and L. E. Svensson (2011, October). Optimal monetary policy in an operational medium sized dsge model. *Journal of Money, Credit and Banking 43*(7), 1287–1331.

Backus, D. and J. Driffill (1985). Inflation and reputation. *American Economic Review 75*(3), 530–38.

Barro, R. J. and D. B. Gordon (1983). A positive theory of monetary policy in a natural rate model. *Journal of Political Economy 91*(4), 589–610.

Benigno, P. and M. Woodford (2012). Linear-quadratic approximation of optimal policy problems. *Journal of Economic Theory 147*(1), 1 – 42.

Berger, H. and U. Woitek (2005). Does conservatism matter? a time-series approach to central bank behaviour. *Economic Journal 115*(505), 745–766.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). Chapter 21 the financial accelerator in a quantitative business cycle framework. Volume 1, Part C of *Handbook of Macroeconomics*, pp. 1341 – 1393. Elsevier.

Bianchi, F. (2012). Regime switches, agents' beliefs, and post-world war ii u.s. macroeconomic dynamics*. *The Review of Economic Studies*.

Blinder, A. S. (2000, December). Central-bank credibility: Why do we care? how do we build it? *American Economic Review 90*(5), 1421–1431.

Chappell, H., T. Havrilesky, and R. McGregor (1993). Partisan monetary policies: Presidential influence through the power of appointment. *The Quarterly Journal of Economics 108*(1), 185–218.

Chen, X., T. Kirsanova, and C. Leith (2013). How optimal is us monetary policy? Technical report, University of Glasgow.

Chib, S. and S. Ramamurthy (2010). Tailored randomized block {MCMC} methods with application to {DSGE} models. *Journal of Econometrics 155*(1), 19 – 38.

Clarida, R., J. Galí, and M. Gertler (1999). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature 37*(4), 1661–1707.

Cogley, T. and T. J. Sargent (2006). Drifts and volatilities: Monetary policies and outcomes in the post wwii u.s. *Review of Economic Dynamics 8*, 262–232.

Coroneo, L., V. Corradi, and P. S. Monteiro (2013). Testing for optimal monetary policy via moment inequalities. Technical report, University of York.

Cukierman, A. (1992). Central bank strategy, credibility, and independence: Theory and evidence. *MIT Press Books 1*.

Davig, T. and E. Leeper (2007). Generalizing the taylor principle. *American Economic Review 97*(3), 607–635.

Debortoli, D., J. Maih, and R. Nunes (2012, 7). Loose commitment in medium-scale macroeconomic models: Theory and applications. *Macroeconomic Dynamics FirstView*, 1–24.

Debortoli, D. and R. Nunes (2006, July). On linear-quadratic approximations. MPRA paper 544, University Library Of Munich.

Debortoli, D. and R. Nunes (2010, May). Fiscal policy under loose commitment. *Journal of Economic Theory 145*(3), 1005–1032.

Debortoli, D. and R. Nunes (2013). Monetary regime-switches and central bank's preferences. Technical report, University of California San Diego.

Dennis, R. (2004, September). Inferring policy objectives from policy actions. *Oxford Bulletin of Economics and Statistics 66*, 745–764.

Dennis, R. (2006). The policy preferences of the us federal reserve. *Journal of Applied Econometrics 21*(1), 55–77.

Dennis, R. (2007, February). Optimal policy in rational expectations models: New solution algorithms. *Macroeconomic Dynamics 11*(01), 31–55.

Erceg, C. J., D. W. Henderson, and A. T. Levin (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics 46*(2), 281–313.

Farmer, R. E., D. F. Waggoner, and T. Zha (2009). Understanding markov-switching rational expectations models. *Journal of Economic Theory 144*(5), 1849–1867.

Faust, J. and L. E. O. Svensson (2001, May). Transparency and credibility: Monetary policy with unobservable goals. *International Economic Review 42*(2), 369–97.

Favero, C. A. and R. Rovelli (2003). Macroeconomic stability and the preferences of the fed: A formal analysis, 1961–98. *Journal of Money, Credit and Banking 35*(4), 545 – 556.

Gamerman, D. and H. F. Lopes (2006). *Markov chain Monte Carlo: stochastic simulation for Bayesian inference*, Volume 68. Chapman & Hall/CRC.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In *In Bayesian Statistics*, pp. 169–193. University Press.

Givens, G. E. (2012, 09). Estimating central bank preferences under commitment and discretion. *Journal of Money, Credit and Banking 44*(6), 1033–1061.

Goodfriend, M. and R. G. King (2005, July). The incredible volcker disinflation. *Journal of Monetary Economics 52*(5), 981–1015.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 357–384.

Hamilton, J. D. (2010). Macroeconomics and Arch. *Festschrift in Honor of Robert F. Engle*, 79–96.

Hamilton, J. D. (2011, February). Historical oil shocks. NBER Working Papers 16790, National Bureau of Economic Research, Inc.

Ilbas, P. (2010). Revealing the preferences of the us federal reserve. *Journal of Applied Econometrics*.

Jensen, H. (2002). Targeting nominal income growth or inflation? *American Economic Review 92*(4), 928–956.

Justiniano, A. and G. E. Primiceri (2008, June). The time-varying volatility of macroeconomic fluctuations. *American Economic Review 98*(3), 604–41.

Kim, C.-J. and C. R. Nelson (1999). *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications*, Volume 1 of *MIT Press Books*. The MIT Press.

Kimball, M. S. (1995). The quantitative analytics of the basic neomonetarist model. *Journal of Money, Credit and Banking 27*(4), 1241–77.

Kydland, F. E. and E. C. Prescott (1977). Rules rather than discretion: The inconsistency of optimal plans. *Journal of Political Economy 85*(3), 473–91.

Kydland, F. E. and E. C. Prescott (1980). Dynamic optimal taxation, rational expectations and optimal control. *Journal of Economic Dynamics and Control 2(1)*, 79–91.

Levine, P., J. Pearlman, and R. Pierse (2008). Linear-quadratic approximation, external habit and targeting rules. *Journal of Economic Dynamics and Control 32*(10), 3315–3349.

Liu, Z., D. F. Waggoner, and T. Zha (2011). Sources of macroeconomic fluctuations: A regime-switching dsge approach. *Quantitative Economics 2*(2), 251–301.

Marcet, A. and R. Marimon (2011). Recursive contracts. *Universitat Pompeu Fabra. Working Paper*.

Peterman, W. B. (2012). Reconciling micro and macro estimates of the frisch labor supply elasticity. Technical report.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies 72*(3), 821–852.

Roberds, W. (1987). Models of policy under stochastic replanning. *International Economic Review 28*(3), 731–755.

Rogoff, K. (1985). The optimal degree if commitment to an intermediate monetary target. *Quarterly Journal of Economics 100*(4), 1169–89.

Romer, C. D. and D. H. Romer (1989, January). Does monetary policy matter? a new test in the spirit of friedman and schwartz. In *NBER Macroeconomics Annual 1989, Volume 4*, NBER Chapters, pp. 121–184. National Bureau of Economic Research, Inc.

Rudebusch, G. and L. E. Svensson (1999). Policy rules for inflation targeting. In *Monetary policy rules*, pp. 203–262. University of Chicago Press.

Salemi, M. K. (2006, October). Econometric policy evaluation and inverse control. *Journal of Money, Credit and Banking 38*(7), 1737–64.

Schaumburg, E. and A. Tambalotti (2007). An investigation of the gains from commitment in monetary policy. *Journal of Monetary Economics 54*(2), 302–324.

Sims, C. A. and T. Zha (2006). Were there regime switches in u.s. monetary policy? *The American Economic Review 96*(1), 54–81.

Smets, F. and R. Wouters (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American Economic Review 97*(3), 586–606.

Söderlind, P. (1999). Solution and estimation of re macromodels with optimal policy. *European Economic Review 93*, 813–823.

Söderström, U., P. Söderlind, and A. Vredin (2005, September 2005). New-keynesian models and monetary policy: A reexamination of the stylized facts. *The Scandinavian Journal of Economics 107(3)*, 521–46.

Svensson, L. E. (1999). Inflation targeting as a monetary policy rule. *Journal of monetary economics 43*(3), 607–654.

Yun, T. (1996). Nominal price rigidity, money supply endogeneity and business cycles. *Journal of Monetary Economics 37*(2), 345–370.

Appendix

A-1 Evaluating the Likelihood Function

We can evaluate the likelihood function in the following manner. M is the number of states that the Markov-switching process can take. Note we combine the 2 two-state switching processes s_t and s_t^v into 1 four-state process S_t, which means $M = 4$. The likelihood function is evaluated in four steps.

Step 1: Perform the Kalman Filter for $i = 1, ..M, j = 1, ..M$

$$\begin{aligned}
\beta_{t|t-1}^{i,j} &= \tilde{\mu} + F_j \beta_{t-1|t-1}^{i} \\
P_{t|t-1}^{i,j} &= F_j P_{t-1|t-1}^{i} F_j' + GQG' \\
\eta_{t|t-1}^{i,j} &= x_t^{obs} - H\beta_{t|t-1}^{i,j} - Az_t \\
f_{t|t-1}^{i,j} &= HP_{t|t-1}^{i,j} H' \\
\beta_{t|t}^{i,j} &= \beta_{t|t-1}^{i,j} + P_{t|t-1}^{i,j} H' [f_{t|t-1}^{i,j}]^{-1} \eta_{t|t-1}^{i,j} \\
P_{t|t}^{i,j} &= (I - P_{t|t-1}^{i,j} H' [f_{t|t-1}^{i,j}]^{-1} H) P_{t|t-1}^{i,j}
\end{aligned}$$

Step 2: Perform the Hamilton Filter

$$\begin{aligned}
P(S_t, S_{t-1}) &= P(S_t | S_{t-1} P(S_{t-1} | \psi_{t-1}) \\
f(x_t^{obs} | \psi_{t-1}) &= \sum_{S_t} \sum_{S_{t-1}} f(x_t^{obs} | S_t, S_{t-1}, \psi_{t-1}) P(S_t, S_{t-1} | \psi_{t-1}) \\
P(S_t | \psi_t) &= \sum_{S_{t-1}} P(S_t, S_{t-1} | \psi_t)
\end{aligned}$$

Note that the conditional density is normal and given by

$$f(x_t^{obs} | S_{t-1} = i, S_{t=j}, \psi_{t-1}) = (2\pi)^{-\frac{N}{2}} |f_{t|t-1}^{i,j}|^{-\frac{1}{2}} exp\{-\frac{1}{2} \eta_{t|t-1}^{i,j'} (f_{t|t-1}^{i,j})^{-1} \eta_{t|t-1}^{i,j}\}$$

Step 3: Perform the Kim & Nelson approximations to collapse the M^2 unobservable $\beta_{t|t}^{i,j}$ into M ones. For each j calculate the following

$$\begin{aligned}
\beta_{t|t}^{j} &= \frac{\sum_{i=1}^{M} P(S_t = i, S_t = j | \psi_t) \beta_{t|t}^{i,j}}{P(S_t = j | \psi_t)} \\
P_{t|t}^{j} &= \frac{\sum_{i=1}^{M} P(S_t = j, S_{t-1} = i | \psi_t) [P_{t|t}^{i,j} + (\beta_{t|t}^{j} - \beta_{t|t}^{i,j})(\beta_{t|t}^{j} - \beta_{t|t}^{i,j})']}{P(S_t = j | \psi_t)}
\end{aligned}$$

Step 4: After performing steps 1-3 $\forall t$ we can evaluate the log likelihood function

$$l(\theta) = \sum_{t=1}^{T} ln(f(x_t^{obs}|\psi_{t-1}))$$

A-2 Metropolis-Hastings Algorithm

This section explains the Bayesian estimation procedure that uses the Metropolis-Hastings algorithm and will be used to estimate all the parameters of the model jointly. Our estimation method follows the Metropolis-Hastings algorithm used in SW. The main difference is that the evaluation of the likelihood has to be modified to deal with the addition of regime-switching. The estimation follows a two step procedure. In the first step we numerically maximize the log posterior distribution to get an estimate of the posterior mode. In the second step, using the posterior mode calculated in the first step as a starting value, we use the Metropolis-Hastings algorithm to completely characterize the posterior distribution.

Let θ be the parameters to be estimated. The M-H algorithm involves generating a draw from a candidate generating density, $q(.)$. Let this candidate draw be called $\theta^{(g+1)}$. Then this new draw is accepted with the following probability.

$$\alpha(\theta^{(g+1)}, \theta^{(g)}) = min\left(\frac{p(\theta^{(g+1)}|Y).q(\theta^{(g)})}{p(\theta^{(g)}|Y).q(\theta^{(g+1)})}, 1\right)$$

Following SW(2007) we use the inverse of the Hessian at the posterior mode (that comes out of the numerical optimization procedure) as the candidate generating density which is centered around the current draw $\delta^{(g)}$.

$$\delta^{(g+1)} = \delta^{(g)} + c\tilde{H}^{-1}$$

where c is a scale factor and $\tilde{H}$ is the Hessian at the posterior mode. This is known as a random walk Metropolis-Hastings step. We then tune the parameter c to get an acceptance rate of between 25% and 35% as recommended by Gamerman and Lopes (2006). The full parameter vector θ is sampled in one block. We have also tried blocking by splitting the parameter vector θ into 2 or more blocks but found that the Metropolis-Hastings algorithm ran most efficiently with one block and had good convergence properties as discussed below.

A-3 Convergence Diagnostics

The Metropolis-Hastings algorithm is run for 500,000 draws where the first 25,000 draws are discarded. Note since the chain is initialized at the posterior mode, a large number of burn-in draws is not required. From the remaining 475,000 draws, one of out of every ten draws is saved resulting in an effective sample of 47,500. Figure A-1 shows the trace plots of the draws from the Metropolis-Hastings algorithm, and as can be seen the draws seem to be mixing well. To get a better idea of the correlation of the draws the top panel of figure A-2 plots the 20th order autocorrelation for each of the estimated parameters. These autocorrelations are all below 0.6 and most them lower than 0.3, suggesting that the dependence in the draws diminishes fairly rapidly. The lower panel shows the inefficiency factors, this is the inverse of the relative numerical efficiency of Geweke (1992). These numbers are mostly below 40 while some of them are a bit higher. Note these are much lower as compared to the SW M-H algorithm as reported by Chib and Ramamurthy (2010). Thus, overall the convergence diagnostics are satisfactory.

A-4 Assumption of exogenous switching

Recall that the shocks that drive the re-optimizations are assumed to be exogenous. There may be a concern that the switching is actually driven by the state of the economy. Here we address this concern by showing that the endogenous variables in the model do not help predict future reoptimization episodes. More specifically we run Granger Causality tests to see whether the data used in the estimation can help forecast changes in the probability of reoptimization. The unrestricted regression involves regressing the smoothed probability on four of its lags and four lags of all the seven macro variables (log difference of real GDP, real consumption, real investment and the real wage, log hours worked, the log difference of the GDP deflator, and the federal funds rate). The restricted regression imposes zeros on the coefficients of the macro variables. Table 4 shows the F statistics and the corresponding p-values of these exclusion restrictions. The first row labeled "All" shows these values for the restriction that jointly all the macro variables have no forecasting power for the probability of commitment. The p value shows that we cannot reject this at the 10% level. The next rows show the tests of whether individually each of the variables can forecast the probability of reoptimization. At the 10% level we fail to reject for all the variables except for investment where the p value is extremely close to 0.1. These test seem to suggest that our assumption about exogenous switching appears to be reasonable.

A-5 Robustness Checks

In this section we discuss a variety of robustness checks. First we start by estimating the model by excluding data since the beginning of the financial crisis. At the onset of the financial crisis, the Federal Reserve responded by lowering the fed funds rate. When the zero lower bound was reached, the Fed took unusual policy actions which included among others, buying long-term Treasury bonds and mortgage-backed securities. As mentioned earlier, in this model optimal monetary policy involves ensuring that the first order conditions of the central bank's optimization problem are satisfied and consistent with household and firm's optimal decisions. As has been shown earlier (for example see Clarida et al. (1999)), the optimal policy can implemented in a variety of ways, including a Taylor-type instrument rule. Since our model does not require optimal policy to be implemented using an interest rate rule, the zero lower bound is not an issue for us. However there might be a concern that since our model does not capture the financial system very well,[26] including data from the financial crisis might bias our estimated results. More specifically, we want to make sure that the the estimates of the probability of commitment and the smoothed probabilities of reoptimization are not sensitive to excluding the financial crisis from the data sample. The fourth row in table 5 shows the estimates of the model where the data sample is restricted to end at Q2:2007. The estimates of γ and w_y are very close to the benchmark case, whereas the estimate of w_r is lower at 0.87. This lower estimate is most likely due to the fact that the Federal Reserve has kept the Fed funds rate constant (around zero) from late 2008 onwards.

In most macro models the fed funds rate is the interest rate used. This is because the behavior of the Federal Reserve is modeled using a Taylor-type short-term interest rate rule. But it's not obvious that the interest rate directly affecting consumers' and firms' behavior is the short term interest rate. Due to the setup of the formulation of monetary policy in our model, it allows us flexibility in choosing the interest rate. We estimate the model replacing the fed funds rate with a longer term interest rate, specifically the interest rate on a 10 year Treasury note. This has the added benefit of allowing us to estimate the model using through the financial crisis without worrying about the zero lower bound. The resulting estimate of the probability of commitment is 0.8 and the smoothed probabilities of re-optimization and high/low volatilities are quite similar to the benchmark case.

As mentioned in the Estimation section, in addition to the values fixed in SW we fix σ_l, the elasticity of labor supply with respect to the real wage. Due to the non-separable form of

[26]However, this model does have a risk-premium shock that behaves similarly to a net worth shock (as in Bernanke et al. (1999)).

the utility function in SW this elasticity is not directly comparable to the popularly discussed Frisch labor supply elasticity. Here the Frisch elasticity depends upon, among other things, σ_l and the level of hours worked. Fortunately, changing the value that σ_l is fixed at, has very little impact on the parameter estimates.[27] There is a debate in the literature regarding what the labor supply elasticity should be set to and range varies from 0.5 to over 2, see Peterman (2012) for details. We consider three additional values of σ_l, 1.92, 3 and 0.5. 1.92 is the estimate of SW, 3 is close to the estimate in Bianchi (2012) (a paper similar to ours) and 0.5 is close to what is typically estimated in micro studies. The estimates of w_y and γ (shown in rows 5,6 and 7) are very similar. The estimate of w_r does change somewhat, see the section on parameter estimates for a more in-depth discussion of this.

Finally we consider different prior specifications. For γ, we consider a beta prior with both shape parameters set to 0.5 (labeled Prior 1 in table 5). This prior distribution gives roughly the same weight to values in the [0.2,0.8] interval while putting more weight on values near the end points 0 and 1. This specification is chosen to ensure that even with a higher prior probability weight on discretion (0) and commitment (1), the data chooses a value of γ close to 0.8 (row 3 in table 5. The other prior specification (labeled Prior 2 in table 5) goes back to the uniform prior for γ but uses a Gamma distribution for w_y and w_r with a higher variance. Specifically we use the Gamma distribution with mean 2 and variance 4, but the resulting estimates are very similar to the benchmark case. In conclusion, the estimate of the probability of commitment γ is stable for all the different specifications considered.

[27]Here we only show the estimates of w_y, w_r and γ but the other estimated parameters are little affected as well.

Table 4: Granger Causality Test

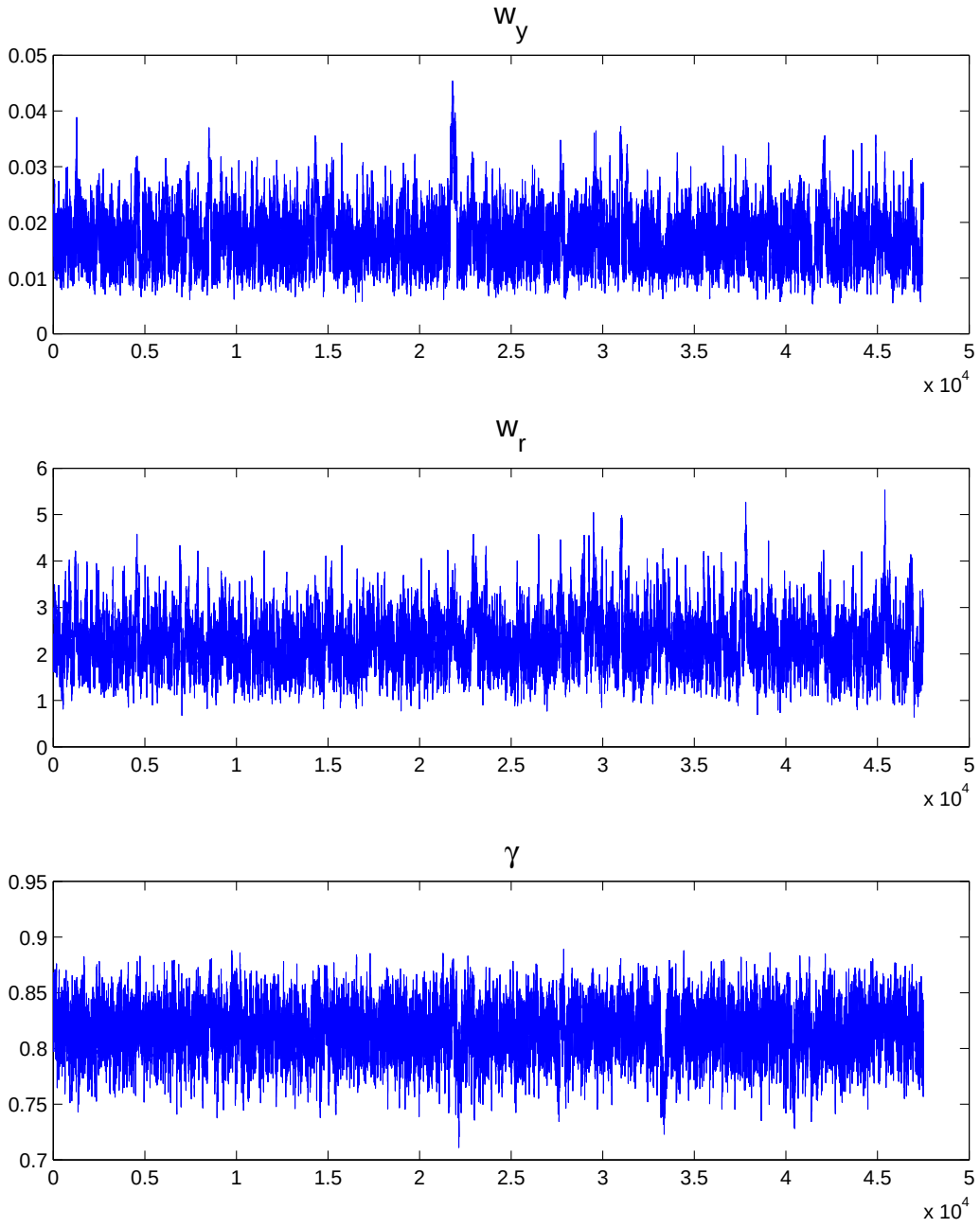
	F statistic	p value
All	1.3993	0.1038
GDP	1.1258	0.3466
Consumption	0.2326	0.9197
Investment	2.0064	0.0965
Wage	1.4927	0.2072
Hours	0.9282	0.4493
Inflation	0.6068	0.6583
Fed Funds	1.1415	0.3393

Table 5: Estimates under various specifications

			Posterior mode		
Data	Prior	σ_l	w_y	w_r	γ
Full	Benchmark	1	0.015	1.824	0.811
Full	Prior 1	1	0.015	1.829	0.812
Full	Prior 2	1	0.016	1.950	0.812
Pre-fin crisis	Benchmark	1	0.031	0.874	0.781
Full	Benchmark	1.92	0.014	1.804	0.812
Full	Benchmark	0.5	0.022	0.879	0.801
Full	Benchmark	3	0.013	1.882	0.811
Full-Long Term	Benchmark	1	0.019	1.244	0.803

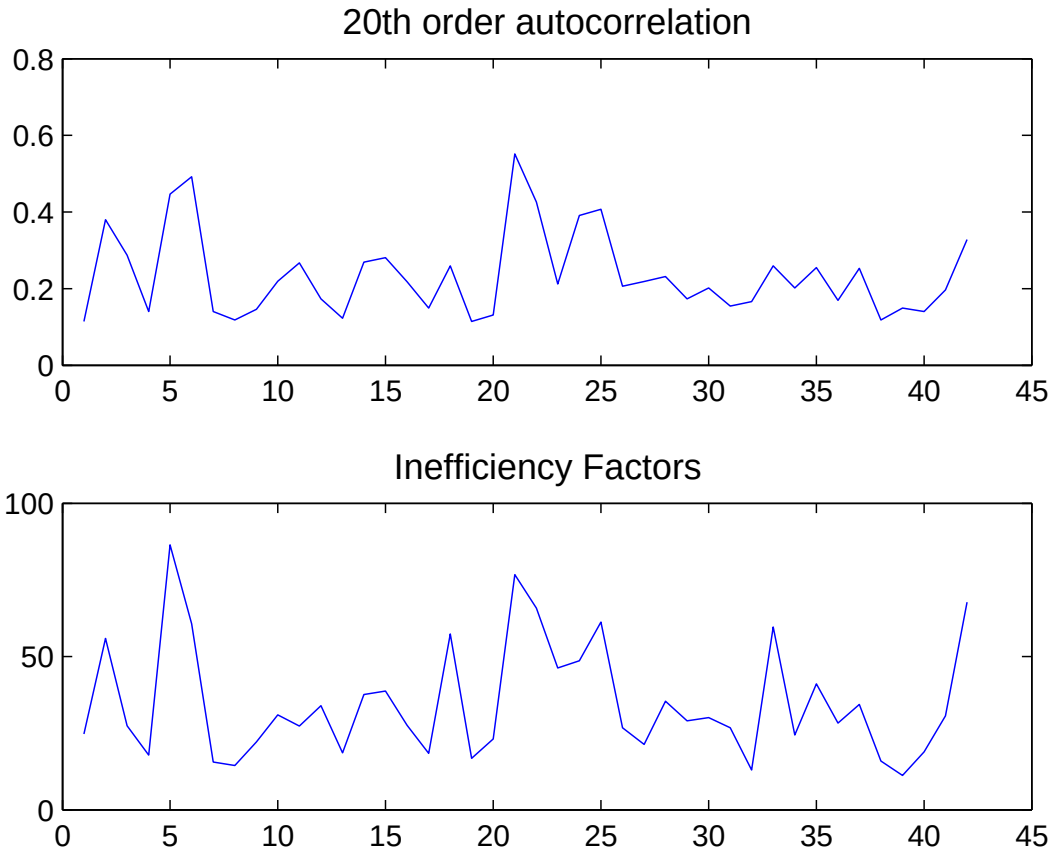
This table shows the posterior mode estimates of the loss function weight on output w_y, the loss function weight on interest rate smoothing w_r and the probability of commitment γ for various specifications.

Figure A-1: Trace Plots



Note: This figure shows the MCMC draws for loss function weight on output gap: w_y, the weight on interest rate smoothing: w_r and the probability of commitment: γ.

Figure A-2: 20th Order Autocorrelations



Note: The top panel of this figure shows the 20th order autocorrelations (y-axis) of the MCMC draws for all the estimated parameters (x-axis) while the bottom panel shows inefficiency factors.