

# Monetary Policy and the evolution of US economy

Fabio Canova

ICREA, Universitat Pompeu Fabra, CREI and CEPR \*

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## Abstract

This paper investigates the relationship between monetary policy and the changes experienced by the US economy using a small scale New-Keynesian model. The model is estimated with Bayesian techniques and the stability of policy parameter estimates and of the transmission of policy shocks examined. The model fits well the data and produces forecasts comparable or superior to those of alternative specifications. The parameters of the policy rule, the variance and the transmission of policy shocks have been remarkably stable. The parameters of the Phillips curve and of the Euler equations are varying.

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# 1 Introduction

Many researchers have noted that the US economy displayed significant changes in the last 30 years. For example, Blanchard and Simon (2000), McConnell and Perez Quiroz (2000) and Stock and Watson (2002)) have documented a marked decline in the variance of real activity and in the variance and the persistence of inflation.

Some authors, in particular Taylor (1998), Sargent (1999) and Clarida, Gali and Gertler (1999), Lubik and Schorfheide (2004), have attributed these changes to a permanent alteration in the relative weight that output and inflation have in the objective function of the monetary authority. The popular version of the story runs as follows: the run-up of inflation in the 1970s occurred because the authorities believed that there was an exploitable trade-off between inflation and output. Since output was low following the two oil shocks, the temptation to inflate to bring output back, or above its potential level, was strong. Between keeping inflation low (and output low) or inflation high (and output high), the monetary authorities systematically choose the latter option. Hence, inflation in the long run turned out to be higher while output simply settled to its potential level. Since the 1980s, the perception of the output-inflation trade-off has changed. The Fed has learned that it was not exploitable and concentrated on the objective of fighting inflation. A low inflation regime ensued, and the predictability of monetary policy contributed to make the macroeconomic environment less volatile and the swings in inflation more unpredictable.

While prevalent, this view underscoring the power of monetary policy is not fully shared in the profession. Several researchers claim that monetary policy has not experienced any permanent regime switch since the late 1970s; that the same policy rule characterizes most of the post WWII experience; that monetary policy has little influence on output fluctuations; and that good luck, as opposed to good policies, is responsible for the observed outcome (see e.g. Bernanke and Mihov (1998), Leeper, Sims and Zha (1998), Hanson (2001), Leeper and Zha (2003)). Others have proposed "real" reasons to explain the changes in inflation and output dynamics (see e.g. Ireland (1999) or McConnell and Perez Quiroz (2000)).

Recently, important progress has been made in the investigation of these issues using models where coefficients are explicitly allowed to vary. Sargent and Cogley (2001) and (2005), who used a reduced form version of a time varying coefficient model, find evidence that supports the causation story running from monetary policy changes to changes in the rest of the economy. Canova and Gambetti (2004) and Sims and Zha (2004), who estimate structural time varying coefficients VAR models, find little posterior evidence supporting this hypothesis. Since these two papers only use a minimal amount of the restrictions implied by the current generation of DSGE models when deriving structural relationships, one may wonder how truly structural the estimated monetary policy reaction function is and whether the stability found is not the result of a gross misspecification of crucial relationships.

Ireland (2001) and Boivin and Giannoni (2002), who explicitly condition their analyses on a small scale DSGE model, find evidence of instability in many reduced form relationships and attribute this instability to monetary policy, but limit their comparison to arbitrarily chosen subsamples. Because output growth (inflation) displays a U shape (inverted U shape)

pattern over the last 30 years, the conclusions one draws may depend on the selected break point. Hence, the evidence these authors provide is not entirely convincing.

This paper provides new evidence on the role that monetary policy had in shaping the changes observed in the US by recursively estimating a small scale DSGE model with Bayesian techniques. Recursive estimation provides a short cut to a more complicated analysis that allows for varying taste, technology and policy parameters into a structural model but requires estimation of second order approximations to the solution. Bayesian methods, which have become a popular tool to bring DSGE models to the data, thanks to the work of Schorfheide(2001), Smets and Wouters (2003), Schorfheide and Del Negro (2004) and Rabanal and Rubio (2005), have inferential and computational advantages over traditional maximum likelihood techniques when dealing with models which are a "false" description of the data generating process. This is important since, despite recent attempts to make them more realistic, DSGEs are still highly stylized; many important relationships are modeled with black-box frictions; and ad-hoc shocks are used to dynamically span the probabilistic space of the data. In these situations, asymptotic standard errors attached to maximum likelihood estimates - which are constructed assuming that the model is "true" - are meaningless. Moreover, unrestricted maximum likelihood estimates are often unreasonable or on the boundary of the parameter space and tricks must be used to produce economically sensible estimates. Posterior standard errors, on the other hand, are meaningful even in models with these features and, as this paper shows, it is possible to produce sensible estimates of the structural parameters in a highly stylized model using relatively loose prior specifications. A Bayesian framework is also preferable to an indirect inference estimation approach (which e.g. finds structural parameters matching impulse responses) in two respects: all the information of the model is efficiently used; the trade-off between identifiability and nonlinearities is dealt with in a more transparent and informative way (see e.g. Canova and Sala (2005)).

The model we consider is basic and does not feature any of the standard frictions typically included to produce a good match with the data. Nevertheless, we show that when the priors are appropriately chosen and the policy rule is carefully specified, the statistical fit is satisfactory, the economic fit reasonable and the forecasting performance comparable to the one obtained with more densely parametrized, unrestricted VAR models.

We estimate the model a number of times over different samples, most of which are of the same length, spanning a twenty year period over the sample 1948-2002, and analyze the evolution of the posterior distributions of the structural parameters and of interesting economic functions of them. Our analysis is geared to shed light on four main issues. First, we would like to know if the posterior distribution of the coefficients of the monetary policy rule has significantly and permanently changed, in particular, making the reaction of interest rates to inflation stronger over time. Second, we would like to know whether there are time variations in the posterior distribution of responses to policy shocks. Even if the reaction function of the Fed were stable, policy shocks may have had different effects over time because of structural changes in the rest of the economy. Third, we want to assess whether the variance of the policy shocks has been reduced over time. Finally, we are interested in

investigating the evolution of the posterior distribution of the reduced form coefficients of the Phillips curve and of the Euler equations and in analyzing which of parameter of tastes and technologies is responsible for the observed changes (see Cogley and Sbordone (2005) for a complementary exercise).

Our results are clear cut and broadly agree with the evidence recently reported in structural time varying coefficient VAR analyses. We find that the posterior distribution of the policy parameters is stable over samples and no evidence of a permanent regime shift, from lax to tough anti-inflation stance, in the 1980's or at any other date in the sample. We also find a remarkable stability in the features of the transmission of monetary policy disturbances and no posterior evidence that the variance of the policy shocks has systematically decreased over time. These similarities stand in contrast with the important variations present in the coefficients of the other two equations. We find that variations of the posterior distribution of the elasticity of labor supply and the risk aversion are responsible for variations in the posterior distribution of the reduced form coefficients of the Phillips curve and the Euler equations. Overall, the evidence suggests that the role that monetary policy had in shaping the observed changes in the US has been overemphasized and that investigations attempting to understand the reasons behind the movements in the parameters of private agents' decisions have the potential to shed important light on the dynamics of the post WWII US economy.

The rest of the paper is organized as follows. Section 2 presents the model, describes the estimation technique and discusses diagnostics used to evaluate the quality of the approximation of the model to the data. Section 3 presents the estimation results for the full sample. Section 4 verifies various hypotheses about the role of monetary policy. Section 5 concludes. Technical details concerning the estimation appear in the appendix.

## 2 The framework of analysis

### 2.1 The Model

The model we consider is a standard New-Keynesian, three equation model, composed of a log-linearized Euler equation, a forward looking Phillips curve and a monetary policy rule. Each equation is driven by an idiosyncratic shock: the ones attached to the Euler equation and to the Phillips curve are not given any structural interpretation while the one attached to the policy rule is interpreted as a monetary policy shock.

The system in log-linear form is:

$$x_t = E_t(x_{t+1}) - \frac{1}{\phi}(i_t - E_t\pi_{t+1}) + e_{1t} \quad (1)$$

$$\pi_t = \beta E_t\pi_{t+1} + (\phi + \vartheta) \frac{(1 - \zeta)(1 - \beta\zeta)}{\zeta} x_t + e_{2t} \quad (2)$$

$$i_t = \psi_r i_{t-1} + (1 - \psi_r)(\psi_\pi \pi_{t-1} + \psi_x x_{t-1}) + e_{3t} \quad (3)$$

where  $\zeta$  measures the degree of price stickiness (in a Calvo staggered price setting),  $\beta$  is the discount factor,  $\phi$  is the constant relative risk aversion parameter,  $\vartheta^{-1}$  is the elasticity

of labor supply, and  $(\psi_r, \psi_\pi, \psi_x)$  are the parameters of the monetary policy rule. Here  $x_t$  is the output gap,  $\pi_t$  is the inflation rate and  $i_t$  is the nominal interest rate. We assume that  $e_{1t}$  and  $e_{2t}$  are AR(1) processes with persistence  $\rho_1, \rho_2$  and standard errors  $\sigma_1, \sigma_2$ , respectively, while  $e_{3t}$  is iid with standard error  $\sigma_3$ . The three shocks are assumed to be contemporaneously uncorrelated.

A system of equations like (1)-(3) can be obtained from a standard dynamics stochastic general equilibrium model with sticky prices, monopolistic competition and preferences which are additive in consumption and leisure when labor is the only productive factor (see e.g. Clarida, Gali and Gertler (1999)). The specification of the policy rule is consistent with the idea that the monetary authority only observes lagged values of the output gap and of inflation when deciding the current interest rate. Such a specification differs from the typical Taylor rule employed in the literature, where the nominal interest rate is allowed to contemporaneously react to the output gap and inflation. We choose this specification for two reasons. First, given existing informational lags, it seems reasonable to assume that the central bank takes one period to react to the development in the private side of the economy. Furthermore, when estimating the contemporaneous coefficients of a standard Taylor rule in a VAR, these turn out to be typically small and, at times, insignificant. Second, a specification which makes interest rates react contemporaneously to output and inflation is economically unsatisfactory. In fact, it forces the smoothness parameters  $\psi_r$  to capture all the dynamics of interest rates and results in an estimate which is statistically indistinguishable from 1 (see also e.g. Ireland (2004)). We explicitly compare the fit of our specification and that of a more standard specification later on.

Although the AR(1) assumption on  $e_{1t}$  and  $e_{2t}$  is standard, some discussion on this choice is required. At a preliminary stage of this project we have tried to make the model more structural, adding a backward looking component to the Phillips' curve and considering an Euler equation with habit persistence in consumption, while making the two shocks iid. As shown in Canova and Sala (2005), it is hard to identify these two features from output gap, inflation and interest rate data and since our analysis uses relatively short samples, biases are likely to be serious. Consequently, we prefer work with a less structural but more easily estimable version of the model, which can parsimoniously capture various forms of misspecification, including omitted variables, and still allows us to draw conclusions on the issues of interest.

In principle, the disturbances appearing in (1)-(3) could be correlated. For example, when deriving these equations from first principles, An and Schorfheide (2005) show that shocks to government expenditure shift both the IS and the Phillips' curve, therefore making the  $e_t$ 's potentially correlated. In our baseline specification, we choose otherwise, primarily because the exact correlation structure of the residuals depends on the type of primitive shocks which are allowed in the economy. Later we show what happens to the fit of the model when a general contemporaneous correlation structure on the residuals is allowed.

Throughout this paper we use a statistically computed measure of the output gap rather than the deviation of output from the level obtained in the flexible price equilibrium. We chose this approach for two reasons. First, a flexible price measure which does not take

into account capital accumulation is likely to be misspecified. Second, as we show later on, this potential misspecification matters and the restrictions imposed on the model by this choice are at odds with the data. Orphanides (2004) has emphasized that output gap measures of any sort are corrupted by considerable measurement error and that such error could be reduced if the growth rate of output is used. We examine whether our conclusions are sensitive to this choice in section 4. To anticipate, our results are robust.

Several authors, including Smets and Wouters (2003), Rabanal and Rubio (2005) and others, have specified more complicated and realistic structures which allow for additional shocks and frictions. We do not follow this route because the model captures sufficiently well the dynamics of output gap, inflation and interest rates observed in the US without any of these features. Moreover, since it is far from clear that the additional frictions are identifiable, and that additional shocks play a significant role for the type of questions we are interested in, the most stripped down specification suffices for our purposes.

## 2.2 The prior, the estimation technique and the measures of fit

The model (1)-(3) contains 12 parameters, 7 structural ones  $\alpha_1 = (\beta, \phi, \vartheta, \zeta, \psi_r, \psi_x, \psi_\pi)$  and 5 auxiliary ones,  $\alpha_2 = (\rho_1, \rho_2, \sigma_1, \sigma_2, \sigma_3)$ . Our exercise is geared to obtain posterior distributions of  $\alpha_T = (\alpha_{1T}, \alpha_{2T})$  over different samples  $T$  and to compare the time series properties of the posterior distributions of a subset of the parameters and of interesting economic functions of them.

Staring at the equations of the model, it is easy to note that  $\vartheta$  and  $\zeta$  are only partially identifiable from the data. To solve this problem one has several options. The first is to be non-structural and try to obtain posterior estimate of the Phillips curve trade-off which eschews the cross equations restrictions present in the model (as e.g. it is done in Lubik and Schorfheide (2004)). Since we are interested in examining the evolution of the private sector parameters which enter the Phillips curve trade-off, we do not follow this approach. In an earlier version we had chosen to specify proper but loose priors for the two parameters and let the data decide in which direction to add whatever information is available. Since a proper prior implies a proper posterior even if the likelihood is uninformative, checking whether the posterior distribution differs from the prior is a necessary condition for conducting inference. However, as a referee pointed out, this condition is not sufficient as conclusions may depend on the specification of the prior. To take care of this objection, we have experimented with two alternative prior specifications, one where  $\zeta$  has a very tight prior centered at the value estimated by Bills and Klenow (2004) and one where  $\vartheta$  has a very tight prior centered at the value estimated using a model-based version of the output gap. As it is shown in section 4, our conclusions are robust to the choice of prior location and tightness for these two parameters.

The system can be rewritten as a VAR(1):  $\mathcal{G}y_{t+1} = \mathcal{H}y_t + \mathcal{J}e_t$  where  $y_{t+1} = (\pi_t, x_t, i_t, \pi_{t+1}, x_{t+1})$  and  $v_t = [0, 0, e_{3t}, e_{1t}, e_{2t}]$  and can be solved using standard first order log-linear

methods. Its solution has a state space format

$$y_{1t+1} = A_1(\alpha)y_{1t} + A_2(\alpha)\epsilon_t \quad (4)$$

$$y_{2t} = A_3(\alpha)y_{1t} \quad (5)$$

where  $y_{2t} = [\pi_t, x_t, i_t]$ ,  $y_{1t} = [\pi_{t-1}, x_{t-1}, i_{t-1}, e_{1t}, e_{2t}, e_{3t}]$  and the matrices  $A_i(\alpha)$ ,  $i = 1, 2, 3$  are complicated nonlinear functions of the structural parameters  $\alpha$ .

Bayesian estimation of (4) and (5) is simple: given some  $\alpha$ , we compute the likelihood of the model, denoted by  $f(y_T|\alpha)$ , by means of the Kalman filter and the prediction error decomposition. Then, for any specification of the prior distribution, denoted by  $g(\alpha)$ , the posterior distribution for the parameters of the model is  $g(\alpha|y_T) = \frac{g(\alpha)f(y_T|\alpha)}{f(y)}$ . The analytical computation of the posterior is impossible in our setup since the denominator of the expression,  $f(y)$ , can be obtained only integrating  $g(\alpha)f(y_T|\alpha)$  with respect to  $\alpha$ , which is a 12 dimensional vector. To obtain numerically a sequence from this unknown posterior distribution, we employ the Metropolis-Hastings algorithm. Roughly speaking, given  $\alpha_0$  and a transition function satisfying regularity conditions, we can produce a sequence from the unknown posterior, iterating on this transition function, after discarding an initial burn-in period of draws. Details on the algorithm, on the selected transition function, on the criteria used to check convergence and on other choices made are in the appendix.

We assume that the prior distribution can be factored as  $g(\alpha) = \prod_{i=1}^{12} g(\alpha_i)$ , and let  $\beta \sim \text{Beta}(98, 2)$ ,  $\phi \sim N(2.0, 0.75^2)$ ,  $\vartheta \sim N(4, 1.25^2)$ ,  $\zeta \sim \text{Beta}(4, 2)$ ,  $\psi_r \sim \text{Beta}(6, 2)$ ,  $\psi_\pi \sim N(2.7, 0.35^2)$ ,  $\psi_x \sim N(1.0, 0.15^2)$ ,  $\rho_1 \sim \text{Beta}(6, 2)$ ,  $\rho_2 \sim \text{Beta}(6, 2)$ ,  $\sigma_1^2 \sim \text{Gamma}(2, 0.001)$ ,  $\sigma_2^2 \sim \text{Gamma}(2, 0.001)$ ,  $\sigma_3^2 \sim \text{Gamma}(2, 0.001)$ .

The prior mean for each coefficient is located around standard calibrated values. Furthermore, the densities we have selected, although proper, are by and large non-informative over a range of economically reasonable parameter values. For example, the risk aversion parameter  $\phi$  has an a-priori range of  $[0, 4.5]$ , the smoothness parameter  $\psi_r$  varies in the range  $[0.11, 0.99]$  while the two policy parameters,  $\psi_\pi$  and  $\psi_x$ , can assume values in the range  $[1.0, 4.5]$  and  $[0.16, 1.75]$ , respectively. The prior range for the stickiness parameter  $\zeta$  is also large and values from 0.05 to 0.99 have a-priori positive probability. We select "loose" priors to minimize subjective information - here limited to produce bounds on the priors consistent with theoretical and empirical considerations - and to allow the posterior to move away from the prior if the data is informative. Since we maintain the same prior in every sample, differences in the location and in the shape of the posterior distribution indicate that there is different information in different samples <sup>1</sup>.

The data we use covers quarterly observations on the output gap (here proxied by GDP in deviation from a linear trend), CPI inflation and the Federal funds rate <sup>2</sup>. The source of

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<sup>1</sup>Since the priors are loose, the exact form of the densities does not matter. The rule we have followed is the following: for parameters which must be positive, gamma distributions are used; for parameters which must be in an interval, beta distributions are used; for all other parameters, normal distributions are employed.

<sup>2</sup>We have examine the sensitivity of our results to different ways of constructing output gaps (Beveridge and Nelson filter) and to the use of CPI inflation (as alternative, we have tried the GDP deflator). None of the qualitative conclusions we reach depend on these choices.

the data is the FREDII databank of the Federal Reserve Bank of St. Louis.

We have checked the quality of the model's approximation to the data in several ways. First, we have conducted a forecasting exercise, comparing the fit of the model, measured here by the marginal likelihood, to the fit obtained with a three variable VAR(3) and a three variable BVAR(3), endowed with a Minnesota prior. Second, we have visually examined the fit of the interest rate equation, plotting the actual interest rate path and the 68 percent posterior band for the interest rate path predicted by the model. Third, we have checked for violations of the Euler condition. That, is we have examined whether lagged values of the output gap, of inflation, or of the real interest rate comove with the quasi-differenced residual of the Euler equation, given posterior draws for the parameters. Since these three statistics examine alternative aspects of the model, they provide complementary information on the success of the estimation process.

### 3 Full sample estimation

We start by presenting estimates for the full sample 1948:1-2002:1. We are primarily interested in demonstrating that the model fits well the data despite its simplicity and, therefore, can be used to undertake the recursive type of analysis we are concerned with. Furthermore, we want to show that alternative specifications, which use either more structural or more parametrized versions of the model, do not fit as well as the chosen one.

Figure 1 presents prior and posterior estimates of the densities of parameters. Densities are obtained with kernel methods, coordinate by coordinate, using 1000 draws from the priors and the posteriors. Dotted lines correspond to priors and solid lines to posteriors. Few features of the figure deserve comments. First, the data appears to be informative. In fact, for 8 of the 12 parameters, the posterior spread is smaller than the prior spread. The only parameters for which this is not the case are those regulating price stickiness  $\zeta$ , and the variance of the three shocks  $\sigma_i$ . In a few instances, the location of the distribution also changes. For example, the risk aversion parameter  $\phi$  has a posterior whose central tendency is somewhat higher than the one of the prior while the opposite is true for the inverse elasticity of substitution parameter  $\vartheta$ . Interestingly, the posterior of  $\psi_\pi$  is centered around 2 and there is less than 10 percent of the posterior mass in the area below 1.3.

The posterior of the two autoregressive parameters is centered at around 0.85 and less than 1 percent of the posterior mass is the area above 0.96. That is, the model has some internal propagation mechanism so that to match the unit root-like dynamics of the output gap and of inflation, no unit-root-like exogenous processes are needed (contrary, e.g. to Smets and Wouters (2003)). The data implies that, a-posteriori, labor supply is sufficiently inelastic (the posterior mean of  $\vartheta$  is 3.51 with standard deviation equal to 0.57) and that agents have a mild aversion toward risk (the posterior mean of  $\phi$  is 2.03 with standard deviation equal to 0.29).

The data does not appear to be very informative about the price stickiness parameter  $\zeta$  and the output gap parameter  $\psi_x$ : in fact, prior and posterior distributions overlap almost entirely. This could be due to lack of information in the data or to the fact that the

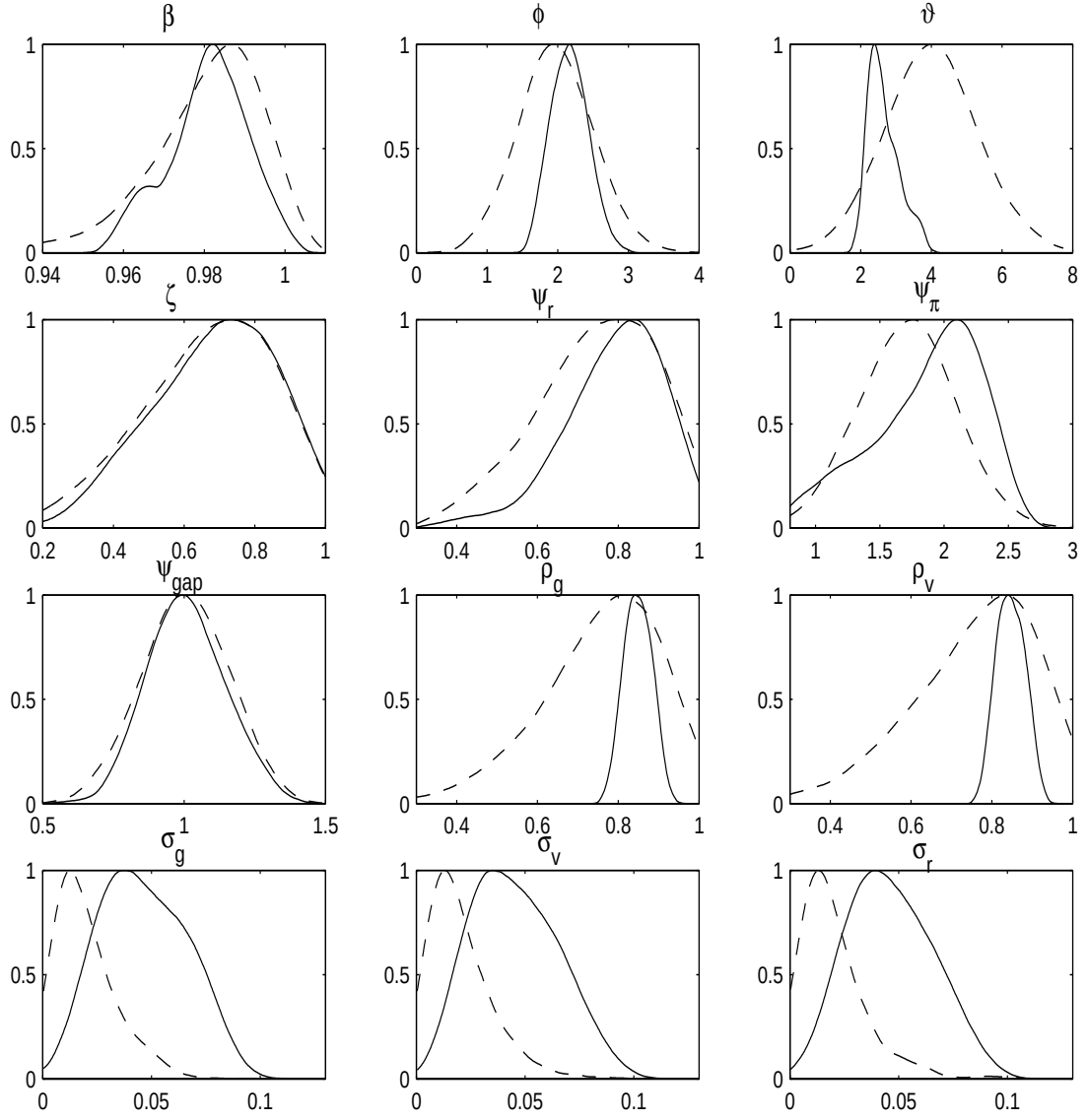


Figure 1: Prior (dotted) and Posterior (solid) densities

prior is too much data based - a great deal of data information has gone into building prior moments so that the prior and the likelihood coincide. The sensitivity analysis we conduct below allows us to distinguish these two possibilities. Finally, the shocks to the three equations have similar posterior variances. Taken at face value this implies that impulses to the three equations have similar magnitude in the sample, a result which agrees with the structural VAR estimates of Canova and De Nicolo (2002), but contrasts with both the common wisdom that monetary disturbances have been a minor source of cyclical fluctuations in the US economy and the maximum likelihood estimates of Ireland (2004). If the variables used in the estimation are imprecisely measured, this could simply reflect the fact that measurement errors dominate in size and variability structural errors.

The forecasting performance of the model is reasonable although less astonishing than that of Smets and Wouters (2005). Bayes factors are 0.79 with respect to a BVAR(3), and 0.81 with respect to a VAR(3), suggesting that our model is at most, 20 percent worse than the best, densely parametrized specification we consider. The model is inferior to the VAR alternatives primarily because the lagged nominal interest rate, which is missing from (2), enters the inflation equation of the VAR with a significant negative sign.

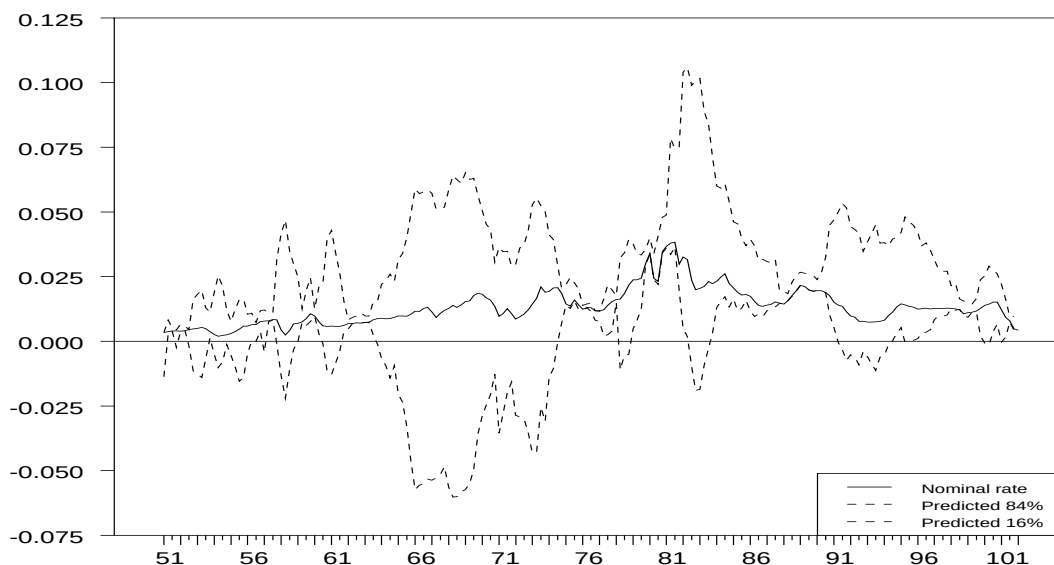


Figure 2: Predicted and Actual Interest rate path, 1950-2002

The model fits reasonably well the Euler equation and only in 0.6 percent of the draws the residuals of the equation violate orthogonality conditions. In these few cases, the information contained in the past output gap explains deviations from the null. The model also fits reasonably well the policy equation. Figure 2 presents the predicted and actual interest rate paths from 1950 to 2002. The actual interest rate path is always inside the posterior 68% band predicted by the model and, except for the 1965-1975 period, posterior

68% bands are reasonably tight and follow the ups and downs of the actual nominal interest rate. Notice also that the model predicts the drastic fall in interest rates occurred in 2001.

The model is relatively poor in matching inflation dynamics. For example, the posterior median of the reduced form coefficient on the output gap is only 0.62 with a standard deviation equal to 1.86, implying that the dynamics of inflation can be represented by a near-random walk. Also, the residuals of the equation are generally correlated with lagged values of the nominal rate. These observations confirm results obtained with other estimation techniques (see Gali and Gertler (1999) or Linde (2005)), and suggest that the New-Keynesian Phillips curve, where the output gap proxies for marginal costs, has hard time to account for the dynamics of inflation. It is worthwhile to stress that adding a backward looking component to the equation (for example, assuming inflation indexation) will improve the dynamic fit decreasing residual serial correlation (see e.g. Rabanal and Rubio (2005)) but will not alter the conclusion that posterior median estimates imply little effects from marginal costs to inflation. In other words, the specification is somewhat poor not because the dynamics are backward looking but because estimates imply that inflation only weakly responds to those endogenous movements in the output gap induced by changes in the marginal costs.

We have checked the robustness of our posterior estimates to changes in the prior distribution. This exercise is important for two reasons. First, since there are posteriors which lie on top of the priors, we can distinguish if this occurs because the prior is too much in agreement with the data or because the likelihood is uninformative. Second, since the priors have subjectively large dispersions, it is important to know how the posteriors change if we are less uncertain about the prior range of values the parameters of the model must take. Table 1 reports the mean and the standard deviation of the prior and the posterior in the baseline case and the posterior moments in two alternative specifications, obtained making the prior progressively more informative. We have done this maintaining the location fixed and rescaling the probability densities after reducing the prior ranges by 10 and 20 percents. In the limit, when priors are very tight, sample information plays no role. Therefore, the degenerate posteriors one obtains in this case, trivially corresponds to those produced calibrating the parameters to a single value. Following Geweke (1998), posterior draws from the new distribution are obtained reweighing the posterior draws obtained in the baseline case with  $w(\alpha) = \frac{g^i(\alpha)}{g^B(\alpha)}$ , where  $g^i(\alpha)$  is the new prior and  $g^B(\alpha)$  is the baseline prior.

The table indicates that the posterior results are reasonably invariant to changes in the prior specification. When the spread of the prior is reduced the posterior means of  $\vartheta$  and  $\phi_x$  tends to increase while the posterior means of  $\phi$ ,  $\zeta$ ,  $\psi_r$ ,  $\sigma_2^2$  and  $\sigma_3^2$  tends to increase. Moreover, as one should expect, estimates are much more precise when we reduce the spread of the prior distribution. There is some mild non-monotonicity as we further restrict the prior spread from 90 to 80 percent of the original one, in particular for  $\psi_r$  and  $\psi_\pi$ , but the results are fairly robust. Since the posterior means of  $\zeta$  and  $\psi_x$  slightly increases and the posterior standards error shrink when the prior spread is reduced, it appears that prior and posterior largely overlap because the prior already contains a substantial amount of data based information. To summarize, the general features of the posterior distributions we

|              | Prior  |               | Basic Posterior |               | 90 percent Spread |               | 80 percent Spread |               |
|--------------|--------|---------------|-----------------|---------------|-------------------|---------------|-------------------|---------------|
|              | Mean   | Standard dev. | Mean            | Standard dev. | Mean              | Standard dev. | Mean              | Standard dev. |
| $\beta$      | 0.9799 | 0.141         | 0.9837          | 8.824e-03     | 0.9906            | 2.481e-04     | 0.9907            | 2.301e-04     |
| $\phi$       | 2.0281 | 0.512         | 2.0391          | 0.298         | 1.2713            | 3.519e-03     | 1.2639            | 1.331e-03     |
| $\vartheta$  | 4.0878 | 1.304         | 3.5156          | 0.574         | 4.3900            | 0.011         | 4.4024            | 5.760e-03     |
| $\zeta$      | 0.6576 | 0.183         | 0.6609          | 0.185         | 0.6779            | 0.109         | 0.7129            | 0.067         |
| $\psi_r$     | 0.7471 | 0.143         | 0.7235          | 0.148         | 0.5179            | 0.033         | 0.5708            | 0.016         |
| $\psi_\pi$   | 1.6958 | 0.346         | 1.5135          | 0.336         | 1.5260            | 8.672e-03     | 1.5302            | 0.010         |
| $\psi_x$     | 1.0006 | 0.151         | 0.9984          | 0.165         | 1.0380            | 0.021         | 1.0426            | 0.020         |
| $\rho_1$     | 0.7457 | 0.143         | 0.8494          | 0.031         | 0.8510            | 0.012         | 0.8586            | 9.884e-03     |
| $\rho_2$     | 0.7457 | 0.140         | 0.8469          | 0.032         | 0.8355            | 0.016         | 0.8017            | 0.013         |
| $\sigma_1^2$ | 0.0200 | 0.139         | 0.0458          | 0.019         | 0.0365            | 5.759e-03     | 0.0295            | 3.332e-03     |
| $\sigma_2^2$ | 0.0210 | 0.141         | 0.0464          | 0.019         | 0.0645            | 0.015         | 0.0933            | 7.329e-03     |
| $\sigma_3^2$ | 0.0210 | 0.140         | 0.0467          | 0.052         | 0.0645            | 0.003         | 0.0517            | 2.303e-03     |

Table 1: Posterior Moments, Different Priors

have constructed are robust; none of the economic conclusions one can derive from these estimates hinges on the spread of the prior distributions.

### 3.1 Alternative specifications

Although the model fits reasonably well the data, we have taken a number of modelling short cuts. Therefore, before performing the recursive analysis, it is useful to check whether more or less structural or densely parametrized specifications fit the data better.

Table 2 presents the marginal likelihood for our benchmark specification and for a number of competitors. We consider a model where the policy rule specifies that interest rates react to current inflation and to the current output gap; a model where the output gap is computed using the flexible price output level; a model where the residuals of the three equations are contemporaneously correlated; and a specification where the output gap coefficient in the Phillips' curve is assumed to be non-structural. When we compute the flexible price equilibrium we assume that the shock driving output is the same as the one hitting the second equation of our system; when we allow shocks to be contemporaneously correlated we assume that they are a-priori drawn from a Wishart distribution.

| Model                               | Log Marginal Likelihood |
|-------------------------------------|-------------------------|
| Baseline model                      | 888.12                  |
| Contemporaneous policy rule         | 351.07                  |
| Contemporaneously correlated shocks | 510.84                  |
| Theory based output gap             | 877.06                  |
| Unstructural Phillips' curve        | -350.84                 |

Table 2: Models comparison, sample 1948-2002

As the table clearly shows, none of the alternative specifications has a marginal likelihood exceeding the one of our baseline model. Hence, the theoretical restrictions imposed by the model-based output gap are not satisfied; the extra parameterization introduced by a general specification of the shocks has negligible predictive power while the reduction produced by a non-structural Phillips' curve is significant; and the contemporaneously specified policy rule takes away internal dynamics which are important to explain the data. Overall, our specification strikes a balance between the desire to have as a structural model as possible and the need to fit the data well.

## 4 Recursive Analysis

There is substantial controversy in the literature regarding the role that monetary policy had in shaping the dynamics of US output and inflation over the last 30 years. While common wisdom suggests that changes in monetary policy "caused" changes in the autocovariance properties of output and inflation, several authors have raised serious doubts about such an interpretation. In particular, the recent work by Sims and Zha (2004) and Canova and Gambetti (2004), who used time varying coefficients in a structural VARs, provide strong evidence against this conventional view.

In the context of the model we consider, we can address four questions which can shed important light on the variations taking place in the autocovariance function of output and inflation. First, do we observe significant changes in the systematic component of monetary policy? That is, does the posterior distribution of the policy parameters shifts significantly (and permanently) in the latter part of the sample? Second, has the variance of the policy innovations permanently shrunk after the mid 1980's? Third, is there a change in the transmission of monetary policy shocks to the economy? Fourth, is there any evidence that the magnitude of the Phillips curve trade-off has been altered significantly over time? What are the reasons for the shift? Is the Euler equation stable?

To address these questions we have estimated the model over a number of samples. We started from the sample [1950:1, 1970:1] and repeated the estimation moving the starting date by one year while keeping the size of the sample constant to 20 years. Keeping a fixed window size is important in order to minimize differences produced by different precision of the estimates. The last subsample is [1982:1-2002:1], which means that we produce 33 posterior distributions for the parameters. We also constructed posterior distributions for one additional shorter sample, [1984:1-2002:1], to compare our results with those present in the literature, where the sample is arbitrarily split at this date. The final sample we consider, [1987:1-2002:1], corresponds to Greenspan's tenure and permits us to compare policies in the 1990's with those of the 1970's and infer to what extent the reaction function of the Fed has turned from weak to aggressive in fighting inflation.

#### 4.1 The systematic component of policy

Figure 3 presents the evolution of the posterior 68 percent band for the coefficients of the policy rule over different samples. For the sake of legibility, the figure reports bands only for selected samples (listed on the horizontal axis of the graph). For intermediate samples, posterior bands monotonically connect those for the reported dates.

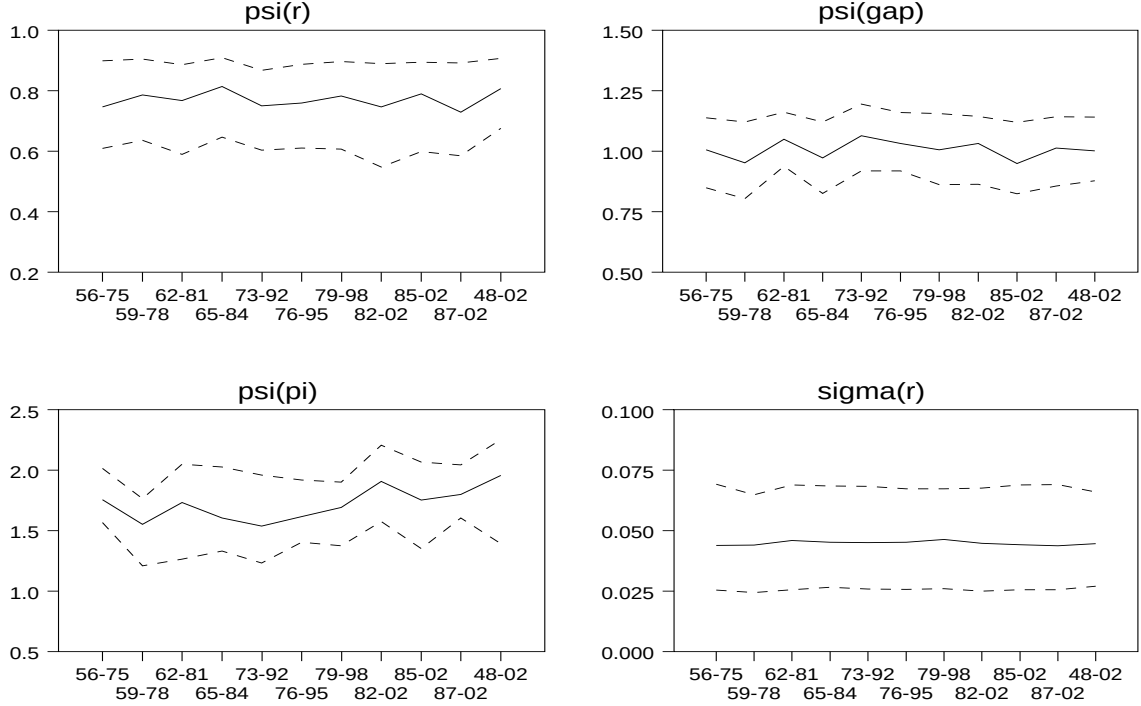


Figure 3: Posterior 68 percent bands for policy parameters, selected samples

Several important features emerge from figure 3. First, there is no posterior evidence that any of the three policy coefficients has permanently shifted over time. Moreover, variations are minor in size and temporary in nature. In fact, the envelope of the posterior 68 percent bands, constructed so that the coverage is at least 68 percent in each sample, includes the median of the posterior for each of the samples. Second, our recursive posterior distribution analysis fails to support the idea that in the pre-1980 period monetary policy was weak in fighting inflation: the shape of the whole distribution is roughly similar during Greenspan and Burns tenures. For example, the posterior median of the inflation coefficient in the 1956-1975 sample (1.75) is slightly lower than the posterior median in the 1987-2002 sample (1.81). However, since the dispersion of posterior estimates is comparable and the posterior distribution of the smoothness parameter  $\psi_r$  is broadly unchanged, one must conclude that the two tenures are characterized by similar regimes.

Remarkable stability is also present in the posterior distribution of the other two policy

parameters. For example, the median value of the posterior distribution of  $\psi_x$  oscillates between a minimum of 0.97 and a maximum of 1.06 and the posterior distribution of the differences between these two estimates is centered around zero and sufficiently symmetric. The smoothness parameter has a posterior median which is in the neighbor of 0.75 and the posterior standard deviation is of the order of 0.15 in every sample we consider. Interestingly, the estimate we obtain imply that the median estimate of the long run response of interest rates to output and inflation over the full sample is strong: about 6 for the former and of 3 for the latter and estimates in different samples are of similar magnitude.

In conclusion, as in Sims and Zha (2004) and Canova and Gambetti (2004), we fail to detect permanent variations in the posterior distribution of the policy parameters. Moreover, we fail to find posterior evidence that the response of interest rates to inflation was weak in the 1970's and strong in the 1990's. In this respect, our analysis confirms Leeper and Zha's (2003) conclusion that policy has been very much as usual over the majority of the samples, and agrees with Bernanke and Mihov's (1998) result that a relatively stable interest rule characterized the behavior of monetary policy in the US over most of the last 50 years.

## 4.2 The variability of policy shocks

Sims and Zha (2004) and Canova and Gambetti (2004) find evidence suggesting that the variance of the shocks hitting their estimated VAR system was reduced over time. In particular, the variance of the policy shock in the end of the 1990's was about 30 percent lower than its largest value at the beginning of the 1980's. It is therefore possible that, although no permanent regime change is detectable, a more credible central bank may have, directly or indirectly, reduced the size of the shocks hitting the policy equation. If policy shocks have significant effects in the economy, monetary policy contributed to stabilize the macroeconomic environment. The low left panel of figure 3 presents the time path of the posterior 68 percent band for the variance of the policy shock. While variations are present, they are small. In particular, we find no posterior evidence of a permanent reduction in the variance of the policy shocks since the mid 1980s, nor that policy shocks under Greenspan's tenure were significantly smaller than in any other period in the post WWII US history.

## 4.3 The transmission properties of monetary policy shocks

While the systematic component of monetary policy appears to be stable and the variance of policy shocks practically unchanged, it is possible that changes in the structure of the economy (in our case, coming from the parameters of preferences and technologies) have altered the transmission of policy disturbances. That is to say, while the systematic component of policy does not show any permanent shift, unsystematic policy shocks may have had different dynamic effects over different samples. To examine this possibility we present responses to policy disturbances in selected samples in figure 4. To make the comparison meaningful, plots are scaled so that the impulse to the policy equation is the same in each sample (and equal to 100 basis points).

The dynamics following monetary policy shocks have been qualitatively similar over time: the interest rate increases while the output gap and inflation fall. The immediate effect on inflation is much larger than the one on output but, in general, less persistent. In fact, the inflation effects of an interest rate shock die out within 3 quarters of the impulse while output effects last one quarter longer. The lack of inflation persistence in response to monetary shocks is a well known fact and the addition of standard friction do not necessarily increase this persistence (see e.g. Neiss and Pappa (2005)). Output is slightly more persistent here than in comparable models because the policy equation is backward looking. Interestingly, the largest response of output and inflation is always contemporaneous. Therefore, the sole presence of monopolistic competition and price stickiness does not imply that output and inflation satisfy the zero restrictions typically used to identify policy disturbances in VARs.

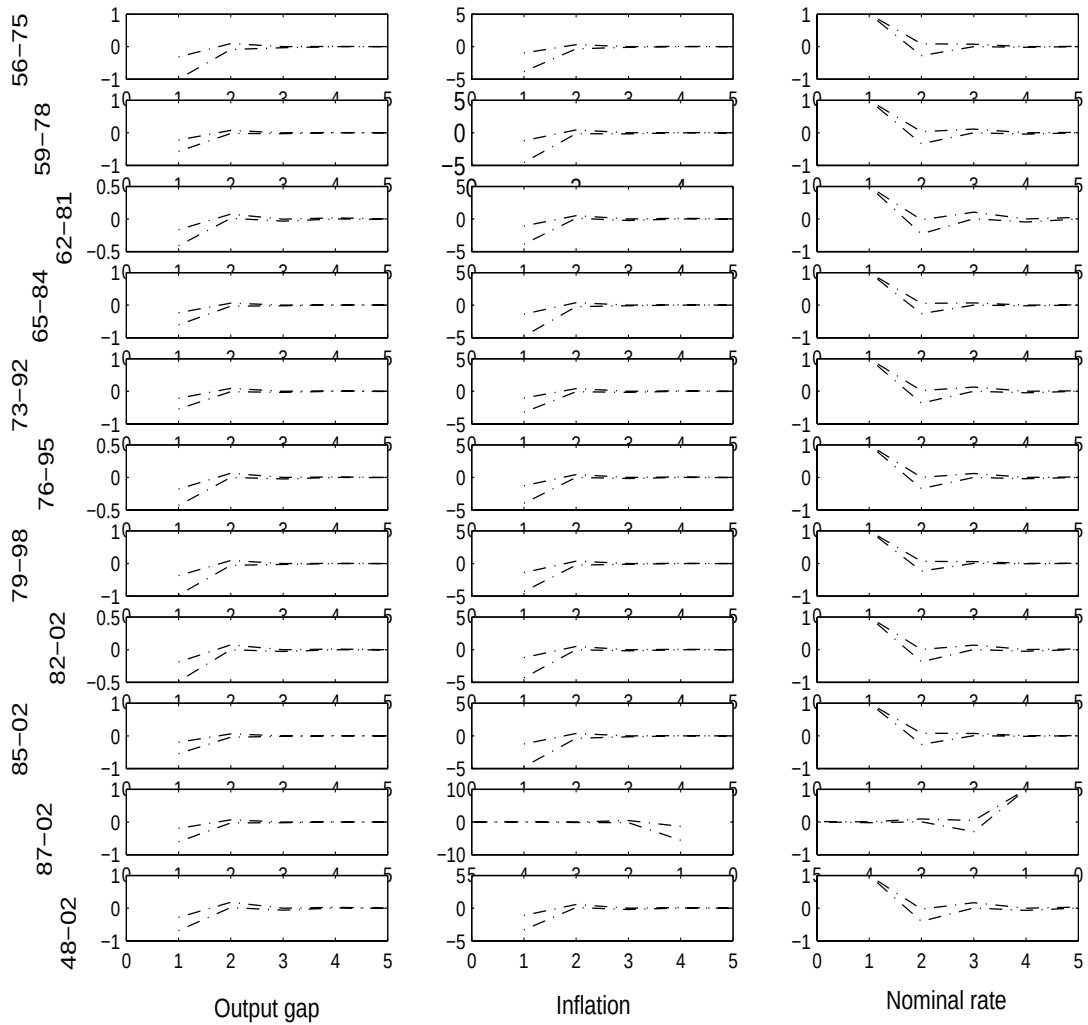


Figure 4: Impulse responses to policy shocks, selected samples

Qualitatively, minor differences across samples emerge. For example, the posterior bands in the 1948-2002 sample are slightly smaller than in any other sample, probably as a result of more precise parameter estimates. Also, output responses are weaker in the 1962-1981, 1976-1995, and 1982-2002 samples, suggesting that the contribution of monetary disturbances to output fluctuations may have changed over time. Finally, the response of inflation to policy shocks is larger in size during Greenspan's tenure.

In sum, also the transmission of policy disturbances is qualitatively unchanged over time. Taken together, the results we have presented in these three subsections indicate that monetary policy does not have much to do with the observed changes in output and inflation. The policy rule has been similar over samples, the variance of the policy shock unchanged and shocks to the policy equation have produced similar responses in the US economy in different samples.

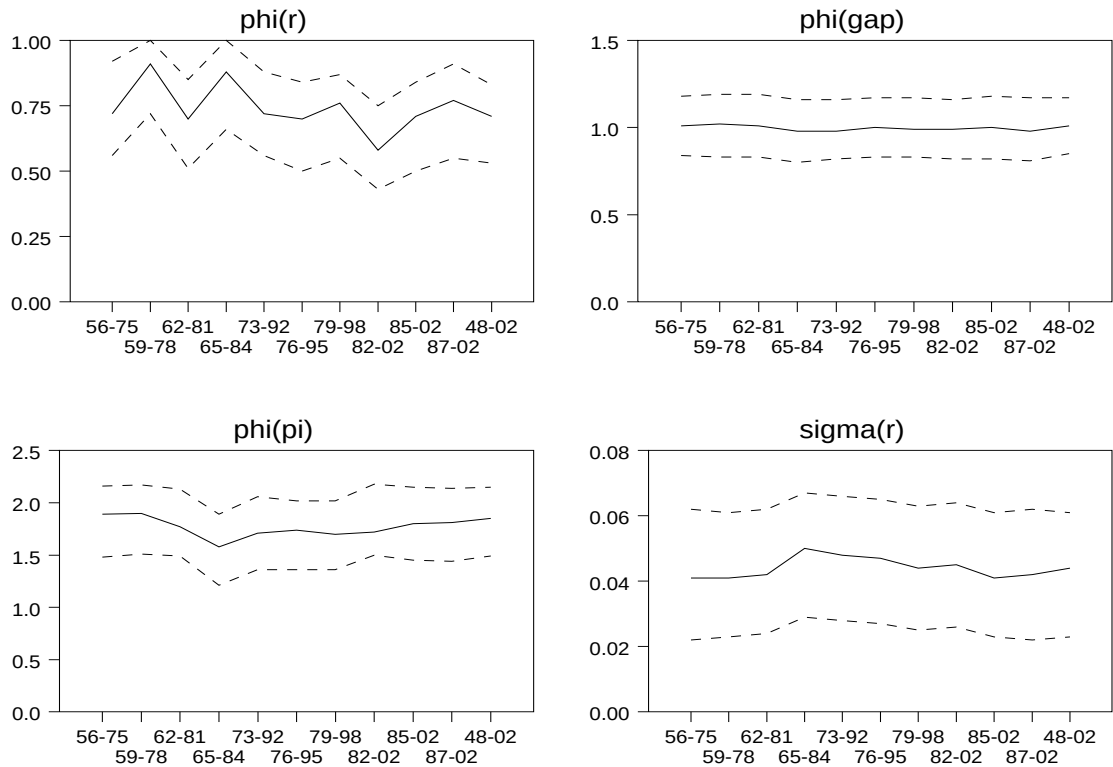


Figure 5: Posterior 68 percent band for the policy parameters: output growth rates

One may wonder if the stability we find is an artifact of sizable measurement errors. In particular, the output gap measure we use is probably subject to a large amount of such an error. Consequently, estimates of the structural parameters and of the impulse responses may fail to move around across samples because of the large amount of measurement error

present in each sample. Similarly, we may fail to detect changes in the posterior distribution of the variance of the policy shock because the variables entering the policy rule are measured with error and such error contaminates the residuals of the equation. We have already argued that model based measures of the output gap do not seem to be the solution as they produce cross equation restrictions which are violated in the data. Orphanides (2004) has argued that measurement errors are significantly reduced if output growth is used in place of the output gap. Do results change when output growth is used in the policy equation? Figure 5, which reports the evolution of the 68 percent posterior band for the policy parameters and for the variance of policy disturbances, shows that none of our conclusions is altered. As a matter of fact, posterior distributions obtained with this specification are even more stable across samples. Hence, measurement error is unlikely to explain why we fail to detect time variations in the system.

Lubik and Schorfheide (2004) have argued, using a model like ours, that the US evidence is consistent with the idea that the pre-1980 period was characterized by indeterminate equilibria and this changed in the post-1980 sample, as the response of interest rates to inflation strengthened. One of the contribution of this paper is to show that we can fit the dynamics of inflation and interest rates well over the last 50 years without any need to resort to indeterminacies: small variations in the parameters of the policy rule, coupled with some variations of the parameters of the private sector behavior (see next) are sufficient to do the job. Nevertheless, it is possible that our failure to detect changes is due to our choice of priors which forces the estimated policy coefficients to produce determinate equilibria. Would results change if the prior allows also for indeterminate solutions? We guess that this is not the case for two reasons. First, our posterior distributions do not show any tendency to pile up at the border of the determinacy region, a symptom indicating that the algorithm is constrained to search in an area of relatively low posterior probability. Second, under indeterminacy a non-structural shock drives the dynamics of the system. Since the fit of the model is roughly the same in every sample we examine, the contribution of this non-structural shock to the dynamics of the system must be small.

#### 4.4 Stability of the other equations

The Phillips curve trade-off in our model is regulated by a (nonlinear) function of four structural parameters: the coefficient of relative risk aversion  $\phi$ , which also regulates the fit of the Euler equation, the inverse elasticity of labor supply  $\vartheta$ , the discount factor  $\beta$ , and the price stickiness parameter  $\zeta$ . As we have mentioned, the posterior median of this trade-off is 0.62 for the full sample suggesting that marginal costs exert a somewhat marginal effect on the dynamics of inflation. However, simply looking at the median value is misleading since the posterior distribution of this coefficient is very skewed and has a very long upper tail: the mean effect is three times as large as the median effect and the upper 5th percentile of the distribution is 7.72.

Narrative evidence obtained plotting the output gap against inflation over time suggests that the slope of the relationship has changed magnitude and sometimes even sign. It is therefore worth studying whether our structural analysis confirms this evidence and, if this

is the case, investigate which of the four structural parameters is responsible for the time variations we observe (see Cogley and Sbordone (2005) for a complementary effort). Given our inability to detect any the relationship between changes in monetary policy and changes in output and inflation processes over time, such an analysis may also shed light on reasons behind the observed changes in the US economy.

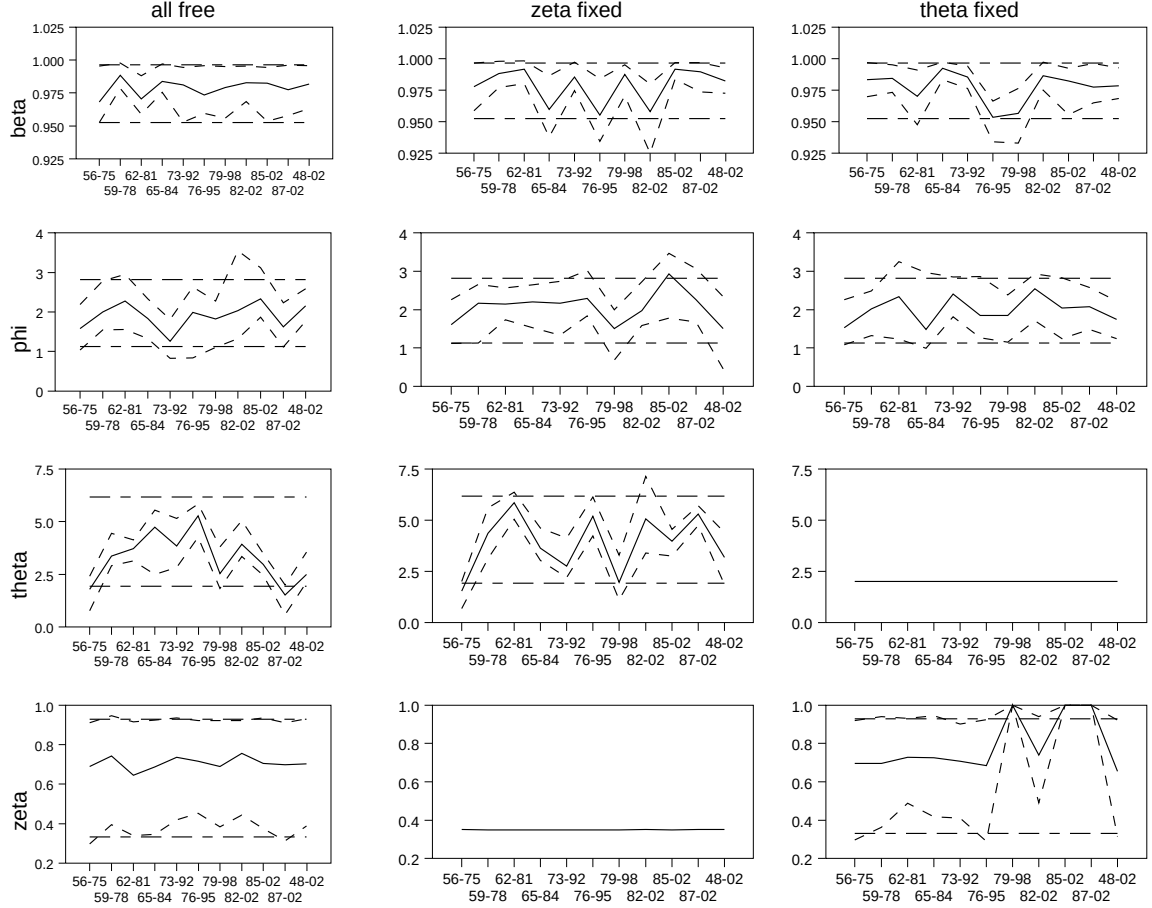


Figure 6: Evolution of private agents parameters: Posterior(solid) Prior (dotted)

While we fail to find sign reversal over the various samples, the posterior distribution for this reduced form coefficient is somewhat unstable. For example, the minimum median value is 0.25 in the 1987-2002 sample and the maximum median value is 1.28 in the 1961-1982 sample and the 68 percent posterior credible set is almost twice as large in the early samples than in the latter ones. Which structural parameter is responsible for this instability? Figure 6, which presents the posterior median and the posterior 68 percent bands for the parameters, suggests that the posterior distributions of the risk aversion parameter and of the inverse elasticity of labor supply are moving over samples and, relatively speaking, the

latter displays the largest variations. For example, the posterior distribution of  $\vartheta$  has a median value of 1.5 in the 1987-2002 sample and a median value of 5.11 in the 1976-1995 sample. By contrast, the parameter controlling price stickiness has been much more stable: the median value of the posterior distribution is always around 0.70, implying slightly less than three quarters between price changes in every sample.

Since the inverse elasticity of labor supply  $\vartheta$  and the price stickiness parameter  $\zeta$  may not be separately identifiable from the data, it could well be that the variations we attribute to the former are in fact due to the latter. We have chosen an non-informative prior on these two parameters to let the data speak on this issue; the verdict from our full sample estimation seems to be that the data have little information about  $\zeta$  and the recursive analysis appears to confirm this. For robustness, we checked whether this outcome changes if rather than specifying a loose but proper prior on both parameters, we choose dogmatic priors on one of the two. The second and the third columns of figure 7 show the resulting posterior distributions. In column two, consistent with the evidence produced by Bills and Klenow (2005),  $\zeta$  has a prior mean of 0.35 and a prior standard deviation of 0.001; in column three,  $\vartheta$  has a prior mean equal to the value estimated using a model based measure of the output gap (2.0) and prior standard error of 0.001. As the figure indicates, changing the location and the spread of the prior of  $\zeta$  changes the location of the posterior for  $\vartheta$  but not the conclusion that variations in this parameter are the largest of all, while changing the location and the spread of the prior of  $\vartheta$  produces unreasonably high median estimates for  $\zeta$ , and somewhat larger variations in the risk aversion parameter.

In sum, figure 6 suggests that both the Euler equation and the Phillips curve have been unstable. While policy coefficients and the parameter controlling pricing decisions of firms appear to be relative similar across samples, the parameters describing private agents' utility function show some changes. Hence, while we can exclude the possibility that monetary policy "caused" the observed changes in the output and inflation process, we can also tentatively suggest that modifications in the labor and goods markets, for example along the lines of those suggested by McConnell and Perez Quiroz (2000), have the potential to account for the observed changes in the US economy.

## 5 Conclusions

This paper recursively estimates a small scale DSGE model using US post-WWII data and Bayesian techniques. The model belongs to the class of New-Keynesian models that have been extensively used in the current literature for welfare and other policy analyses. Bayesian techniques are preferable to standard likelihood methods or to indirect inference (impulse response matching) exercises, because the model we consider is clearly false and possibly misspecified. We show that the method delivers reasonable posterior distributions for the structural parameters when priors are broadly non-informative and the policy reaction function schrewdly chosen. We also show that the model tracks the ups and downs of the actual interest rate quite well; that parameter estimates do not imply violations of theoretical orthogonality conditions and that, in a forecasting sense, the model is competitive

with alternative specifications.

We estimate the model a number of times, recursively, using a different starting date, keeping the window size fixed, to analyze the role that monetary policy had in shaping the observed changes in US output and inflation.

We find that the posterior distributions of the policy parameters are relatively stable over samples and there is no posterior evidence in favor of a permanent regime shift from a lax to a tough anti-inflation stance. In particular, the posterior distribution of the inflation coefficient in the policy equation is roughly similar in both the pre-1978 and in the post-1982 period in shape and location. Moreover, there is a remarkable stability in the features of the transmission mechanism of monetary policy disturbances and no posterior evidence that the variance of the policy shocks has systematically decreased. We show that the instabilities in the posterior distribution of the reduced form coefficients of the Phillips curve and the Euler equations are largely due to the instability of the parameters of agents' preference and that these changes are both economically and statistically relevant.

All in all, it appears that the role that monetary policy had in shaping the observed changes in the US economy has been largely overemphasized and that understanding the reasons behind movements in agents' preferences over subsamples is likely to shed important light on the dynamics of output and inflation in the post WWII era.

Our conclusions agree to a large extent to those put forward by Sims and Zha (2004) and Canova and Gambetti (2004), who estimated structural VAR models with time varying (continuously or with Markov switches) coefficients. Relative to their analyses, we are able to go beyond the simple documentation of instabilities and pin down the structural parameters which cause this instability. Our results are also consistent with the analyses of Bernanke and Mihov (1998) and Leeper and Zha (2003). As these authors we find that monetary policy was reasonably characterized by the same interest rate rule for the majority of post WWII sample and that, in many respects, the systematic component of policy in the 1990's was very similar to the one in the 1970's.

To the extent that shocks driving the equations of the model are truly structural, our analysis also suggests that impulses causing business cycle fluctuations have been similar in size across shocks and over samples. Furthermore, given the relatively large magnitude of policy shocks, our results also hints to the fact that macroeconomic performance could have been significantly improved by tightening policymakers ability to attach randomness to their decision rules.

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## Appendix

### The Metropolis-Hasting Algorithm

In order to obtain draws from the unknown posterior distribution of the parameters we use the following algorithm:

1. Choose a  $\alpha_0$ . Evaluate  $g(\alpha_0)$  and use the Kalman filter to evaluate the likelihood  $\mathcal{L}(y_t|\alpha_0)$ .
2. For each  $i = 1, \dots, N$  set  $\alpha_i = \alpha_{i-1}$  with probability  $1 - p$  and  $\alpha_i = \alpha_i^*$  with probability  $p$ , where  $\alpha_i^* = \alpha_{i-1} + v_i$  and  $v = [v_1, \dots, v_N]$  follows a multivariate uniform distribution and  $p = \min\{1, \frac{\mathcal{L}(y_t|\alpha_i^*)g(\alpha_i^*)}{\mathcal{L}(y_t|\alpha_{i-1})g(\alpha_{i-1})}\}$ .
3. Repeat steps 1. and 2.  $\bar{L} + L$  times and discard the first  $\bar{L}$  draws and keep one out of  $J$  of the remaining  $L$  draws to reduce serial correlation.

An important issue concerns the convergence of simulated draws. In particular, it is very important to adjust the variance of the innovations  $v_i$  (that is, the range of the uniform distribution) to get a reasonable acceptance rate. If the acceptance rate is "too small" the chain will not visit the parameter space in a reasonable number of iterations. If it is too high, the chain will have the tendency not to stay long enough in the high probability regions. We use an adaptive scheme to explore the parameter space where for the first 5000 draws the acceptance rate is lower than  $p$  and depends on the size of the posterior kernel at the draw and at the previous value (only draws for which the increment in the posterior is at least 30 percent are kept). In all our samples, the acceptance rate oscillates between 30% to 41%. We draw chains of 50000 elements each time the model is estimated. We check for convergence using the cumulative sum of the draws (CUMSUM) statistics. We found that convergence typically obtains within 25000 iterations. We set  $\bar{L} = 40000$  and choose  $J = 10$ , which means that we keep 1000 draws for each sample for inference.

### The Marginal likelihood

When comparing different model specifications we compute the marginal likelihood of each model. For each model  $\mathcal{M}_i$ , we approximate  $\mathcal{L}(y_t|\mathcal{M}_i)$  using  $[\frac{1}{L} \sum_l \frac{f(\alpha_l^i)}{\mathcal{L}(y_t|\alpha_l^i, \mathcal{M}_i)g(\alpha_l^i|\mathcal{M}_i)}]^{-1}$  where  $\alpha_l^i$  is the draw  $l$  of the parameters  $\alpha$  of model  $i$  and  $f$  is a truncated normal distribution with mean  $\bar{\alpha}^i = \frac{1}{L} \sum_l \alpha_l^i$ , variance  $\Sigma^i = \frac{1}{L} \sum_l (\alpha_l^i - \bar{\alpha}^i)(\alpha_l^i - \bar{\alpha}^i)'$  and the truncation eliminates the region of the parameter space which exceeds a  $\chi^2(k_i)$ , where  $k_i$  is the number of parameters in model  $i$  (see Geweke (1998)). Therefore, the marginal likelihood is computed using the harmonic mean of the draws with weights given by  $f(\alpha_l^i)$ .