Inflation models, optimal monetary policy and uncertain unemployment dynamics: Evidence from the US and the euro area*

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Abstract

This paper explores the role that model uncertainty plays in determining the effect of monetary policy shocks on unemployment dynamics in the euro area and the US. We specify a range of BVARs that differ in terms of variables, lag structure, and the way the inflation process is modelled. For each model the central bank sets the interest rate minimizing a loss function. Given this solution, we quantify the impact of a monetary policy shock on unemployment for each model, and measure the degree of uncertainty as represented by the dispersion of both the policy rule parameters and the impulse response functions between models. The comparative evidence from the US and the euro area data indicates that model uncertainty is indeed an important feature, and that a model combination strategy might be a valuable advise to policymakers.

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1 Introduction

This paper explores the role that the imperfect knowledge of the structure of the economy plays in the uncertainty surrounding the effects of rule-based monetary policy on unemployment dynamics in the euro area and the US.

An extended (empirical and theoretical) literature focuses on the relationship between monetary policy and labour market dynamics (e.g. Brash 1995; and Blanchard 2003). Explanations of why monetary policy shocks seem to have heterogeneous effects on the unemployment performance of different countries have mainly focused on the presence of (i) nominal rigidities (e.g. Jonsson 1997; and Lockwood et al. 1998), (ii) wrong estimates of the NAIRU (e.g. Staiger et al. 1997; and Estrella and Mishkin 1999); and (iii) changes in labour market institutions or on the interactions between shocks and institutions (e.g. Nickell 1997; Blanchard and Wolfers 2000).

The heterogeneous results of these studies, as well as of the various economic and econometric models employed, suggests that the size and the timing of the effect that a monetary policy action might have on labour market variables in general and on unemployment in particular is highly uncertain.

Since Brainard's (1967) seminal paper, a great deal of literature has described how central banks should take uncertainty into account in their decision-making process. Three types of uncertainty are usually identified: data, parameter, and model uncertainty. Authors usually take into account only one source of uncertainty at a time. Orphanides (2001) and Aoki (2003), for instance, focus on whether data uncertainty, reflected in a substantial difference between real-time and final estimates of inflation and the output gap, might produce misleading policy recommendations. Others, such as Sack (1999), Söderström (2002), Orphanides and Williams (2005), and Wieland (2000) analyse the effect that parameter uncertainty might have on the formulation of monetary policy. Finally, Levin et al. (2003), Onatski and Williams (2003), Brock et al. (2004), and Svensson and Williams (2007) concentrate on model uncertainty.

Although with notable differences, overall these studies lead to the conclusion that the effects of a given policy measure on the real activity or on unemployment might largely depend on the three sources of uncertainty a central bank must cope with when formulating its policy. Most of this literature, however, focuses only on how should monetary policy systematically react to changes in unemployment and inflation, and not so much on the effects that the choice of the rule under uncertainty eventually brings about in terms of, say, responses of (and uncertainty around) unemployment to the policy shock.

For instance, a common result when analysing the optimal behaviour that a central bank should follow in response to developments in the economy consists of a considerable difference between the reaction coefficients implied by the optimal policy rules and those implied by the historical evidence. Precisely, the historical behaviour of central banks is usually less aggressive than the one implied by optimal rules. Some authors, such as Rudebusch (2001), and Tetlow and von zur Muehlen (2001), relate this attenuated monetary policy to the uncertainty the policymakers face when setting interest rates.

Our paper aims at bridging the gap between the literature on the effects of monetary policy shocks on unemployment on one side, and the literature on the choice of the policy rule under uncertainty on the other. Concretely, we analyse the effect of a policy action on unemployment by (i) estimating the policy rules, (ii) measuring the impact that a monetary policy based on these rules has on unemployment, and (iii) quantifying the uncertainty surrounding both (i) and (ii). The joined study of the *systematic portion* (i.e. the reaction function) and *the stochastic component* (i.e. the monetary shock) of policy behaviour exhaustively explains the causes of the policy-instrument variability.

We also aspire at providing some reference values for the reaction coefficients in a policy rule and for the responses of unemployment to a monetary policy shock. Our results can therefore be taken as a benchmark for future references, for we explicitly deal with model, parameter and (to some extent) data uncertainty. Our strategy is easily illustrated. We assume that the monetary authority determines the interest rate which minimizes expected losses of a social objective function that depends on the deviations between inflation and unemployment from their target values, and possibly on other contemporaneous and lagged variables, including lags of the policy variables. The economy is alternatively summarised by a range of multivariate models that differ in the way the inflation process is modelled, in terms of the variables entering in the model, and in the lag structure. The structure of the economy is therefore uncertain in the double sense that parameter uncertainty arises from the imprecise estimation of the dynamics of the economy and model uncertainty is defined relative to a certain baseline model as introduced and largely discussed, for instance, by Brock et al (2007), or Onatski and Williams (2003).

The approach we take is Bayesian, and a complete model involving unobservables (e.g. parameters), observables (e.g. data), and variables of interest (e.g. policy rule, impulse response functions) is identified by a joint distribution of these elements. Concretely, if M denotes a model, θ_M denotes unobservables parameters, D denotes the observables, and ω is a vector of interest, then the model M specifies the joint distribution

$$p\left(\theta_M, D, \omega \mid M\right) = p\left(\theta_M \mid M\right) p\left(D \mid \theta_M, M\right) p\left(\omega \mid D, \theta_M, M\right) \tag{1}$$

The objective of inference, then, is expressed as the posterior density of ω:

$$p(\omega \mid D, M) = \int p(\omega \mid D, \theta_M, M)\, p(\theta_M \mid D, M)\, d\theta_M \tag{2}$$

which is the relevant density for the decisionmakers. In this framework, model uncertainty is accounted for with the incorporation of several competing models $M_1, M_2, ..., M_J$; parameter uncertainty is reflected in a series of informative priors on the unobservables $p\left(\theta_{M_j} \mid M_j\right)$; and data uncertainty might be relevant, for the data we rely on are subject to measurement error and can be subject to considerable revision.

The objective is to evaluate the degree of dispersion of $p(\omega \mid D, M_j)$ between models. The use of different data vintages – as represented, for instance, by the latest available series as opposed to the preliminary or real time estimates – can then provide an illustration of the need to take seriously the issue of data revision.

As said, the policymaker minimizes a loss function - subject to the economy as represented by one of the models - and sets up a policy rule (reaction function) which we choose to be of two types: (i) a linear optimal feedback rule (OFR), where the nominal interest rate depends on all observable variables included in the model, and which appear to have a closed-form solution; and (ii) an optimized Taylor rule (TR), where the interest rate is only a function of the current value of the unemployment gap and the inflation rate, similar to the original work of Taylor (1993), and the weights attached to both variables are obtained with a grid search procedure.

In light of uncertainty about the correct model of inflation, we then report the probability distribution of the response of the unemployment rate to a monetary policy shock, and provide various measures of dispersion to quantify the uncertainty surrounding the effects of policy across the model space. In particular, we are interested in checking (i) how the responses vary across models, (ii) how sensitive are the policy rules to model selection; and (iii) how much dispersion in loss occurs when different models are considered to evaluate the responses. The paper can be considered as an extended application of the methodological approach suggested, for instance, by Brock et al (2007). Like in their work all models are equally likely a priori; unlike their assumption we specify informative priors and compare models on the basis of their marginal likelihoods.

Using data for the US and the euro area, we show that simple linear autoregressive models that differ in several dimensions may give rise to a significant degree of uncertainty in the distribution of optimal policy parameters, expected losses and impulse responses. Simple or weighted averages across models help dampen this uncertainty and provide a more consistent representation of the policy rules and of the effects that policy actions based on such rules have on unemployment than the one given by the 'best' model. Although by choosing the best model the policy maker can not be seriously misled about the policy parameters, (s)he might nonetheless incur in a higher associated cost. Results would also recommend choosing a relatively parsimonious representation of the economy, regardless of the country and the policy rules. Finally, even though both the US and the euro area data have a clear preference for a reduced set of models, the differences between the best and the average models may be remarkable. For instance, averaging across models seem to provide impulse responses which are more in line with sound theoretical arguments as, for instance, in the case of the well known “price puzzle”.

The remainder of the paper is structured as follows. Section 2 describes the general framework with the model space and the solution to the central bank’s problem. Section 3 reports the empirical findings in terms of expected loss, policy parameters, and effects of a monetary policy shock on the unemployment gap in the designed uncertainty environment. Section 4 summarizes the paper’s main findings and concludes.

2 Model uncertainty and optimal monetary policy: the macroeconometric framework

In this section we illustrate the empirical framework to answer our questions of interest. The standard elements of the analysis comprise: (i) a set of monetary policy rules; (ii) a monetary policymaker who choose the parameters of the rules minimizing a loss function; (iii) a set of models which summarise the constraints faced by the policymaker in his minimization problem.

The context is quite standard and can be summarised along the following lines.

The set of models account for the uncertainty surrounding the representation of the economy. As described in Brock et al. (2007) model uncertainty can be stemming from sources as different as economic theory, specification conditional on theory, and heterogeneity regarding the data generating process, among others. In our framework we will generate the model space by limiting the analysis to multivariate dynamic linear models (VARs) which entail policy and non-policy variables, with different prior assumptions on both sets of variables, as well as on the lag structure.

The structural behavior of the non-policy variables is assumed to be given by the estimates of the model. Using this estimated structure, the solution to the minimization problem yields the values of the loss function under alternative policy parameters. A given set of these parameters will then minimize the expected loss for each model. The interest rate policy that results from this optimization problem can be a function of all current and lagged variables in the economy (Optimal Feedback Rule), or simply a function of inflation and unemployment gap similarly to the original work by Taylor (1993) (Optimized Taylor Rule), in a way that takes into consideration the dynamic behavior of these variables.

Finally the optimal or optimized rules become part of the interest rate equation in a structural VAR, and its disturbance is used to quantify the uncertainty surrounding the effect of a monetary policy shock on the unemployment gap using a standard Impulse Response Function (IRF) analysis as, e.g., in Stock and Watson (2001).

Next, we detail these elements backwards, starting from the model and then turning to the policymakers and the rules.

2.1 The model space

We start by specifying a range of multivariate linear dynamic models which span the model space. The class of simultaneous equation models considered here takes the following general VAR form:

$$\begin{aligned} Z_t &= \sum_{j=1}^{p} \mathbf{A}_j Z_{t-j} + \sum_{j=1}^{p} \mathbf{b}_j i_{t-j} + \varepsilon_t^z \\ i_t &= \sum_{j=1}^{p} \mathbf{c}_j' Z_{t-j} + \sum_{j=1}^{p} d_j i_{t-j} + \varepsilon_t^i \end{aligned} \tag{3}$$

where Z_t is a vector of non-policy variables; i_t is the policy variable; $\mathbf{A}, \mathbf{b}, \mathbf{c}, d$ are comformable matrices and vectors; ε_t^Z and ε_t^i are vectors of serially uncorrelated structural disturbances.[1]

The characteristics of the model space are easily described.

The non-policy block Z_t contains at least the inflation rate (π_t) and the (negative) unemployment gap ($\tilde{u}_t$), calculated as the difference between the natural rate of unemployment (u_t^*) and its actual value (u_t).

Three sets of prior beliefs shape the dimensions of model uncertainty that characterize the model space. The first one has to do with the way inflation is modelled. Concretely, four general prior assumptions are made according to whether inflation is left unrestricted (UN), or whether it is treated in the system as a random walk (RW), an AR(p) process, or a white noise (WN). In all cases we take a Bayesian perspective and place the needed exclusion restrictions through the allocation of probability distributions to the model's coefficients. The starting point is always a Minnesota-type of prior: in the first case (UN) we complement the autoregressive representation with the specification of a vague prior distribution and a loose tightness on all coefficients; in the other three setups, instead, we assume that inflation follows one of the three processes by setting accordingly the mean of own-lag coefficients, and allow for a much tighter precision placed on all coefficients of the inflation equation as compared to the precision placed on the coefficients of other equations. In other words, priors are always informative and differ in the relative tightness placed on the coefficients in the equation for π_t.

[1] The set up is similar the one used e.g. by Sack (2000) in a related context.

While the RW and the AR hypotheses are relatively standard in the VAR literature (see e.g. Doan et al. 1984; Stock and Watson 2007), the WN assumption has been recently validated in studies on inflation persistence that cover especially the last 10-15 years of sample observations. Benati (2008), for instance, shows that on recent samples the WN assumption might have become a reasonable one in several countries, including UK and the euro area, the latter especially after the creation of EMU.

In the second set of priors, we enlarge the model space by changing the model specification in the non-policy block, and considering all combinations of three additional endogenous variables: the labour force participation rate (pr_t); the exchange rate (e_t); and a commodity price inflation rate (cp_t).

The inclusion of the participation rate is motivated by the possibility of embracing a more comprehensive dynamics of the labour market, as a negative impact on output of an increase in the nominal interest rate may have diverse effects on the non-working labour force and ultimately on the unemployment rate.[2] The inclusion of the participation rate would account for these affects and provide a cleaner picture of the transmission mechanism.

While the inclusion of an exchange rate might not be suitable for the US to have a desirable equilibrium outcome (e.g. Taylor 2001), it might nonetheless be appropriate for the Euro area (e.g. Peersman and Smets 2003; Altavilla 2003). In any case, its inclusion is intended to reflect the external environment, as well as its conditionality role for monetary policy, as it is an important part of the monetary transmission mechanism in an open economy. The monetary policy rule used here, therefore, will react to the exchange rate dynamics as this may help stabilize the economy, for if the central bank responds to exchange rate fluctuations, it might enforce faster convergence of macro variables in response to shocks (see also Svennsson 2000, on this point).

Finally, we include a commodity price inflation rate which should control for the expected future inflation, as it has become customarily in recent applied works on the transmission mechanism of monetary policy shocks (see e.g Sack 2000.).

In the last set of prior assumptions different lag structures model alternative ways of capturing the dynamics of the system. The Wold theorem implies that VAR residuals must be white noise. Sometimes this feature happens to be verified with a parsimonious representation of the lag structure, perhaps with a rich number of endogenous variables. The VAR however easily becomes overparametrised, as the number of coefficients grows as a quadratic function of the number of vari-

[2] In fact, after a recessive shock, non-employed labour force of a given area can (i) remain unemployed, (ii) migrate to another area, or (iii) stop looking for a job and become "discouraged workers". For detailed analysis of these hypothesis and of the concept of discouraged workers see e.g. Long (1953), Benati (2001); Darby et al. (2001); Blundell et al. (1998); Clark and Summers (1982).

ables and proportionately to the number of lags. To trade-off between parsimonious and realistic assumptions, we combine dogmatic with flexible priors and consider models where we progressively fix the lag length p, so that we have models with one, two, three, or four lags. Then, for models where $p > 1$, a tight Minnesota prior on coefficients different from the own lag is used.

Summing up, then, the models space is composed of $128 = 4 \times 2^3 \times 4$ models, i.e. 4 models based on the assumptions on the inflation dynamics; 2^3 combinations of models with a fixed block $[\tilde{u}, \pi, i]$ and three additional non-policy variables; and 4 lag assumptions, from $p = 1$ to $p = 4$ for each model. Each model is seen as a particular representation of the economy that the central bank may assume when solving its dynamic control problem to appropriately set the interest rate.

2.2 The Central Bank's Problem

The central bank minimizes an intertemporal loss function that has a positive relationship with the deviation between target variables and the target levels for these variables:

$$L_t = E_t \left\{ \sum_{\tau=0}^{\infty} \delta^{\tau} \left[\vartheta \tilde{u}_{t+\tau}^2 + \lambda \pi_{t+\tau}^2 + \gamma \left(i_{t+\tau} - i_{t+\tau-1} \right)^2 \right] \right\} \tag{4}$$

where E_t denotes the expectations conditional upon the available information set at time t, while δ is a given discount factor, with $0 < \delta < 1$. Moreover ϑ, λ, and γ are non-negative weights the central bank attaches to inflation stabilization, unemployment gap and interest rate smoothing, respectively.

We assume an inflation target of zero percent. As a benchmark for our analysis, we also assume $\vartheta = 4$, $\lambda = 1$, and $\gamma = 0.5$. Based on an Okun's gap type of relationship, the variance of the unemployment gap is about 1/4 of the variance of the output gap, so this choice of ϑ corresponds to equal weights on inflation and output gap variability.[3]

As shown in Rudebush and Svensson (1999), for $\delta = 1$, we can rewrite the optimization problem interpreting the intertemporal loss function as the unconditional mean of the period loss function. Specifically, the loss function can be written as the weighted sum of the unconditional variances of the goal variables:

$$E\left[L_t\right] = \vartheta Var\left[\tilde{u}_t\right] + \lambda Var\left[\pi_t\right] + \gamma Var\left[i_t - i_{t-1}\right] \tag{5}$$

The aim is to minimize this loss subject to

$$X_{t+1} = \Xi X_t + \Psi i_t + \eta_{t+1} \tag{6}$$

[3] We also checked how sensitive are results to alternative settings. In particular we were able to confirm the previous findings of the literature that the posterior distribution of the policy reaction to both unemployment and interest rate shifts monotonically with the values of these parameters in a reasonable range. These changes in the policy rules, however, do not seem to have a significant effect on the shape or the magnitude of the impulse response functions.

which is the State space representation of the VAR (3). The dynamic of the state is governed by the matrix Ξ and the vector Ψ whose values are given by the point estimates of the corresponding VAR coefficients, and depend on the particular model considered in the estimation. As a consequences, we have 128 state-space representations for each country. For example, in a model with 4 non-policy variables with two lags under the unrestricted prior for inflation, the state space has the following representation:

$$X_t = \begin{bmatrix} \tilde{u}_t \\ \tilde{u}_{t-1} \\ pr_t \\ pr_{t-1} \\ e_t \\ e_{t-1} \\ \pi_t \\ \pi_{t-1} \\ i_{t-1} \end{bmatrix}, \Xi = \begin{bmatrix} a_{11}^1 & a_{11}^2 & a_{12}^1 & a_{12}^2 & a_{13}^1 & a_{13}^2 & a_{14}^1 & a_{14}^2 & b_{15}^2 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21}^1 & a_{21}^2 & a_{22}^1 & a_{22}^2 & a_{23}^1 & a_{23}^2 & a_{24}^1 & a_{24}^2 & b_{25}^2 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31}^1 & a_{31}^2 & a_{32}^1 & a_{32}^2 & a_{33}^1 & a_{33}^2 & a_{34}^1 & a_{34}^2 & b_{35}^2 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ a_{41}^1 & a_{31}^2 & a_{42}^1 & a_{42}^2 & a_{43}^1 & a_{43}^2 & a_{44}^1 & a_{44}^2 & b_{45}^2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \Psi = \begin{bmatrix} b_{15}^1 \\ 0 \\ b_{25}^1 \\ 0 \\ b_{35}^1 \\ 0 \\ b_{45}^1 \\ 0 \\ 1 \end{bmatrix}, \eta_t = \begin{bmatrix} \eta_t^u \\ 0 \\ \eta_t^{PR} \\ 0 \\ \eta_t^e \\ 0 \\ \eta_t^\pi \\ 0 \\ 0 \end{bmatrix}$$

Writing the target variables as a function of the state variable X_t we have:

$$Y_t = \begin{bmatrix} \tilde{u}_t \\ \pi_t \\ i_t - i_{t-1} \end{bmatrix} = C_X X_t + C_i i$$

with

$$C_X = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \end{bmatrix}, \text{ and } C_i = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

The loss function can therefore be expressed as:

$$\begin{aligned} E(L_t) &= E\left[Y_t' K Y_t\right] \\ &= trace\,(K\Sigma_{yy}) \end{aligned}$$

where

$$K = \begin{bmatrix} \vartheta & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \gamma \end{bmatrix}$$

and Σ_{yy} is the unconditional variance matrix of the goal variables.

2.3 The policy rules

Following Rudebush and Svennsson (1999), we consider a general feedback instrument rule which has the following linear form:

$$i = fX_t \tag{7}$$

where f is a conformable row vector.

The problem of minimizing in each period the loss function in (4) subject to (6) is standard,[4] and results in an optimal linear feedback rule which, under the limit assumption of $\delta = 1$, converges to a vector f that fulfills:[5]

$$f = -\left(R + \Psi' \Lambda \Psi\right)^{-1} \left(U' + \Psi' \Lambda \Xi\right) \tag{8}$$

The optimal value of (5) is given by

$$E\left(L_t\right) = trace\left(\Lambda \Sigma_{\eta\eta}\right). \tag{9}$$

This rule is less restrictive than a classical Taylor rule, as in this case the interest rate is a function of all current and lagged values of the non-policy variables and lagged values of the interest rate.

We also compare results to those obtained under an optimized classical Taylor rule that allows the interest rate to react only to unemployment gap and inflation, that is:

$$\begin{aligned} i_t &= f \cdot \begin{pmatrix} \tilde{u}_t \\ \pi_t \end{pmatrix} \\ f &= \left[f_{\tilde{u}}\left(\Xi, \Psi\right) \quad f_{\pi}\left(\Xi, \Psi\right)\right] \end{aligned} \tag{10}$$

where we have made explicit that the parameters of the rule depend on the VAR coefficients in an open form, and need to be recovered with an optimization routine.[6] Note that if we set to 3 the coefficient in the Okun's law, the values of the coefficients corresponding to the ones suggested by Taylor (1993) would be $f_{\tilde{u}} = f_{\pi} = 1.5$ with $r_t^* = \pi_t^* = 2$.[7]

In our empirical exercise we also allow for the presence of a lagged interest rate, as most previous estimates of the same rule find that the latter has a significant effect, possibly capturing an interest rate smoothing (e.g. Clarida et al. 2000), or other relevant but omitted macroeconomic variables (e.g. Sack 2000).

[4] See Rudebush and Svensson (1999) for the derivation of the unconditional variance of the goal variables.

[5] Where the matrix Λ satisfies the Riccati equation: $\Lambda = Q + Uf + f'U' + f'Rf + M'\Lambda M$ and $M = \Xi + \Psi f$, $C = C_X + C_i f$, $Q = C_X' K C_X$, $U = C_X' K C_i$, $R = C_i' K C_i$.

[6] The policy rules considered in the analysis are alternative specifications of the classic rule proposed by Taylor (1993). When considering the unemployment gap (instead of the output gap), the Taylor rule (TR) has the following generic form: $i_t = r_t^* + \pi_t^* + f_\pi\left(\pi_t - \pi_t^*\right) + f_u\left(u_t^* - u_t\right)$, where the interest rate (i_t) depends on the "natural" interest rate (r_t^*), the deviation of actual inflation (π_t) from a constant given inflation target (π_t^*) and the difference between the natural rate of unemployment (u_t^*) and its actual value (u_t).

[7] Stock and Watson (2001) use a coefficient of 2.5 in the Okun's law, implying $f_u = 1.25$; Orphanides and Williams (2005) use a coefficient of 2 in the Okun's law, which implies $f_u = 1$. This range of values is approximately taken as a benchmark in our empirical examination.

3 From the models to the data

In this section, we apply the framework illustrated above to US and euro area data, describe carefully the estimation technique and present the results in terms of properties of the model and impulse response dispersion.

3.1 Data and transformations

The data are quarterly values of inflation, interest rate, unemployment rate, exchange rate, labour force participation rate, and a commodity price index for the euro area and the US, covering 1970:1 to 2006:4. Sources are Datstream and the Area Wide Model (AWM) database (Fagan et al., 2005).

The inflation rate is calculated as the four-quarter percentage change of CPI. The US interest rate is the Federal Funds rate; the euro area interest rate is the short-run rate of the AWM database. The unemployment gap is calculated as the difference between the natural rate of unemployment (u_t^*) and its actual value (u_t). The former in turn is computed with Baxter and King (1999) detrending approach. Exchange rates and commodity price are used in standardized four-quarter growth rates. All series are demeaned.

3.2 Estimation algorithm

The reduced form of (3) is estimated using Bayesian techniques and informative priors. Concretely, if β denotes the vector of all VAR coefficients and Σ denotes the variance-covariance matrix of the reduced form disturbances, then $\theta_{M_j} = (\beta, \Sigma \mid M_j)$. Given the data as summarised by the likelihood $p\left(D \mid \theta_{M_j}, M\right)$, and a prior distribution $p\left(\theta_{M_j} \mid M_j\right)$, the Bayesian algorithm implies obtaining the posterior $p\left(\theta_{M_j} \mid D, M_j\right)$. In turn, given the estimated dynamic behavior of the non-policy variables as summarised by the latter posterior distribution, we solve the minimization problem and recover the distribution of the parameters of the rule that minimize the loss function.[8] If we denote with ω_1 the vector of such parameters, its posterior distribution $p\left(\omega_1 \mid D, M_j\right)$ is derived from

$$p\left(\omega_1 \mid D, M_j\right) = \int f \cdot p\left(\theta_{M_j} \mid D, M_j\right) d\theta_{M_j} \tag{11}$$

where f is given by (8) or (10).[9] Finally, given the posterior mean of ω_1, we compute the distribution of the unemployment response to a monetary policy shocks. The algorithm is applied for each model M_j, country and policy rule.

[8] Following Sack (2000), the reaction function estimated from the VAR is ignored when solving the central bank's minimization problem.

[9] Note that the policy rule is assumed to be deterministic. Therefore its posterior uncertainty fully derives from the uncertainty of the VAR coefficients.

The following independent prior assumption is specified for each model (now omitting M_j):

$$\begin{aligned} p(\theta) &= p(\beta)\,p(\Sigma) \\ p(\beta) &= N\left(\underline{\beta}, \underline{V_\beta}\right) \\ p\left(\Sigma^{-1}\right) &= W\left(S^{-1}, \nu\right) \end{aligned}$$

where $W\left(S^{-1}, \nu\right)$ denotes a Wishart distribution with scale matrix S^{-1} and degrees of freedom ν; and $N\left(\underline{\beta}, \underline{V_\beta}\right)$ denotes a Normal distribution with mean $\underline{\beta}$ and variance-covariance matrix $\underline{V_\beta}$.

The general form of $p(\beta)$ in all models is the one of a Minnesota-type of assumption, where the prior mean of coefficients for the first own lag is equal to one and the others are set equal to zero; individual components of β are independent of each other, i.e. $\underline{V_\beta}$ is a diagonal matrix; and the diagonal elements of $\underline{V_\beta}$ have the usual structure:

$$v_{ij,l} = \begin{cases} (\gamma_1/l)^2 & \text{if } i = j \\ (\gamma_1\gamma_2\sigma_i/l\sigma_j)^2 & \text{if } i \neq j, \end{cases} \tag{12}$$

where $v_{ij,l}$ is the prior variance of $\beta_{ij,l}$ (coefficient in equation i relative to variable j at lag l), γ_1 is the general tightness, γ_2 is the tightness on "other coefficients", and l is the lag.

For all models we assume $\gamma_1 = 0.1$ and $\gamma_2 = 1$, and estimate the variances σ_i and σ_j from AR(p) regressions on a training sample (1971:1-1990:4). In all restricted models for inflation (AR, RW and WN) the own-lag coefficient of the prior mean $\underline{\beta}$ is set accordingly, and the tightness is set to $10^{-3}\gamma_1$. For the AR assumptions the own-lag coefficients of the prior mean $\underline{\beta}$ are estimated on a training sample with univariate AR(p) regressions.

Regarding the prior for Σ, the prior scale matrix S is set equal to $10^{-1}I$, and the degrees of freedom ν equal $n + 3$, thus ensuring an informative but relatively vague prior assumption for Σ.

Given the independent structure of the prior, a closed form solution for the posterior distribution of the parameters of interest is not available. It is easy to show, however, that a Gibbs sampler can be employed because the full conditional distributions $p(\beta \mid \Sigma, D)$ and $p(\Sigma \mid \beta, D)$ are easily derived (see Appendix). The sampler is initialised using the ML estimate of Σ on a training sample. For each draw of $\theta = (\beta, \Sigma)$, then, the parameters of the rule are derived from the minimization problem. This algorithm provides the posterior distribution (11).

In the case of the optimised Taylor Rule, we use a grid search procedure to solve for the values of f that minimize the criterion function (5). Because the computation with high-order models becomes immediately cumbersome, we solve the optimisation problem by using the posterior mean of β and Σ, instead of grid-search for each draw of them.

In the case of the optimal feedback rule, instead, the computational burden is not so heavy, for the optimal values of (8) and (9) are straightforward to compute. However, in order to ensure that the parameters of the rule have meaningful signs, we restrict the prior to be

$$q(\theta) = p(\theta) \cdot \Im(\omega_1 \in \mathcal{F})$$

where $\Im(\omega_1 \in \mathcal{F})$ is the indicator function that equals 1 if $\omega_1 \in \mathcal{F}$ and 0 otherwise, and $\mathcal{F}$ is the relevant region. The corresponding posterior distribution is therefore $q(\theta \mid D) = p(\theta \mid D) \cdot \Im(\omega_1 \in \mathcal{F})$. Strictly speaking, an importance sampling algorithm should be used instead of the Gibbs sampling, and an importance function elicited. It is easy to show, however, that if the importance function is the unrestricted posterior distribution we can still rely on the Gibbs sampling, drawing from the unrestricted posterior and discarding draws which violate the restrictions.[10]

Finally, an equal prior probability $p(M_j) = 1/J$ is assigned to each model, therefore the posterior probability of the models is proportional to their marginal likelihood, i.e.

$$\begin{aligned} p(M_j \mid D) &= \frac{p(M_j)\, p(D \mid M_j)}{\sum_j p(M_j)\, p(D \mid M_j)} \\ &= \frac{p(D \mid M_j)}{\sum_j p(D \mid M_j)} \end{aligned} \tag{13}$$

where $p(D \mid M_j) = \int p\left(D \mid \theta_{M_j}, M\right) p\left(\theta_{M_j} \mid M\right) d\theta_{M_j}$ is the marginal likelihood of model M_j. An analytical evaluation of this integral is not possible given our prior assumptions, therefore we simulate it from the Gibbs output using the harmonic mean of the likelihood values at each draw of θ (Newton and Raftery, 1994).[11]

Results (discussed in the next subsections) are based on 10000 iterations of the Gibbs sampling, after discarding an initial 5000 burn-in replications and using the remaining 5000 for inference.

3.3 Properties of model space and rules

We describe here some properties of the model space focusing on the Marginal Likelihood, the parameters of the rules, and the expected losses.

Table 1 reports summary statistics on the distribution of the Relative Marginal Likelihood (RML) across all models, for both the US and the euro area (EA). The RML is defined as in (13), where j goes from 1 to 128. Given the prior assumption that the models are all equally likely, the RML gives the posterior model probability which measures how likely the data believe a given model to be the correct one.

[10] In particular we assign a zero weigth to negative values of the parameters attached to the negative unemployment gap, the inflation gap and the lagged interest rate.

[11] As it is well known (Kass and Raftery 1995), the harmonic mean converges almost surely to the correct value but does not generally satisfy a Gaussian central limit theorem. The measure can therefore be unstable, but it has proven to provide more reliable estimates than, for instance, Chib's (1995) measure (see Osiewalski and Pipien, 2004; Canova and Ciccarelli, 2008).

The marginal likelihoods turned out to be substantially different across models, as shown by the difference between the higher and the lower part of the distribution, and by the fact that only for 13 percent of the models for the US and 25 percent for the euro area the RML is greater than the equal weight (EW).

Table 1 about here

The finding can be better appreciated from Figure 1, where we plot the RML of each model. Models are ordered according to the number of variables: the first 16 models are specified with three variables; the next 48 models contain four variables, and so on. The exact place of each model is described in appendix A (Table A1).

The data seem to support relatively parsimonious models, as the figure shows that the best models are clustered around specifications with 3 and 4 variables. The same specification with 4 variables which includes the participation rate is the preferred one both for the US and for the euro area data. Interestingly, the models which receive less support by the data always include the depreciation rate, regardless of the other variables included and of the country.

Figure 1 about here

Table 2 reports the estimates of the loss and of the relevant long run parameters of the Optimal Feedback Rule (OFR) and the Taylor Rule (TR) relative to the models with the highest and the lowest marginal likelihood. Note that while there is not much difference in the losses across models and rules, optimal policy parameter estimates might vary substantially. Interestingly, the OFR estimates relative to the best model are not only consistent with the literature, but also broadly in line with the original (1993) Taylor rule. Moreover, losses seem to be smaller for both countries and rules in the models with the lowest RML. A regression analysis across models, however, does not seem to confirm any clear pattern between the posterior probability of a given model – as summarised by the marginal RML – and the optimal policy parameters or the associated expected losses (see below).

Table 2 about here

Standard decision theory arguments imply that it is not desirable to simply rely on results for the best model, regardless of the selection criterion, as this practice ignores both model and parameter uncertainty. The distributions of the optimal policy parameters and the associated expected losses across models therefore are summarised in Figure 2 and 3.

In Figure 2 we report the posterior distributions of the relevant parameters and of the losses relative to the OFR, for each model. The solid black line that goes through the areas is the posterior median of each model. The shaded areas comprise the 99 percent of the posterior distribution around it, as in a fan chart representation: there is an equal number of bands on either side of the central band. The latter covers the interquartile range and is shaded with the deepest intensity. The next deepest shade, on both sides of the central band, takes the distribution out to 80%; and so on, until the 99% of the distribution is covered.

We represent the models on the x-axes organised according to some level of complexity. Models are ordered first according to the prior for inflation (the first 32 models correspond to the UN prior, the subsequent to the RW, then to the AR, and the last 32 models to the WN), and then, inside each prior, they are sorted in ascending lag length order.

Figure 2 about here

In Figure 3 we summarise instead the distribution of the optimal policy parameters and expected losses by only taking the posterior median across models. In this way we can visually compare results also across the two rules.[12] The box plots report therefore the extreme values and the interquartile ranges computed using the posterior medians across the 128 models in a given class (OFR or TR) of the relevant policy parameters $f_u/\left(1-f_i\right)$, $f_\pi/\left(1-f_i\right)$ and f_i that yielded the minimum expected loss. The empty circles in the box plot are the weighted averages of the results, where the weights are given by the RML. The filled square represents instead results associated with the best models.

Figure 3 about here

Four sets of considerations emerge from the analysis of these charts.

First, the ranges of results are on average consistent with previous literature, as the bulks of the distributions are concentrated on values in line both with the theory and with previous empirical

[12] Recall that due to the complexity of the grid search in the TR, we simulate the posterior distribution of parameters and losses only for the OFR, whereas for the TR we compute the estimates of f using the posterior mean of $\theta = (\beta, \Sigma)$.

findings. This is true for both classes of rules, which also deliver very similar results. The dispersion across models seems to be only marginally larger for the TR than for the OFR in both countries.

A closer look shows that the rough interquartile range of the optimal long-run reaction of unemployment is $[1.3 - 3.5]$ for the US and $[0.3 - 1.8]$ for the euro area; the long run reaction of inflation is in the range $[1.2 - 2.5]$ for the US and $[1.5 - 2.7]$ for the euro area; and the lagged interest rate coefficient is in the range $[0.1 - 0.7]$ for both countries. The weighted averages and the results associated with the best models are very much similar to the median values. These findings indicate that in both countries the policies have on average been marginally more aggressive than the original Taylor rule, and that there seem to be a significant effect of the lagged interest rate, which indicates that interest rate smoothing is a robust feature of the policy. Very similar results have been found by Brock et al. (2007), Levin and Williams (2003), and Clarida et al (2000), among others, for the US; and by Smets and Wouters (2005), and Gerlach and Schnabel (2000), among others, for the euro area.

Not surprisingly, results are also fairly consistent with the somewhat expected idea that the long run reaction of the euro area policy rate to inflation is greater than the one to real activity. The opposite seems to be true on average for the US policy, which gives slightly less weight to inflation than to the unemployment gap. The comparison across countries also shows that on average the US policy is more reactive to the unemployment gap than the euro area policy, whereas the latter is more reactive to the inflation gap than the US policy.

Second, there is a higher posterior uncertainty around the US estimates of the policy parameters than around the euro area ones, as the more disperse distribution around US values seems to indicate in Figure 2. This might be the result of different sampling variability across the two data sets together with the use of the same model specifications and similar informative priors. Note, however, that this result does not seem to hold when we consider the uncertainty around the expected losses, which is fairly similar in both countries.

Third, some clear clusters with respect to expected losses seem to emerge across models. Figure 3 shows that the expected losses associated with the US policy parameters are overall lower than those associated with euro area parameters for both rules. The range of values is again compatible with the existing literature that uses similar values for the weights in the loss function, and, if anything, our estimates seem to be on the lower side (see e.g. Brock et al., 2007; and Rudebush and Svennson, 1999 for a comparison). Another feature we have noticed if we ordered in Figure 2 the losses following an ascending level of complexity as determined first by the lag length, is that specifications with one lag display a less volatile expected loss and a lower median level (the latter is particularly evident in the case of US). This would imply that the more complex is the model economy, the higher and more imprecise is the expected loss that the policy maker faces. The result would then suggest as a strategy for the policy maker to choose parsimonious models, although they do not necessarily correspond to the ones with the highest RML. As a matter of fact, a clear connection between the posterior probability of the models and the associated expected losses is faded, as a scatter plot of both measures would show (Figure 4), although the chart in Figure 3 shows that losses associated with the best models (the filled square symbols in the box plots) are always in the upper tail of the distributions.

If instead we look at the order the losses according to the prior assumption for inflation, there is an overwhelming evidence that, for the AR prior, losses are systematically higher regardless of the country and of other rearrangements. Notably, under the AR prior the values of the losses are on average much closer to those that have been found in similar estimations by previous studies, as our AR prior resembles more closely their estimation assumptions.

Figure 4 and 5 about here

Finally, there is a clear negative relationship which relates the optimal policy parameters and the model complexity as represented by the lag length, as in each block of 32 models the median values are clearly decreasing. This pattern is persistently more evident for the euro area than for the US, and also confirms previous results (see e.g. Brock et al. 2007). Moreover, if we scatter plot the policy parameters against the posterior weights of the model (RML), we find a significant negative relationship, which is particularly evident if we restrict the attention to the models with the highest posterior probability and to the long run reaction of unemployment and inflation rate (Figure 5). This finding might not be surprising, and somewhat confirm the prior idea that the models preferred by the data are associated with policy parameters which are a priori regarded as more likely by the profession.

In sum, all charts and tables discussed in this section confirm that simple linear autoregressive models that differ in several dimensions may give rise to a significant degree of uncertainty in the distribution of optimal policy parameters and expected losses. Simple or weighted averages across models help dampen this uncertainty and provide a more consistent representation of the policy rules than the one based on 'best' models selected using their posterior probability. Although by choosing the best model the policy maker can not be seriously misled about the policy parameters, (s)he might nonetheless incurr in a higher associated cost. Results – that are very much consistent with previous literature – would also recommend choosing a relatively parsimonious representation of the economy, regardless of the country and the policy rules.

3.4 Uncertain effects on unemployment: Impulse response dispersion

In this subsection we report the probability distribution of the unemployment gap response to a monetary policy shock and measure its dispersion in light of the uncertainty about the correct model discussed above.

Using the structural VAR in (3), we assume that the central bank sets the policy variables i_t according to the two policy rules OFR and TR as estimated in the previous step. The estimated equation error ε_t^i can be interpreted as a monetary policy shock, as also discussed e.g. by Stock and Watson (2001), or Sack (2000). The shock is identified by (i) replacing the parameters of the policy equation with the posterior means of the f estimated above, while leaving unrestricted all the other parameters of the VAR; and (ii) imposing the timing assumption that the central bank reacts contemporaneously to all variables in the economy, whereas the policy rate does not contemporaneously affect the rest of the economy. The former restriction is placed in the form of a normal distribution with a very tight variance. The latter restriction is a pure zero-restriction. A relatively vague Minnesota prior is assumed on the rest of parameters in the two blocks.

How do the impulse responses of (negative) unemployment gap to a surprise 100 basis point increase in the policy rate look like? Before examining the degree of dispersion across models, rules and countries, and focus only on the reaction of unemployment, we plot in Figure 6 the impulse responses of unemployment, inflation and interest rate computed averaging over all models with the optimal feedback rule and the Taylor rule, for both the US and the euro area. Dashed lines represent the 68 percent confidence bands computed for the OFR.

Note that the responses have the expected signs across countries and rules, and, except for the somewhat uncertain response of inflation in the euro area, they are also significant. The impacts do not seem statistically different across rules in the two countries, as both rules are backward-looking. There are however some differences across countries in the responses of both unemployment and inflation, in the lags and the magnitude. Average responses are somewhat more pronounced in the euro area. Cumulatively after 36 quarters the effect on the unemployment gap is on average of 0.2 percentage point for the US and between 0.3 (TR) and 0.5 (OFR) for the euro area, whereas the effect on inflation is on average of 1.0 percentage point in the US, and between 1.2 (OFR) and 1.6 (TR) percentage points in the euro area. Note finally that, as in previous studies (see e.g. Stock and Watson, 2001 for the US and Peersmann and Smets, 2003) the lags of inflation are quite long and most of the decline occurs between the third and the fourth year after the monetary contraction across both countries and rules.

Figure 6

We turn now to focus on the reaction of the unemployment rate across models. In Figure 7 we report these responses for both countries and rules. To jointly visualize the dispersion within and between models we report the posterior distribution of the IRF obtained from the MCMC simulation by 'fan-charting' separately three quantiles of such distributions – the median responses, the 16th percentile and the 84th percentile – for all models. Therefore, in the charts with the title 'median', for instance, we plot the 'fan-chart' distribution of the median responses across models. In each chart, the shaded areas represent the dispersion across models. The principle is the same as in a fan chart representation: There is an equal number of bands on either side of the central band. The latter covers the interquartile range across models and is shaded with the deepest intensity. The next deepest shade, on both sides of the central band, takes the distribution out to 80%; and so on, until the 99% of the distribution is covered. The solid black line that goes through the areas is the weighted average of each quantile (median, 16th and 84th percentile) across models, where the weights are given by the RML of each model.

Several comments are in order.

First, the impulse responses look reasonably well behaved and their pattern fairly robust across models, countries and rules. An important dimension of such robustness is that, although model responses are dispersed, significance of the average results at the expected horizons appears to be a robust feature. Given the timing assumption, the initial rate hike results in a null contemporaneous effect on the economy. On average across models, rules and countries most of the significant economic slowdown occurs in the first two years after the rate hike, when the cumulative impact on the unemployment gap is between -0.2 and -0.4 percentage points, on average across models, rules and countries. Some differences between countries have already been highlighted above.

Second, overall the results do not seem to be extremely sensitive to the policy rule used in the identifying assumption of the structural VAR. The result does not come entirely as a surprise, for both rules are backword-looking, although the OFR is less restrictive than TR being a function of all current and lagged values of the non-policy variables and lagged values of the interest rate.

Third, there is a reasonable degree of uncertainty across models, for a given rule or country, which is a direct consequence of the dispersion of policy parameters. Interestingly, results for the euro area are in general much more dispersed than those for the US. This is particularly true at all steps for the OFR and at the longer steps for the TR, as shown also in Figure 8 where we report the standard deviation at each step of the impulse responses across models. This evidence suggests that, even if the degree of dispersion in the distribution of policy parameters and expected losses is broadly similar across country, the conclusion on the effects of a monetary policy shock can be more uncertain possibly due to a different sampling variability or a different interactive dynamics of the variables in the two model economies. With the exception of the TR for the euro area, the uncertainty is also bigger around the peak values of the responses, usually between one and two years.

Figure 7 and Table 3 about here

Fourth, a complementary inference can be derived from Table 3, where we quantify the information contained in Figure 7, and report the cumulative impacts between horizons. These numbers can provide useful benchmark references for future studies that wish to quantify the effect of a monetary policy shock in the US and the euro area, if such quantification is obtained with a structural VAR model that uses similar variables over an analogous sample of data. One conclusion is that the effect is certainly significant between 1 and 8 quarters in both countries. Another conclusion is that quantitative results, which are relatively similar for different rules in each country, differ across countries: the cumulative average impact in the euro area after two years is around 0.45, whereas the same impact for the US is around 0.3.

Figure 8 about here

Finally, given the relatively high degree of uncertainty, it is recommendable that the policy implications would not be derived conditionally on a single model but rather on a weighted average. Note from the black line in the charts of Figure 6 and the numbers of Table 3 that the weighted average across models always provides a lower response than the median model. This implies, among other things, that the models which receive more support by the data – and therefore are weighted more in the average – tend to dampen the response of unemployment to a monetary policy shock relatively to the other models.

A question arises naturally then: Would the policy maker who chooses a single model come to a very misleading conclusion about the effect of a monetary policy shock? Part of the answer can be found in Figure 9, where we plot the average responses of the three main variables together with the responses obtained from the best models. In both cases we focus on results obtained under our preferred rule (OFR).

Figure 9 about here

Differences do seem relevant in both countries. In particular, the response of the unemployment gap in the best models are more pronounced for the two countries, both at the peak and cumulatively. Even more interestingly, while the response of inflation computed from the best model shows a "price puzzle" for both countries – more markedly significant for the US than for the euro area economy – with consequent associated long lags, the average responses computed across all models almost eliminate the initial upward swing and provide a more reasonable timing and magnitudes of the inflation responses.

Some important conclusions can therefore de drawn from the whole discussion. One conclusion is that the average results for the US and the euro area are qualitatively similar, with the latter being more dispersed than the former. Another conclusion is that dispersion across models is a feature not only of the policy rules but also of the impulse response functions, and that policymakers face considerable uncertainty about the future development of relevant variables and the impact of a given measure. Averaging is therefore a good advise to the policymaker to dampen out this dispersion. Finally, even though the data have a very strong preference for a small subset of models, the differences between the best and the average models may be remarkable, with the results of the latter being more in line with theoretical arguments as, for instance, in the case of the cutback of the well known "price puzzle". Overall, therefore, our results confirm that the model-combination strategy that central banks already follow when assessing the risks to price stability or deciding a given policy is indeed an appropriate strategy.

3.5 The real-time dilemma: Preliminary vs. latest available data

We conclude our empirical exploration with a simple additional exercise, and check how sensitive might the previous results be to data uncertainty, by estimating the policy rules and running the same impulse response analysis on preliminary instead of fully revised data.

The idea is that all relevant information for monetary policy is measured with error. As early releases of data can be noisy, the difference between the response coefficients obtained using real-time vs. fully revised (or latest available) data might measure the uncertainty that policymakers face when making decisions using policy rules.

The scope of this analysis is much more limited than the one conducted above. In particular: (i) we focus only on US data, as the real-time data for the euro area have a much smaller coverage; (ii) we consider only the simplest set of models with three variables, as none of the additional variables included in the extended models is either revised or simply available in the existing real-time data sets. Moreover, we use a different definition for inflation and take the growth rate of the output deflator, which is a variable subject to revision, whereas the CPI used so far is typically not revised.

In this way we have two (unemployment and inflation) of the three variables of the VARs subject to revision, instead of just one (unemployment).

The data used come from the real-time data set for macroeconomists, developed at the Federal Reserve Bank of Philadelphia and described in great details for instance in Crushore and Stark (2001).

Table 4. about here

Table 4 reports the average rule coefficients for the three variables of interest and the two rules across models. Consistently with the results of previous studies (see e.g. Aoki 2003; and Jarkko and Yates 2005), the response coefficients in both the optimal feedback rule and the Taylor rule are higher when we run the estimation with the data available in real-time, which implies that both policies might be more aggressive than what a revision of data would entail.

In line with the previous literature, therefore, our results also strengthen the case for a more cautious monetary policy strategy. Specifically, in order to reduce policy mistakes, central banks should not react strongly to out-of-target developments in inflation and unemployment gap and should attenuate the response coefficients in an optimal policy rule, for the measurement error in early vintages of data significantly affects the real-time results with the consequence that a fine-tuning monetary policy might amplify the business cycle.

How much sensitive could then be the response of unemployment to a monetary policy shock given these differences in the policy rules due to the various data vintages? A simple way of answering this question is to visually compare the difference between the impulse responses obtained with the two sets of data. Figure 10, for instance, compares the weighted average across models of the median, the 16th and 84th percentile responses (36 steps) obtained using the fully revised data set (vertical axis) with the same percentiles based on real time data (horizontal axis). If the response functions were unaffected by the data sets, we should expect all points to lay on the 45 degree line.

Figure 10 about here

The charts indeed show some notable divergence, as the points summarizing the impulse response distribution tend to deviate from the diagonal for both the optimal feedback rule and the Taylor rule. Data revisions therefore affect the probability distribution of the unemployment response to a monetary shock, though the differences seem quantitative in line with the uncertainty and the ranges reported in the previous subsection, and not as much informative as one would argue.

This simple experiment would therefore indicate that the analysis conducted in real-time to evaluate the effects on unemployment of a monetary policy shock would not lead to a significantly different conclusion from an ex-post one based on fully revised data. This is in part due to the limitation of the current comparison. As stressed in another paper (Altavilla and Ciccarelli 2007), results based only on the comparison between preliminary vs. latest available data might not be as informative as those that would instead be based on all available vintages or revisions. Our recommendation in evaluating the use of real-time data in policy experiments – to check if and how revisions systematically affect the results – would be for a much more comprehensive approach that makes use of the whole revision process. Such an extension goes however well beyond the scope of this paper.

4 Conclusions

This paper has shown that model uncertainty plays a crucial role in determining the effects of monetary policy shocks on unemployment dynamics in the euro area and the US.

Following previous methodological works, for instance by Brock et al (2007), we have specified a range of 128 BVAR models that differ in terms of variables, lag structure, and the way the inflation process is modelled. Each model is a constraint for the central bank which sets the interest rate minimizing a loss function. Given the solution in terms of policy rule, we quantify the impact of a monetary policy shock on unemployment, and measure the degree of uncertainty as represented by the dispersion of both the policy rule parameters and the impulse response functions across models.

The comparative evidence from the US and the euro confirm that simple linear autoregressive models that differ in several dimensions may give rise to a significant degree of uncertainty in the distribution of optimal policy parameters, expected losses and impulse response functions. Simple or weighted averages across models help dampen this uncertainty and provide a more consistent representation of both the policy rules and the effects on unemployment than the one based on 'best' models selected using their posterior probability. Moreover, even though the data seem to have a very strong preference for a small subset of models, the differences between the best and the average models may be remarkable. In particular averaging across models seem to provide impulse responses which are more in line with theoretical arguments as, for instance, in the case of the cutback of the well known "price puzzle".

We have also shown that, even though by choosing the best model the policy maker can not be seriously misled about the policy parameters, (s)he might nonetheless incur in a higher associated cost. Results – that are very much consistent with previous literature – would also recommend the choice of relatively parsimonious representations of the economy, regardless of the country and the policy rules. Overall our results –which are very similar for US and the euro area – confirm that the model-combination strategy that central banks already follow when assessing the risks to price stability or deciding a given policy is indeed an appropriate strategy.

To some extent, and given the scope of the analysis, our quantitative results can also be used as references for the quantification of policy rules and impulse responses in similar future studies.

Finally, a preliminary and incomplete evidence seems to indicate that data vintages and revisions might make a difference in the choice of the policy parameters as well as in the effects on unemployment of a policy measure. A much deeper analysis which exploits information contained in all vintages or historical revisions might be needed, perhaps in a unified framework that simultaneously consider data, parameter and model uncertainty.

Appendix

A Models

The following table (A1) describes the 128 models that form the model space. The first column reports the model number. In the second column the models specification is detailed with the number and the type of variables used; the third column reports the codification where V stands for variable, L for lags and P for prior of inflation.

Table A1 here

B Derivation of the posterior

By stacking appropriately variables and coefficients in the VAR (3), we can re-write it as:

$$y_t = (I_n \otimes W_t)\,\beta + \varepsilon_t \tag{14}$$

where, y_t is the $(n \times 1)$ vector of endogenous variables $[Z_t'\ i_t']'$, $W_t = \left(y_{t-1}', ..., y_{t-p}'\right)'$ is $k \times 1$, β is the $nk \times 1$ vectorization of the matrices $\{\mathbf{A}, \mathbf{b}, \mathbf{c}, d\}_{j=1,...,p}$, ε_t is the $(n \times 1)$ vector of reduced form innovations $\left[\varepsilon_t^Z\prime, \varepsilon_t^i\right]'$, and $k = np$ is the number of parameters in each equation.

Because by assumption it is $p(\varepsilon_t) = N(0, \Sigma)$, the likelihood is proportional to

$$L(D \mid \beta, \Sigma) \propto |\Sigma|^{-T/2} \exp\left\{-\frac{1}{2}\sum_t [y_t - (I_n \otimes W_t)\,\beta]'\,\Sigma^{-1}\,[y_t - (I_n \otimes W_t)\,\beta]\right\} \tag{15}$$

where, as in the text, D represents the stacked data.

Given the joint prior distribution on the parameters, $p(\beta, \Sigma)$, the joint posterior distribution of the parameters conditional on the data is obtained through the Bayes rule

$$\begin{aligned} p(\beta, \Sigma \mid D) &= \frac{p(\beta, \Sigma)\, L(D \mid \beta, \Sigma)}{p(D)} \\ &\propto p(\beta, \Sigma)\, L(D \mid \beta, \Sigma), \end{aligned}$$

We have assumed an independent Normal-Wishart distribution for the prior, with

$$p(\beta) = N\left(\underline{\beta}, \underline{V_\beta}\right) \propto \left|\underline{V_\beta}\right|^{-1/2} \exp\left\{-\frac{1}{2}\left(\beta - \underline{\beta}\right)' \underline{V_\beta}^{-1}\left(\beta - \underline{\beta}\right)\right\} \tag{16}$$

and

$$p\left(\Sigma^{-1}\right) = W\left(S^{-1}, \nu\right) \propto |\Sigma|^{-(\nu-n-1)/2} \exp\left\{-\frac{1}{2} tr\left(S\Sigma^{-1}\right)\right\} \tag{17}$$

The joint posterior density for (β, Σ) is proportional to the product of (15), (16), and (17). Given the independency assumption, such posterior does not take the form of a standard distribution and cannot be directly used for inference. A Gibbs sampling algorithm is instead available, for the conditional posterior of both β and Σ are simple to derive. The conditional posterior of β is derived by multiplying (15) and (16), and ignoring the terms that in the product do not involve β. It is given by

$$\begin{aligned} p(\beta \mid D, \Sigma) &= N\left(\bar{\beta}, \bar{V}_\beta\right) \\ &\propto \exp\left\{-\frac{1}{2}\left(\beta-\bar{\beta}\right)' \bar{V}_\beta^{-1}\left(\beta-\bar{\beta}\right)\right\} \end{aligned} \tag{18}$$

where

$$\begin{aligned} \bar{V}_\beta &= \left(\sum_t \left(I_n \otimes W_t\right)' \Sigma^{-1}\left(I_n \otimes W_t\right) + \underline{V_\beta}^{-1}\right)^{-1} \\ \bar{\beta} &= \bar{V}_\beta\left(\sum_t \left(I_n \otimes W_t\right)' \Sigma^{-1} y_t + \underline{V_\beta}^{-1}\underline{\beta}\right) \end{aligned}$$

Similarly, the conditional posterior for Σ is derived by multiplying (15) and (17). Ignoring the terms that do not involve Σ, we have

$$\begin{aligned} p\left(\Sigma^{-1} \mid D, \beta\right) &= W\left(S^{*-1}, \nu^*\right) \\ &\propto |\Sigma|^{-(\nu^*-n-1)/2} \exp\left\{-\frac{1}{2} tr\left(S^* \Sigma^{-1}\right)\right\} \end{aligned} \tag{19}$$

where

$$\begin{aligned} S^* &= S + \sum_t \left[y_t - \left(I_n \otimes W_t\right)\beta\right]\left[y_t - \left(I_n \otimes W_t\right)\beta\right]' \\ \nu^* &= \nu + T \end{aligned}$$

Starting from arbitrary values of Σ, a Gibbs algorithm samples alternately from (18) and (19).

The RATS codes used to perform estimation and inference are available from the authors upon request.

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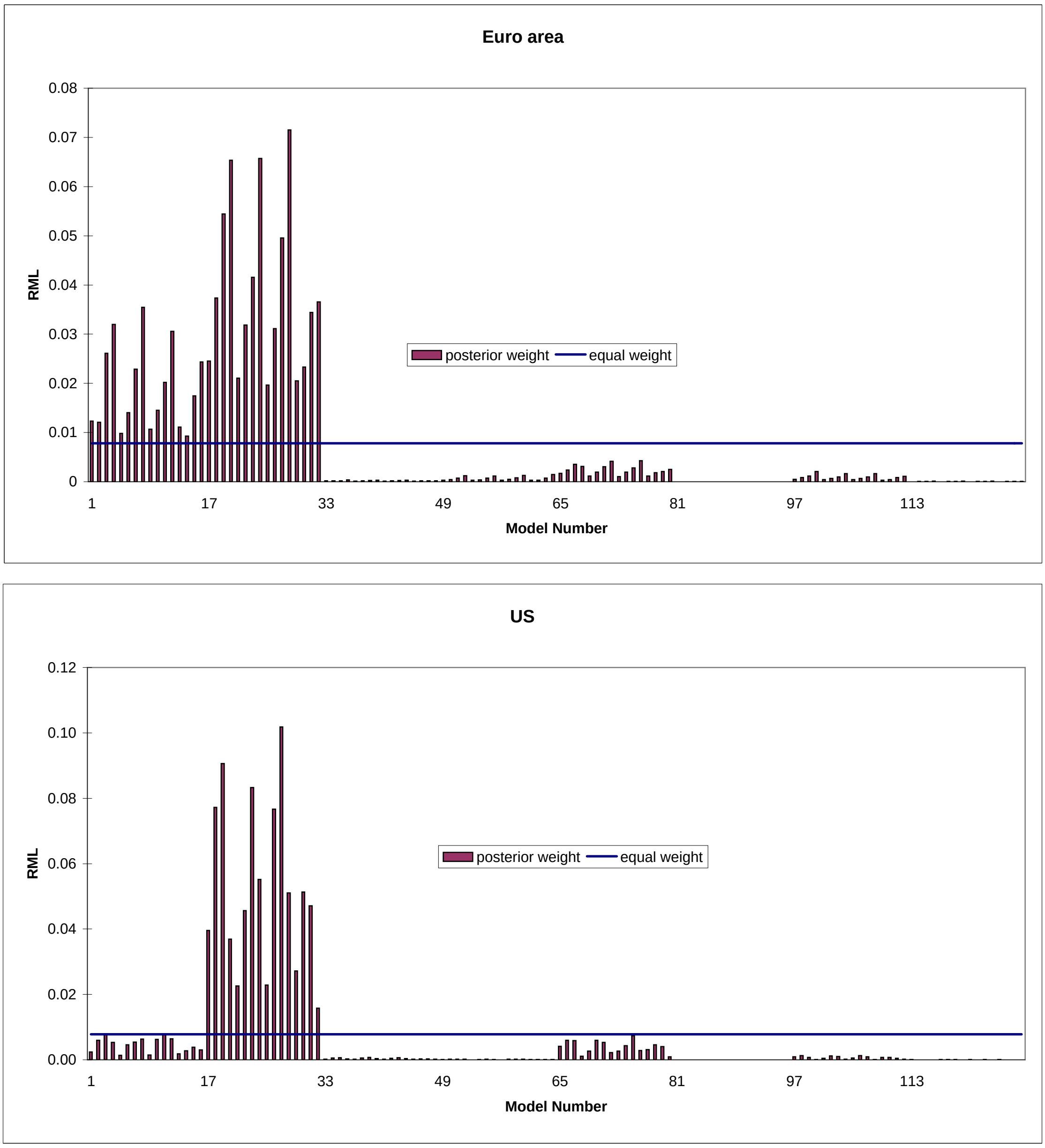
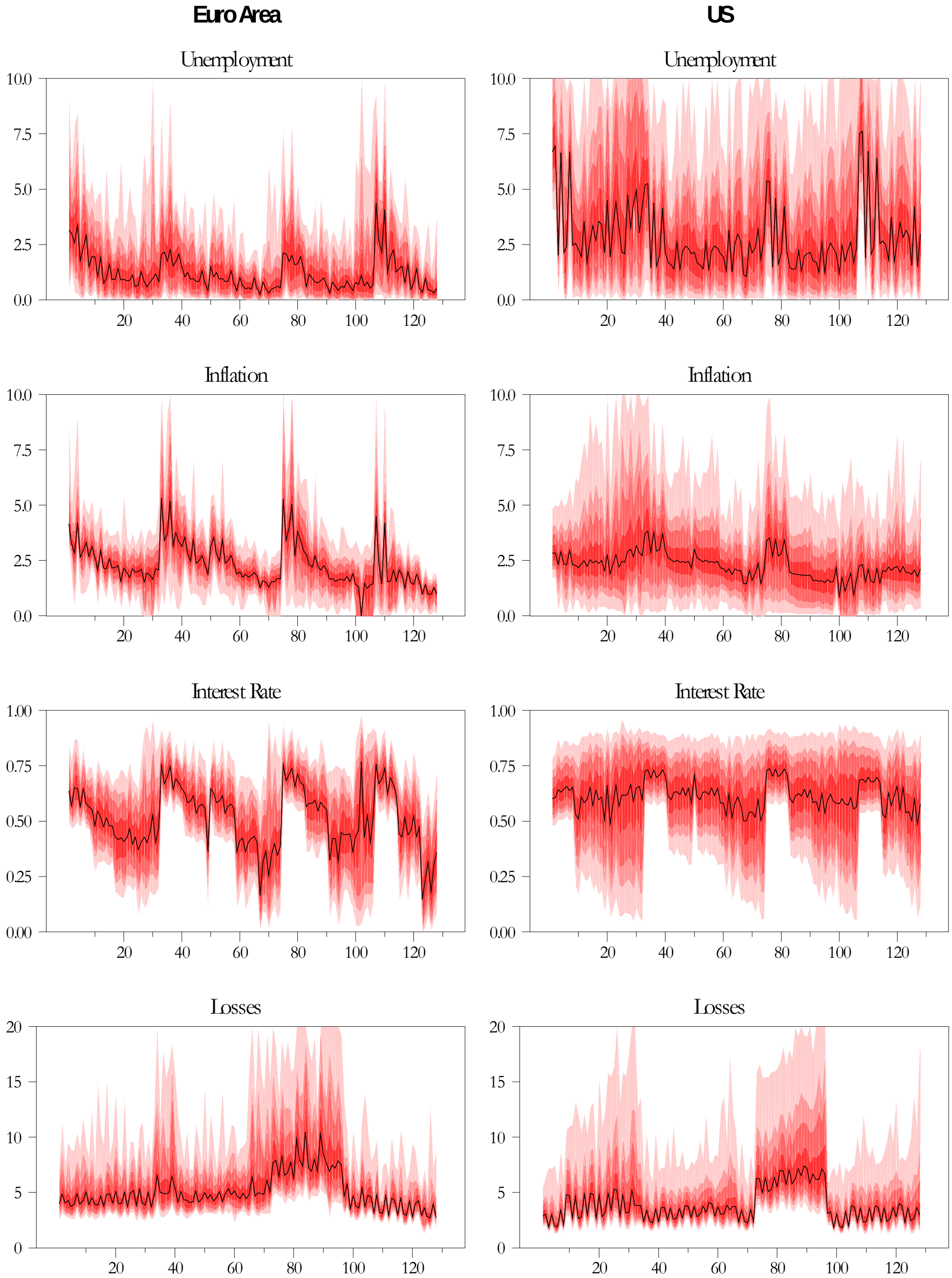
Figure 1. Relative Marginal Likelihoods



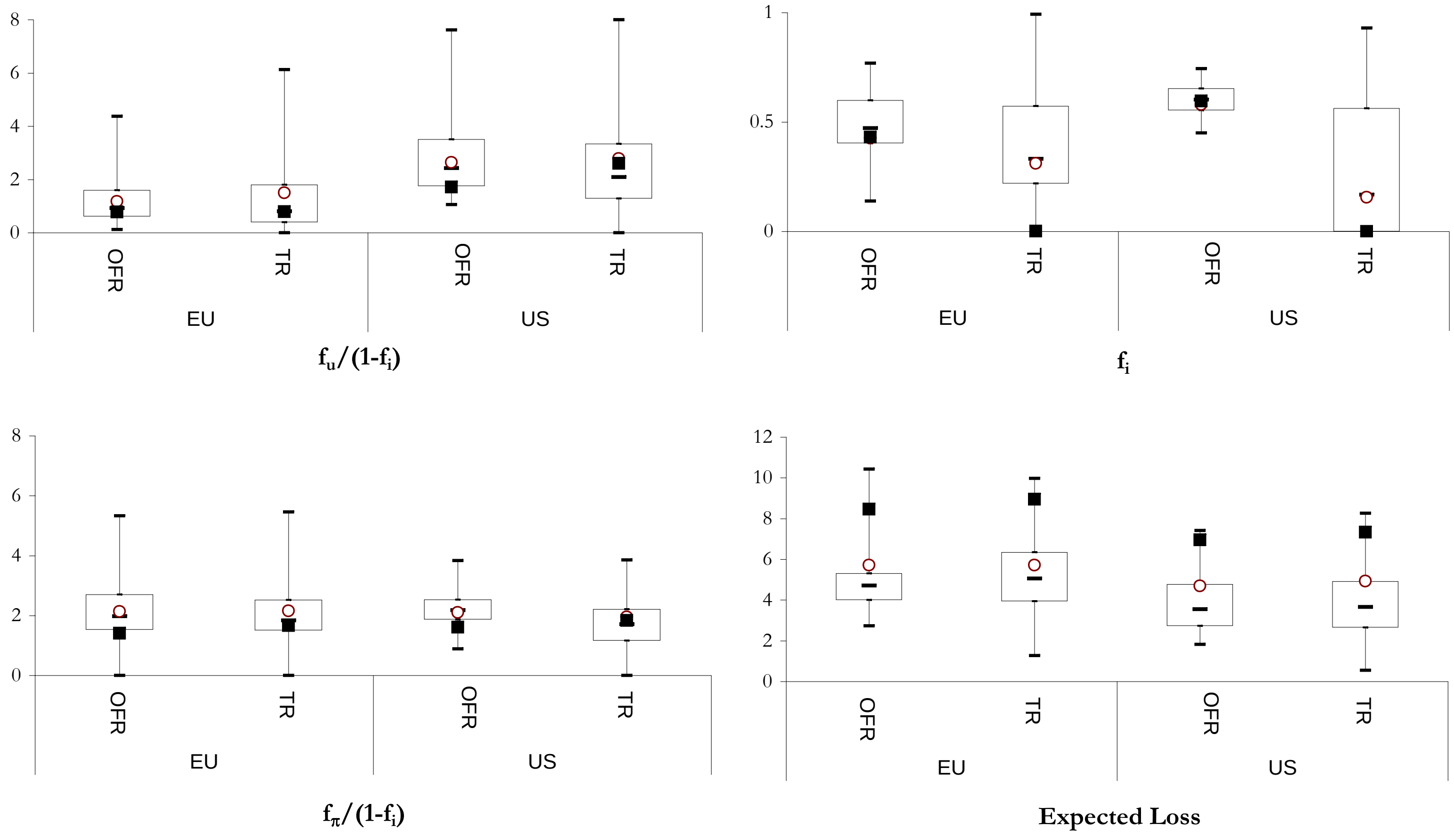
Note: The models on the x-axis are ordered by lags, priors on inflation, and number of variables. The first 16 models are those with 3 variables; the next 48 models are those with 4 variables; and so on. See Table A1 for an exact mapping.

Figure 2. Posterior distributions of policy parameters and expected losses



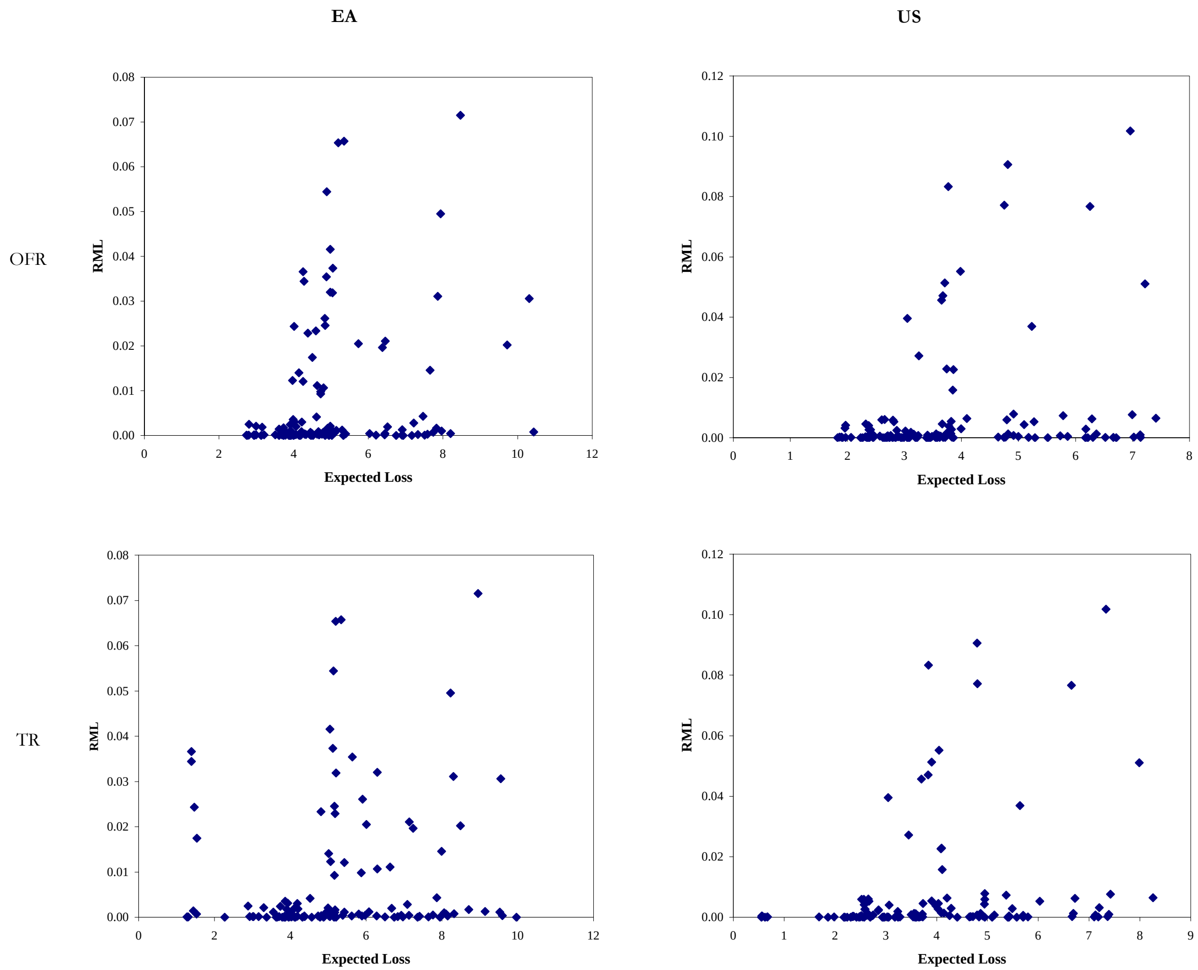
Note: The models on the x-axis are ordered by level of complexity as determined by the prior on inflation and the number of lags. Therefore models with the UN prior are placed first ; models with the RW prior come next and so on. Inside each block, then, models are ordered according to the number of lags.

Figure 3. Distributions across models of the median policy parameters and expected losses



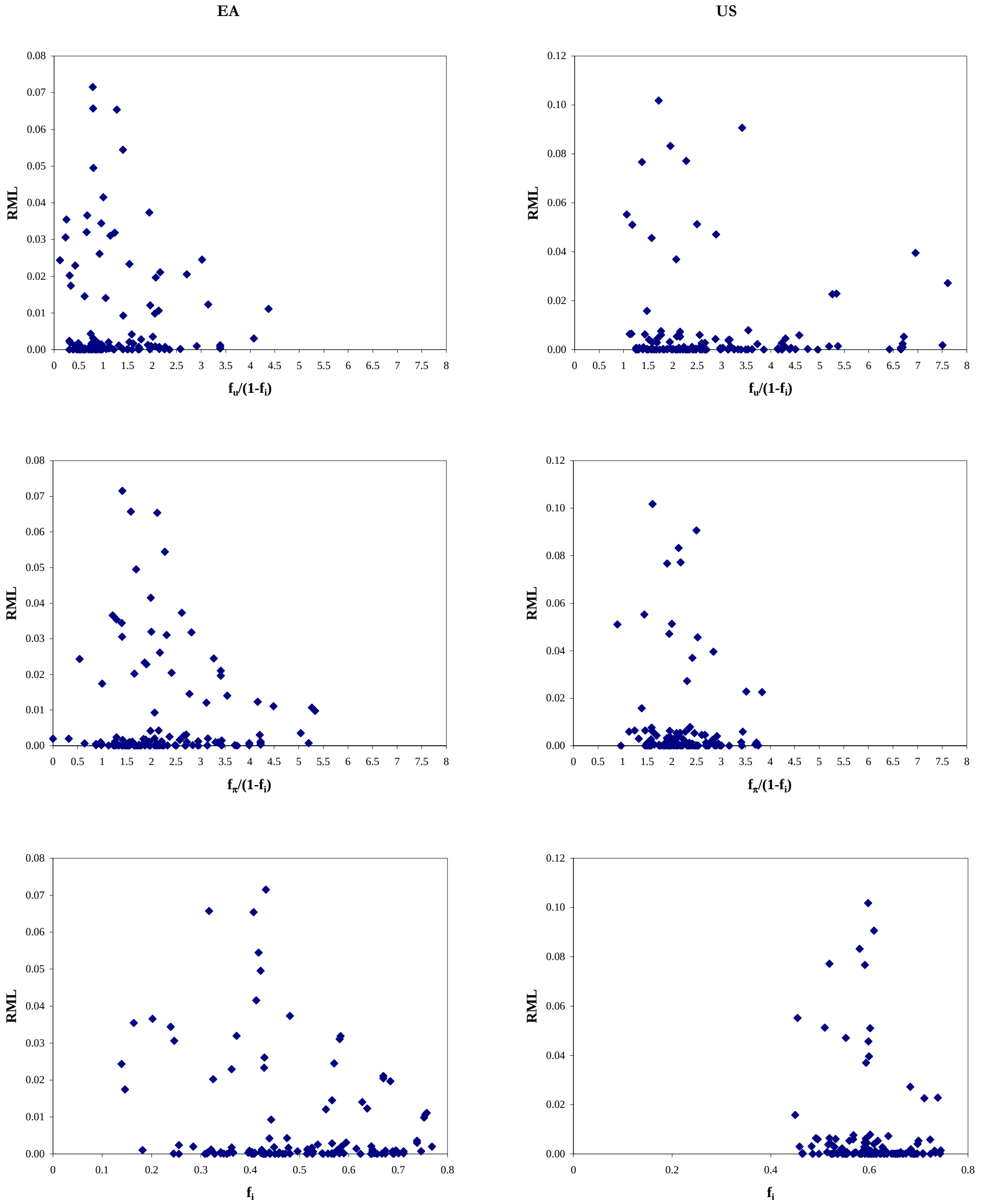
Note: The box plots report minimum, maximum, and interquartile range for each rule and country. Empty circles represent the best models; full squares are the weighted averages

Figure 4. Dispersion of expected losses



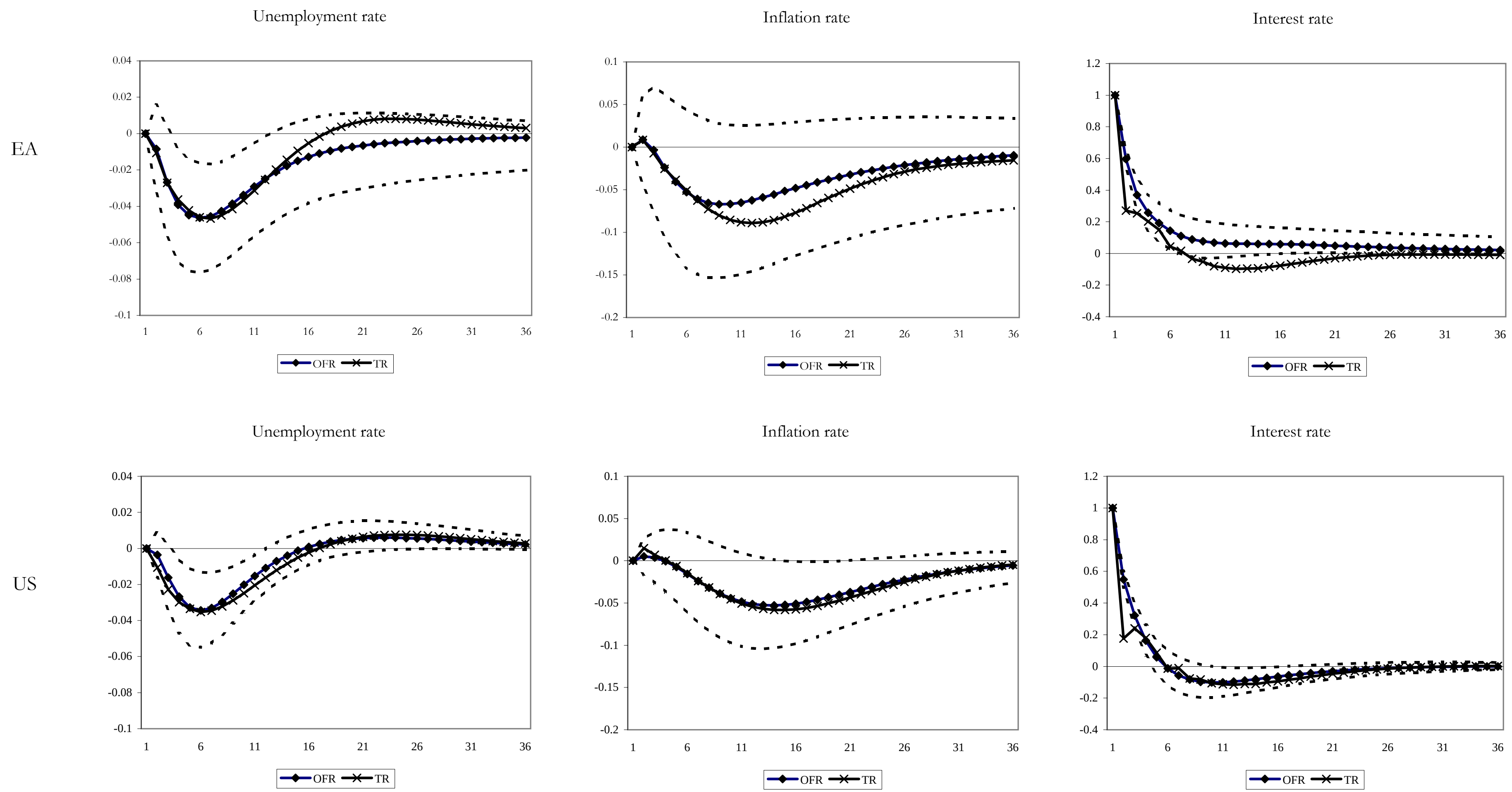
Note: The charts report scatter plots of the minimum expected losses of all models (x-axis) against the relative marginal likelihoods of the models (y-axis)

Figure 5. Dispersion of policy parameters. OFR



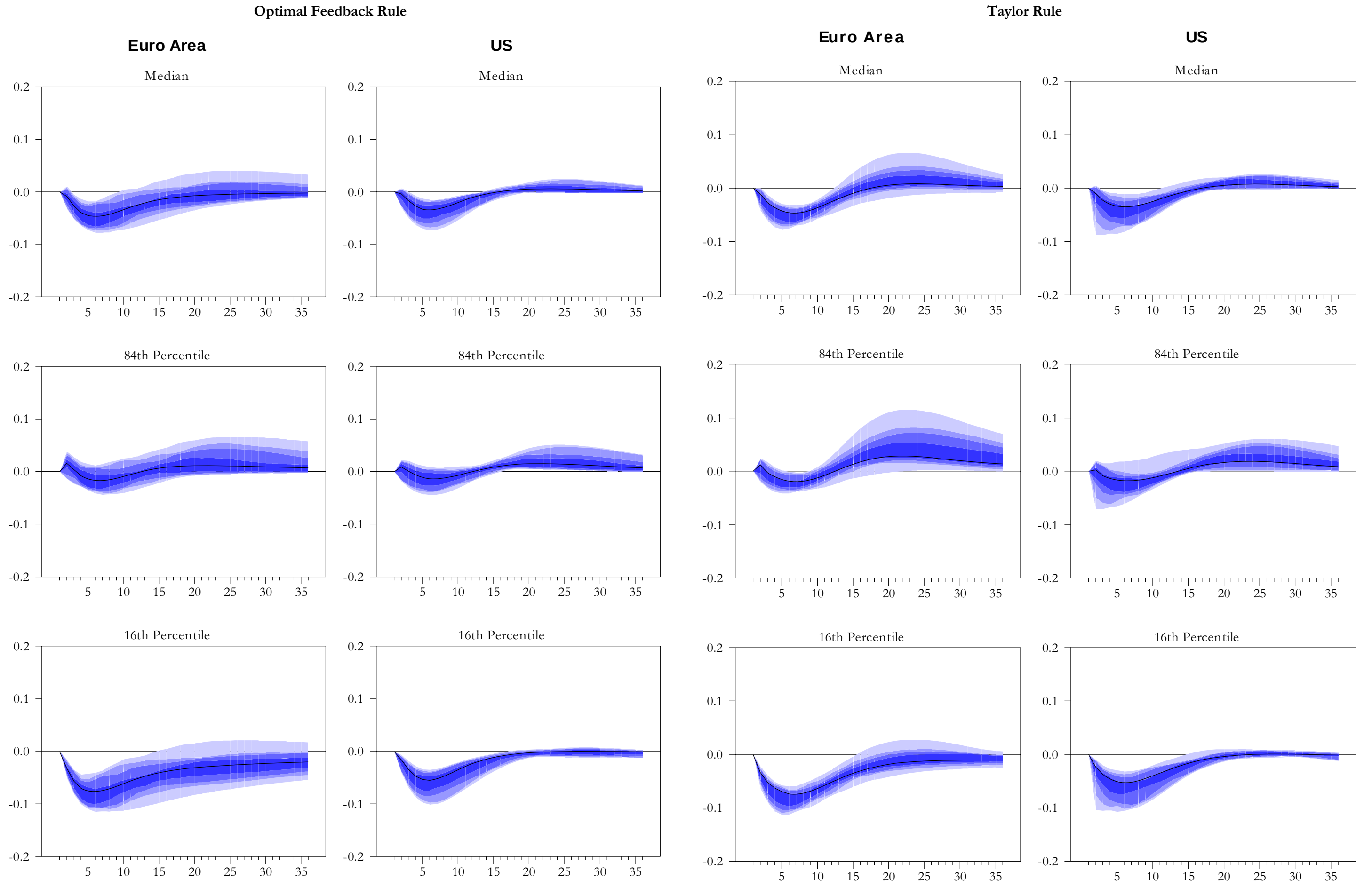
Note: The charts report scatter plots of the optimal policy parameters of all models (x-axis) against the relative marginal likelihoods of the models (y-axis)

Figure 6. Impulse response functions. Weighted averages across models



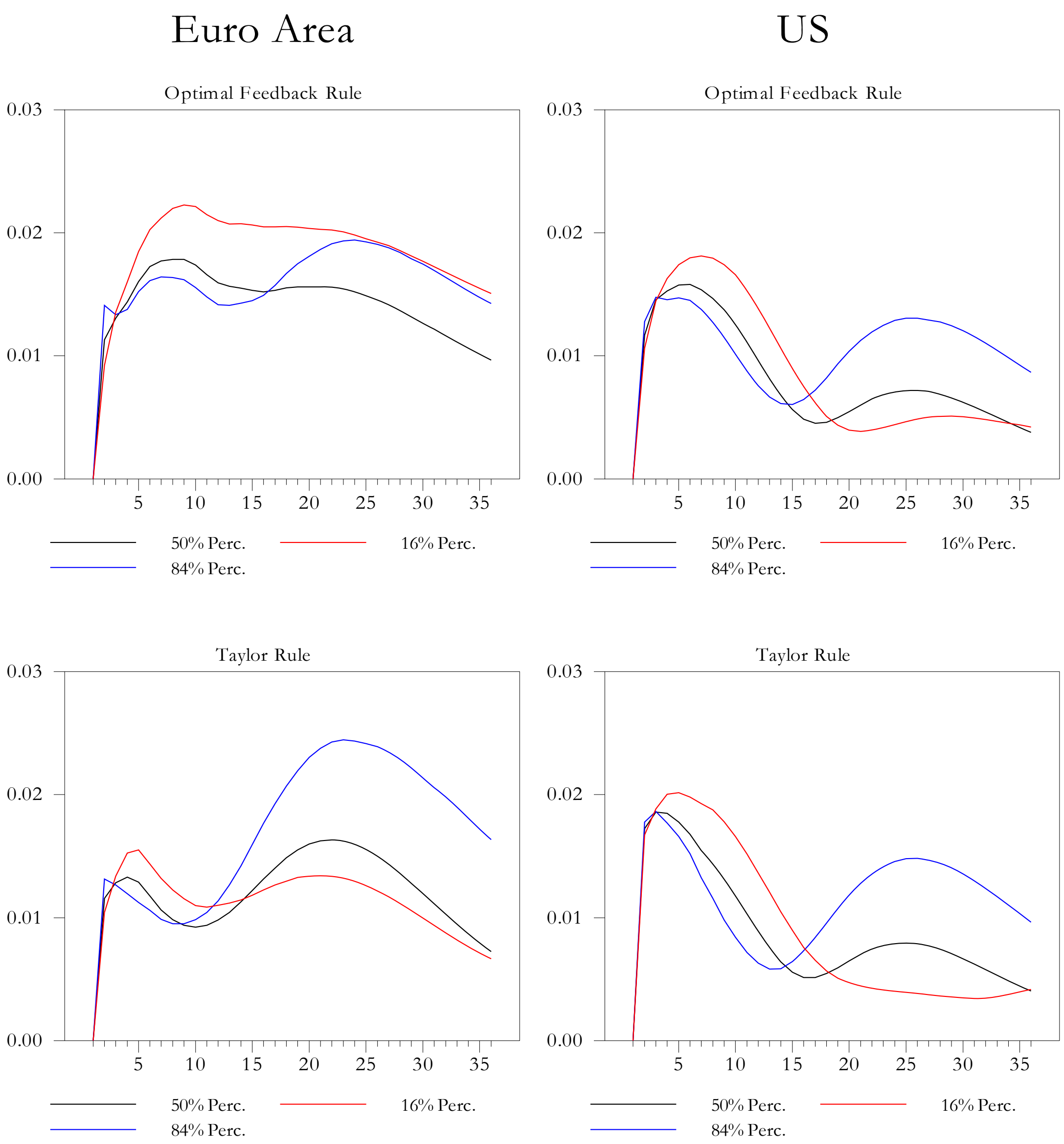
Note: The charts plot the weighted average unemployment responses to a monetary policy shock identified with the optimal feedback rule (OFR) and the Taylor rule (TR). Dashed lines are the 68 percent confidence bands of the impulse responses relative to the OFR for each variable and country.

Figure 7. Impulse response dispersion across models



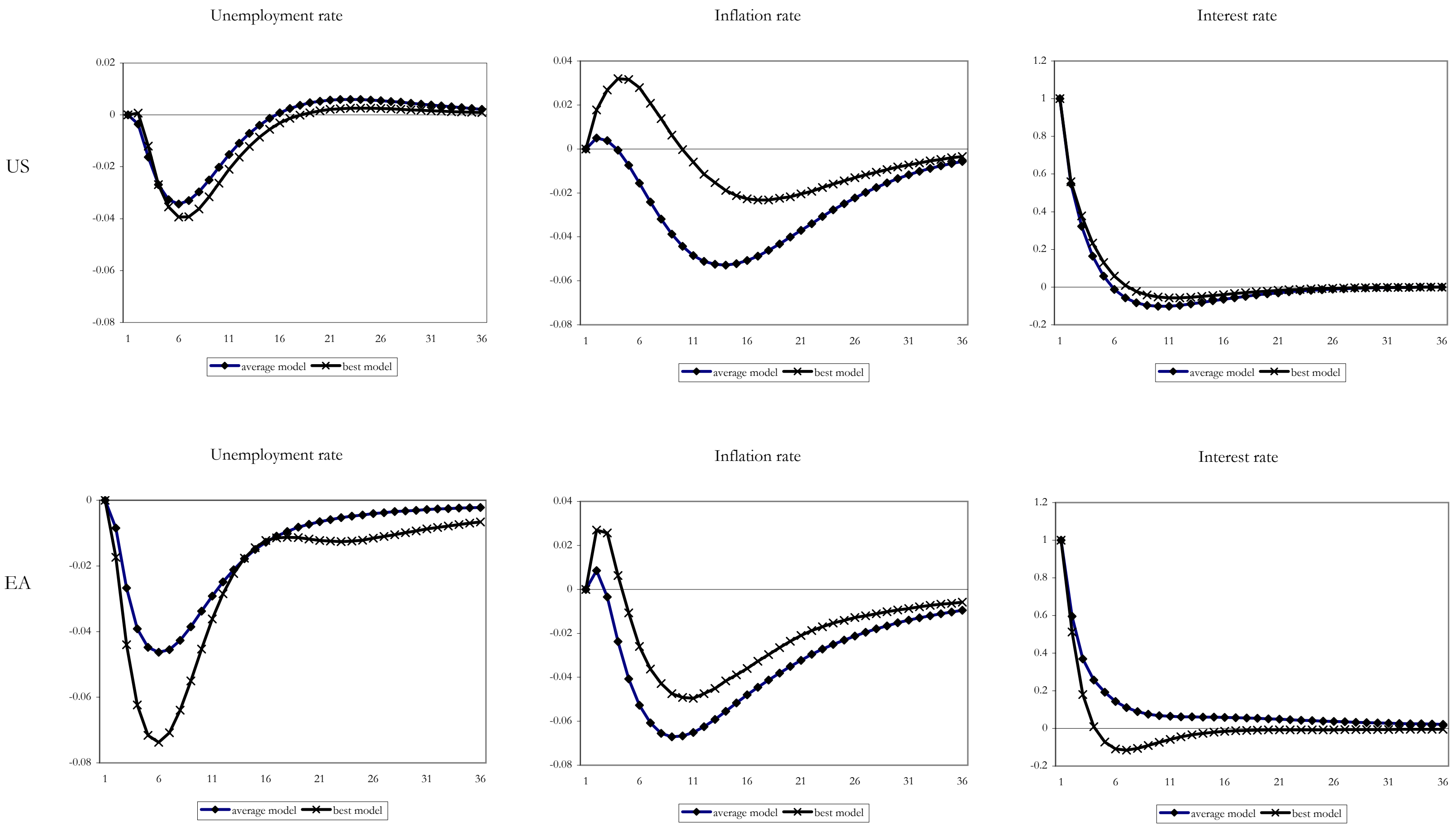
Note: the `fan-chart' distribution across models of the median, the 16th and the 84th percentile responses are reported in each chart. The shaded areas represent the dispersion across models. The principle is the same as in a fan chart representation: there is an equal number of bands on either side of the central band. The latter covers the interquartile range across models and is shaded with the deepest intensity. The next deepest shade, on both sides of the central band, takes the distribution out to 80%; and so on, untile the 99% of the distribution is covered. The solid black line that goes through the areas is the weigthed average of each quantile (median, 16th and 84th percentile) across models, where the weights are given by the RML of each model.

Figure 8. Standard deviations across IRF



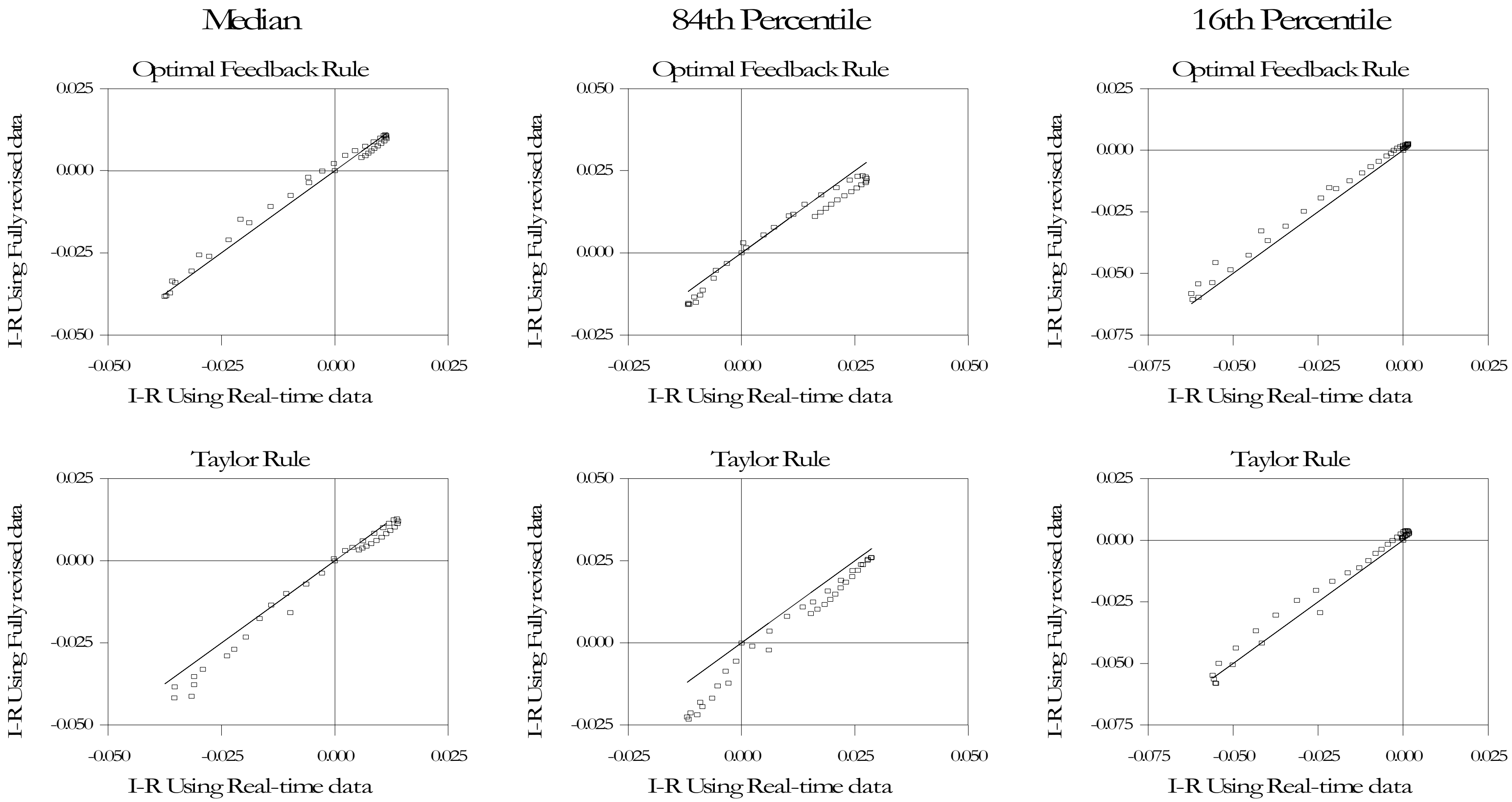
Note: The charts plot the standard deviation of three percentiles (black= 50%, red = 16%, blue = 84%) of the unemployment responses distribution across models for each step ahead.

Figure 9. Comparison between IRF of best and average model



Note: The charts plot the median unemployment responses relative to the best model and the weighted average model to a monetary policy shock identified with the optimal feedback rule (OFR). Dashed lines are the 68 percent confidence bands of the impulse responses relative to the OFR for each variable and country.

Figure 10. Fully revised vs. real-time data: IRF



Note: Circles represent the (weigthed) average IRF. On the x-axis are the IRF computed using the real time data. On the y-axis are the IRF computed using the latest available data. 36 steps are reported. Diagonals are the 45 degree lines.

Table 1. Relative Marginal Likelihood- Summary Statistics

STATISTICS	US	EA
Minimum	0.000001	0.000002
Q1	0.00006	0.000123
Median	0.000475	0.000724
Q3	0.004102	0.004293
Maximum	0.101785	0.071508
Equal weight (WE)	0.007813	0.007813
Fraction of models with RML>EW	0.132813	0.5
Sum of RML for models with RML>EW	0.917233	0.852669
Sum of RML	1	1

Note: This table reports the distribution across models of their Relative Marginal Likelihoods (RML), given in Eq. (13) and computed using the harmonic mean of the Gibbs output.

Table 2. Properties of the models with lowest and highest RML

				OFR				TR			
	Variables	Lags	Prior Type	$f_u/(1-f_i)$	$f_\pi/(1-f_i)$	f_i	Loss	$f_u/(1-f_i)$	$f_\pi/(1-f_i)$	f_i	Loss
Highest RML											
US	u,pr,π,i	3	3	1.7	1.6	0.6	7	2.6	1.8	0	7.3
EA	u,pr,π,i	4	3	0.8	1.4	0.4	8.5	0.8	1.7	0	9
Lowest RML											
US	u,pr,π,Cp,e,i	4	4	2.3	2.5	0.7	2.9	3.9	1.3	0.8	2.9
EA	u,pr,π,e,i	1	2	0.6	1.7	0.4	4.9	1.3	4.2	0.7	4.8

Note: The table reports the posterior mean values of the optimal policy parameters and the expected losses for the models with the highest and the lowest RML.

Table 3. Cumulative impulse response functions

Optimal Feedback Rule

	EA												US											
	16th				median				84th				16th				median				84th			
Steps	min	**median**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**mdian**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**mdian**	**wgt. av.**	max
1	-0.05	-0.04	-0.03	-0.02	-0.03	-0.01	-0.01	0.01	-0.01	0.01	0.02	0.04	-0.04	-0.02	-0.02	-0.01	-0.03	0.00	0.00	0.01	-0.02	0.01	0.01	0.02
2	-0.08	-0.06	-0.06	-0.04	-0.05	-0.03	-0.03	-0.01	-0.02	0.00	0.00	0.03	-0.07	-0.04	-0.03	-0.02	-0.05	-0.02	-0.02	0.00	-0.03	0.00	0.00	0.02
4	-0.21	-0.15	-0.15	-0.09	-0.14	-0.09	-0.08	-0.03	-0.06	-0.02	-0.02	0.03	-0.18	-0.11	-0.10	-0.06	-0.13	-0.06	-0.06	-0.02	-0.08	-0.02	-0.02	0.03
8	-0.46	-0.32	-0.29	-0.13	-0.30	-0.19	-0.17	-0.04	-0.17	-0.08	-0.06	0.07	-0.38	-0.21	-0.20	-0.12	-0.27	-0.14	-0.12	-0.05	-0.17	-0.06	-0.05	0.03
12	-0.43	-0.24	-0.22	-0.05	-0.27	-0.13	-0.11	0.03	-0.14	-0.03	-0.01	0.12	-0.27	-0.12	-0.11	-0.06	-0.16	-0.05	-0.05	-0.01	-0.09	-0.01	-0.01	0.04
16	-0.38	-0.19	-0.16	0.01	-0.20	-0.07	-0.06	0.09	-0.08	0.02	0.03	0.18	-0.14	-0.05	-0.04	-0.01	-0.06	0.00	0.00	0.03	-0.01	0.04	0.04	0.09
20	-0.34	-0.15	-0.13	0.06	-0.14	-0.04	-0.03	0.14	-0.03	0.03	0.04	0.24	-0.06	-0.02	-0.01	0.01	-0.01	0.02	0.02	0.07	0.02	0.06	0.06	0.17
24	-0.30	-0.12	-0.11	0.08	-0.10	-0.04	-0.02	0.16	-0.02	0.03	0.04	0.26	-0.04	-0.01	0.00	0.02	-0.01	0.02	0.02	0.10	0.02	0.06	0.06	0.20
28	-0.27	-0.11	-0.10	0.09	-0.08	-0.03	-0.01	0.16	-0.01	0.03	0.04	0.27	-0.04	0.00	0.00	0.03	-0.01	0.02	0.02	0.10	0.01	0.05	0.05	0.20
32	-0.24	-0.10	-0.09	0.08	-0.06	-0.02	-0.01	0.15	-0.01	0.02	0.03	0.25	-0.04	0.00	0.00	0.03	-0.01	0.01	0.01	0.08	0.00	0.04	0.04	0.17
36	-0.22	-0.09	-0.08	0.07	-0.05	-0.02	-0.01	0.13	-0.01	0.02	0.03	0.23	-0.05	0.00	0.00	0.01	-0.01	0.01	0.01	0.05	0.00	0.02	0.03	0.13
cumulative impact after 2 years	-0.80	-0.57	-0.52	-0.27	-0.52	**-0.32**	**-0.46**	-0.06	-0.27	-0.08	-0.06	0.17	-0.68	-0.37	-0.35	-0.21	-0.48	**-0.22**	**-0.26**	-0.06	-0.29	-0.06	-0.06	0.10

Taylor Rule

	EA												US											
	16th				median				84th				16th				median				84th			
steps	min	**median**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**mdian**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**median**	**wgt. av.**	max	min	**mdian**	**wgt. av.**	max
1	-0.06	-0.04	-0.03	-0.02	-0.04	-0.01	-0.01	0.00	-0.02	0.01	0.01	0.02	-0.10	-0.03	-0.02	-0.01	-0.09	-0.02	-0.01	0.00	-0.07	0.00	0.00	0.02
2	-0.09	-0.06	-0.05	-0.04	-0.06	-0.03	-0.03	-0.01	-0.03	-0.01	0.00	0.02	-0.10	-0.04	-0.04	-0.02	-0.09	-0.03	-0.02	0.00	-0.07	-0.01	-0.01	0.02
4	-0.22	-0.15	-0.13	-0.11	-0.15	-0.10	-0.08	-0.05	-0.08	-0.04	-0.03	0.01	-0.21	-0.11	-0.10	-0.06	-0.17	-0.08	-0.06	-0.02	-0.13	-0.04	-0.03	0.03
8	-0.42	-0.32	-0.29	-0.22	-0.28	-0.20	-0.18	-0.12	-0.15	-0.09	-0.07	0.00	-0.40	-0.24	-0.20	-0.12	-0.28	-0.16	-0.13	-0.04	-0.20	-0.09	-0.07	0.08
12	-0.32	-0.22	-0.22	-0.12	-0.20	-0.11	-0.11	-0.03	-0.11	-0.01	-0.02	0.10	-0.28	-0.16	-0.13	-0.05	-0.17	-0.10	-0.07	0.01	-0.09	-0.04	-0.03	0.13
16	-0.23	-0.13	-0.13	0.00	-0.12	-0.01	-0.03	0.13	-0.05	0.09	0.06	0.30	-0.14	-0.07	-0.06	0.01	-0.06	-0.02	-0.02	0.06	-0.01	0.02	0.03	0.17
20	-0.17	-0.06	-0.08	0.09	-0.08	0.04	0.02	0.24	-0.01	0.14	0.11	0.43	-0.06	-0.02	-0.02	0.04	-0.01	0.03	0.02	0.08	0.00	0.08	0.06	0.20
24	-0.14	-0.03	-0.05	0.11	-0.05	0.05	0.03	0.26	0.01	0.14	0.11	0.46	-0.03	0.01	0.00	0.04	-0.01	0.05	0.03	0.10	0.00	0.11	0.07	0.24
28	-0.11	-0.02	-0.05	0.10	-0.04	0.05	0.03	0.23	0.01	0.13	0.09	0.42	-0.02	0.01	0.00	0.04	-0.01	0.05	0.03	0.10	0.00	0.11	0.07	0.24
32	-0.10	-0.02	-0.04	0.06	-0.03	0.04	0.02	0.17	0.01	0.11	0.07	0.35	-0.02	0.00	0.00	0.03	0.00	0.03	0.02	0.08	0.00	0.08	0.05	0.23
36	-0.10	-0.02	-0.04	0.03	-0.03	0.03	0.01	0.11	0.00	0.08	0.06	0.29	-0.04	0.00	0.00	0.02	0.00	0.02	0.01	0.06	0.00	0.05	0.04	0.19
cumulative impact after 2 years	-1.05	-0.75	-0.69	-0.49	-0.69	**-0.44**	**-0.43**	-0.21	-0.37	-0.15	-0.12	0.12	-0.99	-0.56	-0.46	-0.25	-0.71	**-0.37**	**-0.31**	-0.06	-0.49	-0.19	-0.13	0.26

Note: The table reports for each quantile of the IRF (median, 16th and 84th) the distribution across models of the cumulative response of unemployment between forecast steps. For instance, at step 4 the cumulative impact between step 2 and step 4 is repor

Table 4. Fully revised vs. real-time data: Long run policy parameters

	Unemployment		Inflation		Interest rate	
	Real-Time	Fully-Revised	Real-Time	Fully-Revised	Real-Time	Fully-Revised
Optimal feedback rule						
Average	3.23	2.50	2.18	1.78	0.58	0.56
St. Dev.	2.02	2.34	0.70	1.20	0.08	0.14
Taylor Rule						
Average	2.13	1.08	1.38	0.75	0.25	0.48
St. Dev.	0.71	0.88	0.49	0.61	0.30	0.31

Note: values are the weighted averages across models, where weights are given by the RML of each model. Only models with three variables are considered.

Table A1. Mapping of the model numbers with the specifications according to number of variables, lags, and priors on inflation

Model number	Specification and order of the variables in the VAR	Codification: V=Variable; L=Lags; P=Prior			
Model 1	3 Variables	3V_1L_1P	Model 65	5 Variables	5V_1L_1P
Model 2	u,p,i	3V_2L_1P	Model 66	u,pr,p,Cp,i	5V_2L_1P
Model 3		3V_3L_1P	Model 67		5V_3L_1P
Model 4		3V_4L_1P	Model 68		5V_4L_1P
Model 5		3V_1L_2P	Model 69		5V_1L_2P
Model 6		3V_2L_2P	Model 70		5V_2L_2P
Model 7		3V_3L_2P	Model 71		5V_3L_2P
Model 8		3V_4L_2P	Model 72		5V_4L_2P
Model 9		3V_1L_3P	Model 73		5V_1L_3P
Model 10		3V_2L_3P	Model 74		5V_2L_3P
Model 11		3V_3L_3P	Model 75		5V_3L_3P
Model 12		3V_4L_3P	Model 76		5V_4L_3P
Model 13		3V_1L_4P	Model 77		5V_1L_4P
Model 14		3V_2L_4P	Model 78		5V_2L_4P
Model 15		3V_3L_4P	Model 79		5V_3L_4P
Model 16		3V_4L_4P	Model 80		5V_4L_4P
Model 17	4 Variables	4V_1L_1P	Model 81	5 Variables	5V_1L_1P
Model 18	u,pr,p,i	4V_2L_1P	Model 82	u,pr,p,e,i	5V_2L_1P
Model 19		4V_3L_1P	Model 83		5V_3L_1P
Model 20		4V_4L_1P	Model 84		5V_4L_1P
Model 21		4V_1L_2P	Model 85		5V_1L_2P
Model 22		4V_2L_2P	Model 86		5V_2L_2P
Model 23		4V_3L_2P	Model 87		5V_3L_2P
Model 24		4V_4L_2P	Model 88		5V_4L_2P
Model 25		4V_1L_3P	Model 89		5V_1L_3P
Model 26		4V_2L_3P	Model 90		5V_2L_3P
Model 27		4V_3L_3P	Model 91		5V_3L_3P
Model 28		4V_4L_3P	Model 92		5V_4L_3P
Model 29		4V_1L_4P	Model 93		5V_1L_4P
Model 30		4V_2L_4P	Model 94		5V_2L_4P
Model 31		4V_3L_4P	Model 95		5V_3L_4P
Model 32		4V_4L_4P	Model 96		5V_4L_4P
Model 33	4 Variables	4V_1L_1P	Model 97	5 Variables	5V_1L_1P
Model 34	u,Cp,p,i	4V_2L_1P	Model 98	u,Cp,p,e,i	5V_2L_1P
Model 35		4V_3L_1P	Model 99		5V_3L_1P
Model 36		4V_4L_1P	Model 100		5V_4L_1P
Model 37		4V_1L_2P	Model 101		5V_1L_2P
Model 38		4V_2L_2P	Model 102		5V_2L_2P
Model 39		4V_3L_2P	Model 103		5V_3L_2P
Model 40		4V_4L_2P	Model 104		5V_4L_2P
Model 41		4V_1L_3P	Model 105		5V_1L_3P
Model 42		4V_2L_3P	Model 106		5V_2L_3P
Model 43		4V_3L_3P	Model 107		5V_3L_3P
Model 44		4V_4L_3P	Model 108		5V_4L_3P
Model 45		4V_1L_4P	Model 109		5V_1L_4P
Model 46		4V_2L_4P	Model 110		5V_2L_4P
Model 47		4V_3L_4P	Model 111		5V_3L_4P
Model 48		4V_4L_4P	Model 112		5V_4L_4P
Model 49	4 Variables	4V_1L_1P	Model 113	6 Variables	6V_1L_1P
Model 50	u,e,p,i	4V_2L_1P	Model 114	u,pr,p,Cp,e, i	6V_2L_1P
Model 51		4V_3L_1P	Model 115		6V_3L_1P
Model 52		4V_4L_1P	Model 116		6V_4L_1P
Model 53		4V_1L_2P	Model 117		6V_1L_2P
Model 54		4V_2L_2P	Model 118		6V_2L_2P
Model 55		4V_3L_2P	Model 119		6V_3L_2P
Model 56		4V_4L_2P	Model 120		6V_4L_2P
Model 57		4V_1L_3P	Model 121		6V_1L_3P
Model 58		4V_2L_3P	Model 122		6V_2L_3P
Model 59		4V_3L_3P	Model 123		6V_3L_3P
Model 60		4V_4L_3P	Model 124		6V_4L_3P
Model 61		4V_1L_4P	Model 125		6V_1L_4P
Model 62		4V_2L_4P	Model 126		6V_2L_4P
Model 63		4V_3L_4P	Model 127		6V_3L_4P
Model 64		4V_4L_4P	Model 128		6V_4L_4P