

Inflation Forecasts, Monetary Policy and Unemployment Dynamics: Evidence from the US and the Euro area[♦]

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Abstract

This paper explores the role that inflation forecasts play in the uncertainty surrounding the estimated effects of alternative monetary rules on unemployment dynamics in the euro area and the US. We use the inflation forecasts of 8 competing models in a standard Bayesian VAR to analyse the size and the timing of these effects, as well as to quantify the uncertainty relative to the different inflation models under two rules. The results suggest that model uncertainty can be a serious issue and strengthen the case for a policy strategy that takes into account several sources of information. We find that combining inflation forecasts from many models not only yields more accurate forecasts than those of any specific model, but also reduces the uncertainty associated with the real effects of policy decisions. These results are in line with the model-combination approach that central banks already follow when conceiving their strategy.

Keywords: Inflation Forecasts, Unemployment, Model Uncertainty

JEL Classification: C53, E24, E37

[♦] We would like to thank Frank Smets and an anonymous referee for comments and suggestions that improved substantially the quality of the paper. This paper should not be reported as representing the views of the ECB, or ECB policy. Remaining errors are of the authors.

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1. Introduction

In this paper we investigate the role that inflation forecasts play in the uncertainty surrounding the estimated effects of alternative monetary rules on unemployment dynamics in the euro area and the US. A significant fraction of this uncertainty is related to the possibility of correctly predicting the time path of inflation and therefore the price level. Then, producing comparative evidence on the relative ability of alternative models to forecast inflation is not only helpful in terms of improving the ability of monetary authorities to set interest rates, but also helps to understand the effects of monetary policy on unemployment for each alternative set of forecasts.

Our paper explicitly deals with these issues. In particular, we *(i)* explore the out-of-sample forecast performance of a set of linear and non-linear competing models of inflation rate determination over horizons from 1 to 8 quarters; *(ii)* evaluate the effect of the policy rate on unemployment in a Bayesian VAR, where the inflation forecast is one of the endogenous variables, and parameter uncertainty is accounted for; *(iii)* employ standard simulation analysis to quantify the model uncertainty surrounding the estimated effect on unemployment of a shock to the interest rate under two different policy rules.

The formulation of a typical Taylor rule assumes that the central bank reacts to some measure of inflation expectation. In our structural specification, the Taylor rule is “forward-looking”, in the sense that the central bank reacts to inflation forecasts, where the latter are obtained using several competing models. Model uncertainty plays a dual role here: on the one hand it reflects the choice of the competing models to forecast inflation; and on the other, we specify two alternative rules, with the central bank reacting either to inflation forecasts and unemployment, or just to inflation.

The main questions we ask in the paper then are: Can we quantify model uncertainty on the real effects of a monetary policy shock? Which kind of estimated effect is associated with the best inflation forecast? And finally, does a forecast combination reduce this uncertainty? The contribution of our paper with respect to the existing literature is twofold. First, we show that imposing appropriate weights on competing models of inflation forecasts – reflecting the relative ability each model has over different sub-sample periods – substantially increases forecast accuracy. Second, with the help of standard VAR techniques we show that, although the estimated effect of a monetary shock on unemployment significantly varies across inflation forecasts, countries, horizons and sub-samples, the combination of inflation forecasts from many models consistently dampens the uncertainty associated with the real effects of policy decisions. In this respect, our conclusions are in line with the literature that deals with the problems related to the information set that should be used when identifying the effect of monetary policy innovations on the economy. They can be seen, for instance, as confirming the results of Bernanke et al. (2005), who show that a factor-augmented VAR (FAVAR) methodology significantly improves the correct measurement of the effect of monetary policy on the economy by extending the information

contained in a standard VAR with a “summary” of other shocks affecting the economy not accounted for by the variables in the VAR. Our results are also in line with the model-combination approach that central banks follow when conceiving their strategy.

The remainder of the paper is structured as follows. Section 2 analyses the forecasting properties over different horizons of eight competing models by employing alternative econometric techniques. Section 3 examines the role of heterogeneous inflation forecasts on the estimated effects of monetary policy on unemployment, under different monetary policy rules. Section 4 presents empirical measures of model uncertainty based on the results obtained in the simulation analysis. Finally, section 5 summarises the paper’s main findings.

2. Forecasting Inflation

A significant fraction of the uncertainty a central bank faces in defining its strategy is related to the possibility of correctly predicting inflation. In fact, in selecting the current level of interest rates central banks usually take into account expected inflation, which may change according to the model used. This has consequences for the types of monetary policy to be implemented. Producing comparative evidence on the relative ability of alternative models in forecasting inflation might improve the ability of monetary authorities to set interest rates. Moreover, each alternative set of forecasts could lead to different reactions of the real economy to monetary policy actions.

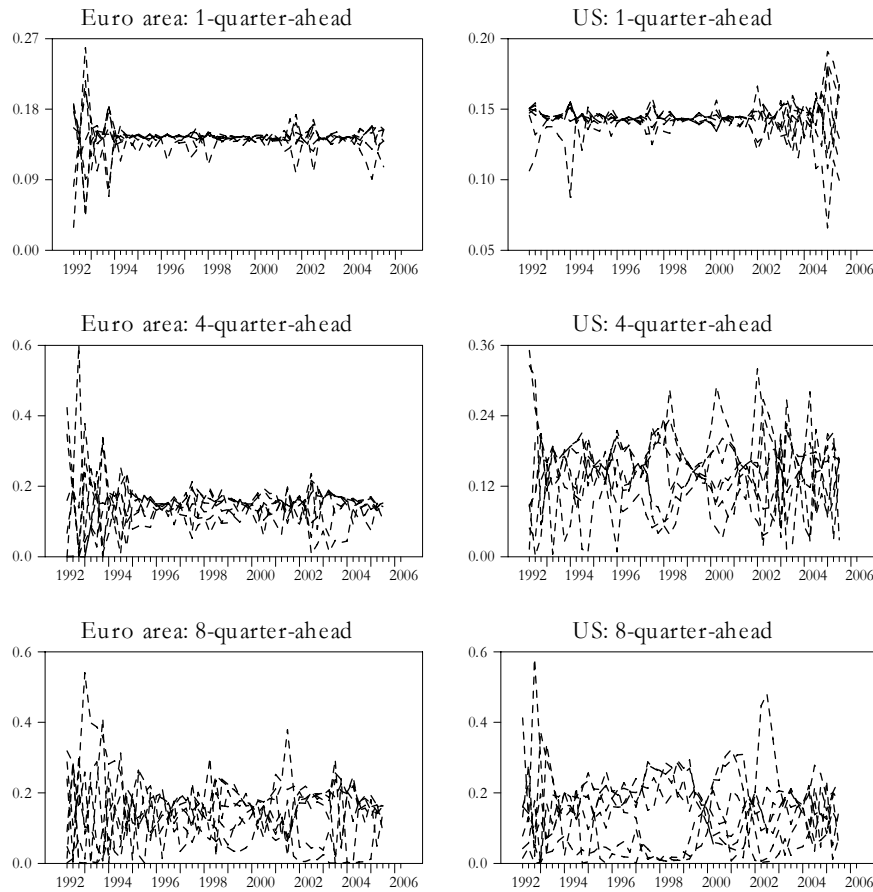
The empirical analysis presented in this section analyses the forecasting properties over horizons from one quarter to eight quarters of eight competing models: a driftless random walk process (RW); a univariate autoregressive moving-average model (ARMA); a spectral model (SP); a four-variable vector autoregressive model (VAR); an exponential smooth transition autoregressive model (ESTAR), a univariate markov-switching autoregressive model (MS-AR); a markov-switching VAR (MS-VAR); and a combination of all the previous methods (COM(1-7)). (For a detailed description of the models see the appendix.)

The idea behind the combination of forecasting techniques is that no forecasting method is fully appropriate for all situations. The combination accounts for the time-varying forecasting ability of alternative models in that a single forecasting model might only be optimal conditional on given realizations, information set, model specification or sample period. By combining methods, we can compensate for the weakness of each forecasting model under particular conditions. While there is broad consensus that appropriate combinations of individual forecasts often improve forecast accuracy (see for example Stock and Watson (2004, 2005) and Timmermann (2006)), the literature has not yet converged to a particular set of forecast weights to be implemented when constructing combined time series. In the present study we compute a combined forecast adapting the methodology proposed in Hong and Lee (2003), Yang (2004) and Yang and Zou (2004). One of the advantages

of their method is that it ensures that the weight attributed to a certain model at time t is larger the greater its ability to forecast the actual inflation rate in period $t-1$.

Figure 1 plots the weights used in computing the combined forecast series. Visual inspection provides useful information concerning the time-varying forecasting ability of competing models. In cases where the weights attributed to each model are very similar, as in the central part of the sample period for the one-quarter-ahead forecast, the relative accuracy of the forecasts produced by each model might not be affected by a particular sub-sample period selected by the evaluation strategy. Moreover, the performance is relatively homogenous across methods. Alternatively, when weights are very dissimilar, the correct choice of the forecasting model might produce a significant improvement in terms of predictive accuracy. The figure also suggests that there is a positive relationship between the volatility of the selected weights, i.e. the number of time periods each model account for the same proportion in the combined series, and the forecasting horizon.

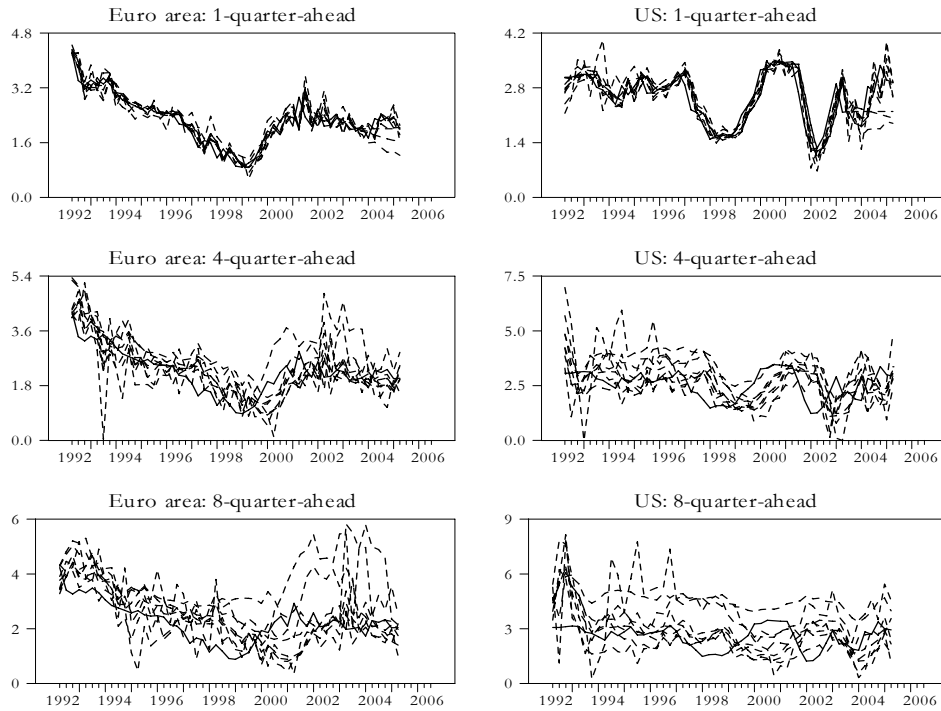
Figure 1. Weights used in the forecast combination



Comparing Out-of-sample Forecasts

The eight models identified above (seven models plus the combination) are used to compute out-of-sample forecasts of the US and the euro area inflation rates. We use quarterly data from 1970:1 to 2005:3. For the evaluation, the models are recursively estimated on a sub-sample of the historical data. Specifically, to generate the h -step ahead inflation forecast at time $t = 1, \dots, T, \dots, T+h$, we estimate using all historical data up to T .¹ Then we compute the corresponding combined forecast series. Finally, the out-of sample forecast of the competing models for alternative periods are evaluated. The forecast accuracy is measured by computing recursive forecasts. The estimation period goes from 1970:1 to 1989:4, while the forecast period goes from 1990:1 to 2005:3. This means that the first sequence of one- to eight-quarter-ahead forecasts is generated starting from 1990:1. Then, the starting date of the forecast period is rolled forward one period, and another sequence of forecasts is generated. This loop is repeated until we have $62 \times$ one-quarter forecasts, down to $54 \times$ eight-quarter forecasts, so that the comparable sample across forecast horizons starts in 1992:1.

Figure 2. Out-of-sample Point Forecasts of competing models



¹ We also adopt an alternative methodology based on rolling, rather than recursive, estimates so that the sample size remains constant. More precisely, for each prediction period, we use a rolling sample of size $T=40$ to estimate the model parameters. The results remain substantially unchanged. The disadvantage of this procedure, however, is that the estimates are sensitive to the size of the selected rolling window.

Figure 2 provides a graphical summary of the performances of the competing models over the entire sample periods in forecasting the two inflation rates.

The charts report the actual inflation rates (solid line) and the eight forecasting models (dashed lines) at the one-, four- and eight-quarter-ahead horizons. Visual inspection seems to suggest, as expected, that short-horizon inflation rate forecasts perform better. The figure also illustrates higher long-horizon forecast volatility. This means that the gains (but also the losses) we can achieve by using a particular model are larger the longer the horizon is. To assess the performance of the alternative models, we analyse the forecast accuracy through a set of statistical measures.

Table 1 reports the Root Mean Square Error (RMSE) and the relative ranking in terms of forecast errors for the 96 cases (eight models, three horizons, two sub-samples). The last column in each panel reports the average rank of the model.

Table 1. Comparing Forecast Accuracy – RMSE

Panel A: 1992:1-2005:3						Panel B: 1998:4-2005:3					
	Euro area	Rank	US	Rank	Avg. Rank		Euro area	Rank	US	Rank	Avg. Rank
1-quarter						1-quarter					
RW	0.29	[2]	0.41	[5]	[3.5]	RW	0.32	[2]	0.51	[6]	[4.0]
SP	0.31	[3]	0.33	[2]	[2.5]	SP	0.37	[5]	0.40	[3]	[4.0]
ESTAR	0.35	[6]	0.46	[7]	[6.5]	ESTAR	0.45	[8]	0.59	[8]	[8.0]
ARMA(1,1)	0.32	[4]	0.43	[6]	[5.0]	ARMA(1,1)	0.35	[3]	0.54	[7]	[5.0]
MS(2)-AR(4)	0.37	[8]	0.40	[4]	[6.0]	MS(2)-AR(4)	0.43	[7]	0.48	[5]	[6.0]
VAR(4)	0.34	[5]	0.37	[3]	[4.0]	VAR(4)	0.38	[6]	0.39	[1]	[3.5]
MS(2)-VAR(4)	0.37	[7]	0.48	[8]	[7.5]	MS(2)-VAR(4)	0.36	[4]	0.45	[4]	[4.0]
COM(1-7)	0.28	[1]	0.33	[1]	[1.0]	COM(1-7)	0.32	[1]	0.40	[2]	[1.5]
4-quarter						4-quarter					
RW	0.55	[3]	0.89	[2]	[2.5]	RW	0.54	[2]	1.06	[3]	[2.5]
SP	0.68	[5]	1.04	[5]	[5.0]	SP	0.73	[6]	1.17	[8]	[7.0]
ESTAR	0.58	[4]	0.90	[3]	[3.5]	ESTAR	0.65	[4]	1.03	[2]	[3.0]
ARMA(1,1)	0.54	[2]	0.92	[4]	[3.0]	ARMA(1,1)	0.55	[3]	1.11	[6]	[4.5]
MS(2)-AR(4)	0.90	[8]	1.16	[6]	[7.0]	MS(2)-AR(4)	1.07	[8]	1.17	[7]	[7.5]
VAR(4)	0.89	[7]	1.25	[7]	[7.0]	VAR(4)	0.65	[5]	1.11	[5]	[5.0]
MS(2)-VAR(4)	0.88	[6]	1.54	[8]	[7.0]	MS(2)-VAR(4)	0.87	[7]	1.09	[4]	[5.5]
COM(1-7)	0.54	[1]	0.81	[1]	[1.0]	COM(1-7)	0.47	[1]	0.90	[1]	[1.0]
8-quarter						8-quarter					
RW	0.83	[4]	1.22	[5]	[4.5]	RW	0.77	[2]	1.27	[4]	[3.0]
SP	0.86	[5]	1.13	[2]	[3.5]	SP	0.86	[4]	1.16	[2]	[3.0]
ESTAR	0.82	[3]	1.14	[3]	[3.0]	ESTAR	0.92	[5]	1.24	[3]	[4.0]
ARMA(1,1)	0.74	[2]	1.35	[7]	[4.5]	ARMA(1,1)	0.78	[3]	1.32	[5]	[4.0]
MS(2)-AR(4)	1.43	[7]	2.28	[6]	[6.5]	MS(2)-AR(4)	1.72	[7]	1.94	[8]	[7.5]
VAR(4)	1.28	[6]	1.64	[8]	[7.0]	VAR(4)	1.37	[6]	1.46	[6]	[6.0]
MS(2)-VAR(4)	1.55	[8]	2.21	[4]	[6.0]	MS(2)-VAR(4)	1.86	[8]	1.59	[7]	[7.5]
COM(1-7)	0.65	[1]	0.92	[1]	[1.0]	COM(1-7)	0.58	[1]	0.78	[1]	[1.0]

When considering the whole forecasting sample (Table 1, panel A) the results indicate that different models are able to beat the random walk at different time horizons. More precisely, while at the one-step-ahead horizon the best performing model is the COM(1,7) followed by the SP, at four- and eight-quarter-ahead horizon, also ESTAR and ARMA(1,1) produce more accurate forecasts than the RW. This evidence also emerges when

analysing the second sub-sample (Table 1, panel B), which ranges from 1998:4 to 2005:3 and embraces the launch of the Euro. In general, it is clear that combining models produce a better forecast accuracy than single forecasting model for this sub-sample too. This is true also if we use a naïve weighting scheme that attaches a constant weight ($1/n$, where n is the number of selected models) to each model at each time period. Table 2 reports the ratio of the RMSE of our scheme (numerator) over the naïve one (denominator).

Table 2. Comparing two weighting schemes – Ratio of RMSE

step-ahead	1992:1 - 2005:3	1998:4 - 2005:3	Percent Improvement
Euro area			
1	1.14	1.13	-14%
4	1	0.94	3%
8	0.85	0.77	19%
US			
1	1.02	1.02	-2%
4	0.95	0.99	3%
8	0.76	0.76	24%

Note, in particular, that the performance of our scheme seems to increase with the forecast horizon. More precisely, the percent improvement is 3% at 4-quarter-ahead and more than 20% at 8-quarter-ahead, on average.

The *RMSE* provides a quantitative estimate of the forecasting ability of a specific model, allowing different models to be ranked, but it does not provide a formal statistical indication of whether one model is significantly better than another. We also explicitly test the null hypothesis of no difference in the accuracy of the two competing forecasts by using forecast encompassing tests. In particular, we use the modified version of the Diebold-Mariano (1995) (MDM) proposed by Harvey et al. (1997), which adjusts for the possible wrong size of the original test when the forecasting horizon increases.

Table 3 reports the statistics of equal forecast accuracy (as measured by MSE) and the associated probabilities under the null (of equal accuracy). These tests refer to the whole forecasting sample (1992:1-2005:3). We follow the suggestion of Harvey et al. (1997) in comparing the statistics with critical values from the t-Student distribution with $(T-1)$ degrees of freedom, rather than from the standard normal distribution. P-values not greater than 0.05 suggest that Model i produces a lower forecast error (in terms of root mean squared error) relative to the Model j at 5% significance level. On the contrary, p -values not smaller than 0.95 mean that Model i generates a higher forecast error at the 5% level.

In absolute terms, if we consider the number of times each model significantly beats its competitors, the two test statistics reveal similar results at different forecasting horizons. Precisely, at one- four- and eight-quarter horizons, combined forecasts are found to be the best performing models. Of a total of 42 cases (seven

competitors and two inflation rates for each of the three horizons), the percentage of times they beat the other model is higher than 75%. This evidence is in line with the results obtained with the RMSE in Table 1.

Table 3. MDM: Model i vs. Model j

<i>Model i</i>	<i>Model j</i>	1quarter-ahead				4quarter-ahead				8 quarter-ahead			
		Euro area		US		Euro area		US		Euro area		US	
		Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value	Test Stat.	p-value
RW	SP	-0.75	0.23	2.06	0.98	-1.73	0.04	-1.60	0.05	-0.56	0.29	1.20	0.88
	ESTAR	-1.80	0.04	-1.57	0.06	-0.64	0.26	-0.20	0.42	-0.09	0.47	0.73	0.77
	ARMA(1,1)	-1.89	0.03	-1.48	0.07	0.32	0.62	-0.68	0.25	1.09	0.86	-1.04	0.15
	MS(2)-AR(4)	-1.90	0.03	1.03	0.85	-2.66	0.00	-3.02	0.00	-2.75	0.00	-7.13	0.00
	VAR(4)	-1.69	0.05	1.50	0.93	-2.10	0.02	-3.68	0.00	-3.84	0.00	-3.29	0.00
	MS(2)-VAR(4)	-2.12	0.02	-0.37	0.36	-4.43	0.00	-3.75	0.00	-3.99	0.00	-4.49	0.00
	COM(1,7)	0.45	0.67	2.45	0.99	0.33	0.63	1.98	0.98	3.20	1.00	5.22	1.00
SP	RW	0.75	0.77	-2.06	0.02	1.73	0.96	1.60	0.95	0.56	0.71	-1.20	0.12
	ESTAR	-1.54	0.06	-2.07	0.02	1.28	0.90	1.03	0.85	0.46	0.68	-0.18	0.43
	ARMA(1,1)	-0.66	0.25	-2.17	0.01	1.67	0.95	1.19	0.88	1.23	0.89	-1.34	0.09
	MS(2)-AR(4)	-1.35	0.09	-2.68	0.00	-1.59	0.06	-1.08	0.14	-2.58	0.01	-6.60	0.00
	VAR(4)	-0.93	0.18	-1.52	0.06	-1.28	0.10	-1.69	0.05	-3.23	0.00	-3.52	0.00
	MS(2)-VAR(4)	-1.62	0.05	-2.97	0.00	-2.25	0.01	-2.72	0.00	-3.56	0.00	-4.79	0.00
	COM(1,7)	1.52	0.94	-0.92	0.18	2.08	0.98	2.53	0.99	2.33	0.99	2.50	0.99
ESTAR	RW	1.80	0.96	1.57	0.94	0.64	0.74	0.20	0.58	0.09	0.53	-0.73	0.23
	SP	1.54	0.94	2.07	0.98	-1.28	0.10	-1.03	0.15	-0.46	0.32	0.18	0.57
	ARMA(1,1)	1.51	0.93	1.05	0.85	0.86	0.81	-0.32	0.37	1.21	0.89	-1.36	0.09
	MS(2)-AR(4)	0.33	0.63	1.48	0.93	-2.41	0.01	-1.87	0.03	-2.67	0.00	-6.25	0.00
	VAR(4)	0.87	0.81	1.69	0.95	-1.99	0.02	-3.13	0.00	-3.48	0.00	-3.31	0.00
	MS(2)-VAR(4)	0.36	0.64	0.54	0.71	-3.45	0.00	-3.32	0.00	-3.90	0.00	-4.33	0.00
	COM(1,7)	2.09	0.98	2.25	0.99	0.65	0.74	1.32	0.91	2.32	0.99	2.15	0.98
ARMA(1,1)	RW	1.89	0.97	1.48	0.93	-0.32	0.38	0.68	0.75	-1.09	0.14	1.04	0.85
	SP	0.66	0.75	2.17	0.99	-1.67	0.05	-1.19	0.12	-1.23	0.11	1.34	0.91
	ESTAR	-1.51	0.07	-1.05	0.15	-0.86	0.19	0.32	0.63	-1.21	0.11	1.36	0.91
	MS(2)-AR(4)	-0.72	0.23	1.36	0.91	-2.60	0.00	-2.00	0.02	-2.90	0.00	-5.61	0.00
	VAR(4)	-0.18	0.43	1.72	0.96	-2.28	0.01	-2.93	0.00	-3.96	0.00	-1.60	0.05
	MS(2)-VAR(4)	-0.82	0.20	0.18	0.57	-4.32	0.00	-3.35	0.00	-4.20	0.00	-4.15	0.00
	COM(1,7)	2.11	0.98	2.48	0.99	0.05	0.52	2.39	0.99	1.17	0.88	3.17	1.00
MS(2)-AR(4)	RW	1.90	0.97	-1.03	0.15	2.66	1.00	3.02	1.00	2.75	1.00	7.13	1.00
	SP	1.35	0.91	2.68	1.00	1.59	0.94	1.08	0.86	2.58	1.00	6.60	1.00
	ESTAR	-0.33	0.37	-1.48	0.07	2.41	0.99	1.87	0.97	2.67	1.00	6.25	1.00
	ARMA(1,1)	0.72	0.77	-1.36	0.09	2.60	1.00	2.00	0.98	2.90	1.00	5.61	1.00
	VAR(4)	0.89	0.81	0.88	0.81	0.04	0.52	-0.85	0.20	0.83	0.80	4.70	1.00
	MS(2)-VAR(4)	0.03	0.51	-1.70	0.04	0.20	0.58	-2.52	0.01	-0.71	0.24	0.37	0.64
	COM(1,7)	2.50	0.99	1.44	0.93	2.81	1.00	4.01	1.00	3.48	1.00	9.16	1.00
VAR(4)	RW	1.69	0.95	-1.50	0.07	2.10	0.98	3.68	1.00	3.84	1.00	3.29	1.00
	SP	0.93	0.82	1.52	0.94	1.28	0.90	1.69	0.95	3.23	1.00	3.52	1.00
	ESTAR	-0.87	0.19	-1.69	0.05	1.99	0.98	3.13	1.00	3.48	1.00	3.31	1.00
	ARMA(1,1)	0.18	0.57	-1.72	0.04	2.28	0.99	2.93	1.00	3.96	1.00	1.60	0.95
	MS(2)-AR(4)	-0.89	0.19	-0.88	0.19	-0.04	0.48	0.85	0.80	-0.83	0.20	-4.70	0.00
	MS(2)-VAR(4)	-0.91	0.18	-2.38	0.01	0.10	0.54	-2.06	0.02	-1.94	0.03	-2.92	0.00
	COM(1,7)	2.75	1.00	0.73	0.77	2.46	0.99	4.58	1.00	5.78	1.00	5.06	1.00
MS(2)-VAR(4)	RW	2.12	0.98	0.37	0.64	4.43	1.00	3.75	1.00	3.99	1.00	4.49	1.00
	SP	1.62	0.95	2.97	1.00	2.25	0.99	2.72	1.00	3.56	1.00	4.79	1.00
	ESTAR	-0.36	0.36	-0.54	0.29	3.45	1.00	3.32	1.00	3.90	1.00	4.33	1.00
	ARMA(1,1)	0.82	0.80	-0.18	0.43	4.32	1.00	3.35	1.00	4.20	1.00	4.15	1.00
	MS(2)-AR(4)	-0.03	0.49	1.70	0.96	-0.20	0.42	2.52	0.99	0.71	0.76	-0.37	0.36
	VAR(4)	0.91	0.82	2.38	0.99	-0.10	0.46	2.06	0.98	1.94	0.97	2.92	1.00
	COM(1,7)	2.78	1.00	2.58	1.00	5.48	1.00	4.18	1.00	4.89	1.00	5.83	1.00
COM(1,7)	RW	-0.45	0.33	-2.45	0.01	-0.33	0.37	-1.98	0.02	-3.20	0.00	-5.22	0.00
	SP	-1.52	0.06	0.92	0.82	-2.08	0.02	-2.53	0.01	-2.33	0.01	-2.50	0.01
	ESTAR	-2.09	0.02	-2.25	0.01	-0.65	0.26	-1.32	0.09	-2.32	0.01	-2.15	0.02
	ARMA(1,1)	-2.11	0.02	-2.48	0.01	-0.05	0.48	-2.39	0.01	-1.17	0.12	-3.17	0.00
	VAR(4)	-2.50	0.01	-1.44	0.07	-2.81	0.00	-4.01	0.00	-3.48	0.00	-9.16	0.00
	MS(2)-AR(4)	-2.75	0.00	-0.73	0.23	-2.46	0.01	-4.58	0.00	-5.78	0.00	-5.06	0.00
	MS(2)-VAR(4)	-2.78	0.00	-2.58	0.00	-5.48	0.00	-4.18	0.00	-4.89	0.00	-5.83	0.00

3. Structural Inference and Policy Analysis

From the previous findings, it is clear that different models may give rise to inflation forecasts which are statistically different, especially if we consider one or two-year-ahead forecasts, i.e. the typical horizon of the

policymaker. In this section we use the previous results to understand in which way inflation forecasts may influence the estimated effects of monetary policy shocks on unemployment dynamics.

We exploit the interrelated ideas that (i) policymakers might have access to several inflation forecasts when taking their decisions; and (ii) they might use different policy rules. Our main purpose is therefore to analyse the role of heterogeneous inflation forecasts on the effects of monetary policy on real activity under different monetary policy rules. From the combination of the two simple features (i) and (ii), our experiment contributes to quantifying the effects of particular shocks under model uncertainty.

As already argued by several scholars, the degree of uncertainty faced by policymakers can be so large that the effects of policy decisions on the economy are perceived at least as ambiguous (see for example Onatski and Williams (2003)). In order to shed some light on the level of this ambiguity, we particularly focus on the ex post analysis of a shock to monetary policy, using a reference model that considers three types of uncertainty: one related to the different ways policymakers form their expectations on future inflation; one related to the different rules adopted to take their decision; and one associated with the parameters of the reference model.

3.1 Model and Estimation

Our reference model is a structural VAR for an open economy, where the set of endogenous variables comprises unemployment, interest rate, exchange rate and inflation forecasts. The main difference with a standard VAR is that we replace current inflation rates with one, four and eight steps-ahead inflation forecasts computed in the previous section. In other words, we take seriously the idea that policymakers, when taking decisions, might use several inflation forecasts, and use the inflation forecasts obtained from each of the eight previous models to check for possible differential effects that the decision on the interest rate could have on unemployment.

Because we use inflation forecasts and not current inflation, the variables cannot be ordered as in a standard recursive VAR as (1) inflation, (2) unemployment rate, (3) interest rate, (4) exchange rate (see e.g. Stock and Watson (2001)). Our VAR, instead, is structural in the sense that we use economic theory to identify the contemporaneous relationships between the variables in the form of two specific non-triangular identifying assumptions, each reflecting a given monetary policy rule. By checking then how sensitive results are to these assumptions, we can quantify the estimated uncertainty relative to the policy rule.

In our experiment we consider two related identifying assumptions on the contemporaneous variance-covariance relationships. In the first, we use a version of the Taylor rule (TR), where the central bank sets the interest rate by reacting to current information on unemployment and to inflation forecasts. In this sense, our TR expresses a mixture of backward and forward-looking behaviour. In the second, we use a complete forward-looking TR where only shocks to inflation expectations are relevant for the decision of the central bank. We will

refer to this scheme as the “Strict Inflation Rule” (SIR). These schemes can be translated algebraically as follows. The VAR is represented by:

$$A(L)Y_t = \varepsilon_t \quad (4)$$

where the vector of endogenous variables is given by: $Y_t = (u_t \ i_t \ e_t \ \hat{\pi}_t)'$; ε_t is a vector of VAR innovations, $A(L)$ is a polynomial matrix in the lag operator and C is a vector of constants. The innovations are related to a vector of VAR structural shocks with mean zero and a diagonal variance-covariance matrix through the relation $\varepsilon_t = A_0 v_t$. The two identification schemes² above are easily summarised then in the following contemporaneous structures:

$$A_0^{TR} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & a_{24} \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & 0 & 1 \end{pmatrix} \quad and \quad A_0^{SIR} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & a_{24} \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix}$$

It should be noted that both schemes give rise to an exact identified model.

We estimate a VAR for each monetary rule and for each inflation forecast. As said above, we also consider uncertainty about the parameters of the model, and assume that they are random variables. Standard Bayesian techniques are employed to estimate the VAR (see e.g. Sims and Zha (1999)), and produce posterior distributions of quantities of interest. If our degree of uncertainty is high, we can attach a diffuse prior on the parameters. This has the advantage that posterior densities will be centred on OLS estimates.

Concretely, the VAR can be rewritten (e.g. Ciccarelli and Rebucci (2003)) as:

$$Y_t = (I \otimes X_t) \beta + \varepsilon_t \quad (5)$$

where ε_t is the vector of VAR innovations assumed to be *i.i.d* $N(0, \Sigma)$. It is easy to show that by combining the likelihood function of this model with the diffuse prior information $p(\beta, \Sigma) \propto |\Sigma|^{-n+1/2}$, the joint posterior $p(\beta, \Sigma^{-1} | Y)$ is a Normal-Wishart distribution, with:

² We examine the robustness of the simulation results by adopting two alternative recursive identification schemes where the ordering of the variables is $(u_t \ \hat{\pi}_t \ i_t \ e_t)'$ and $(u_t \ i_t \ \hat{\pi}_t \ e_t)'$, where the contemporaneously exogenous variables are ordered first. In these specifications, the (exogenous) exchange rate shocks are extracted by conditioning on the current value of the unemployment rate, the interest rate and the expected inflation. Despite some differences, the evidence emerging from this analysis suggests that the size and the timing of the unemployment response are similar across the identification schemes. (To save space, these simulations are not presented, but all results can be made available upon request).

$$p(\Sigma^{-1} | Y) = \mathcal{W} \left[\left(T \hat{\Sigma} \right)^{-1}, T - k \right] \quad (6)$$

and, conditional on Σ ,

$$p(\beta | Y, \Sigma) = N \left[\hat{\beta}, \Sigma \otimes (X'X)^{-1} \right] \quad (7)$$

Where $\hat{\beta}$ and $\hat{\Sigma}$ are the OLS estimates of β and Σ . Therefore, inference on any functions of the parameters is easily conducted by first sampling Σ and then, given this draw, by sampling β .

Given that both identification schemes are exact, there is a one-to-one mapping between Σ and A_0 , and therefore it is relatively easy to recover the latter from the former. Uncertainty about Σ will translate into uncertainty about A_0 .

3.2 Results

Our simple framework can be used to analyse the two types of policies mentioned above: a surprise monetary intervention and a change in the policy rule. The first is summarised, for instance, in the impulse responses of the rate of unemployment to a monetary policy shock for each inflation forecast. The second is simply carried out by comparing the impulse responses in the two models and measuring the difference. We use data for the US and the euro area. The sample used for the analysis is 1990-2005. Results are reported in Figures 3-7 and Tables 4-7.

3.2.1 A Benchmark

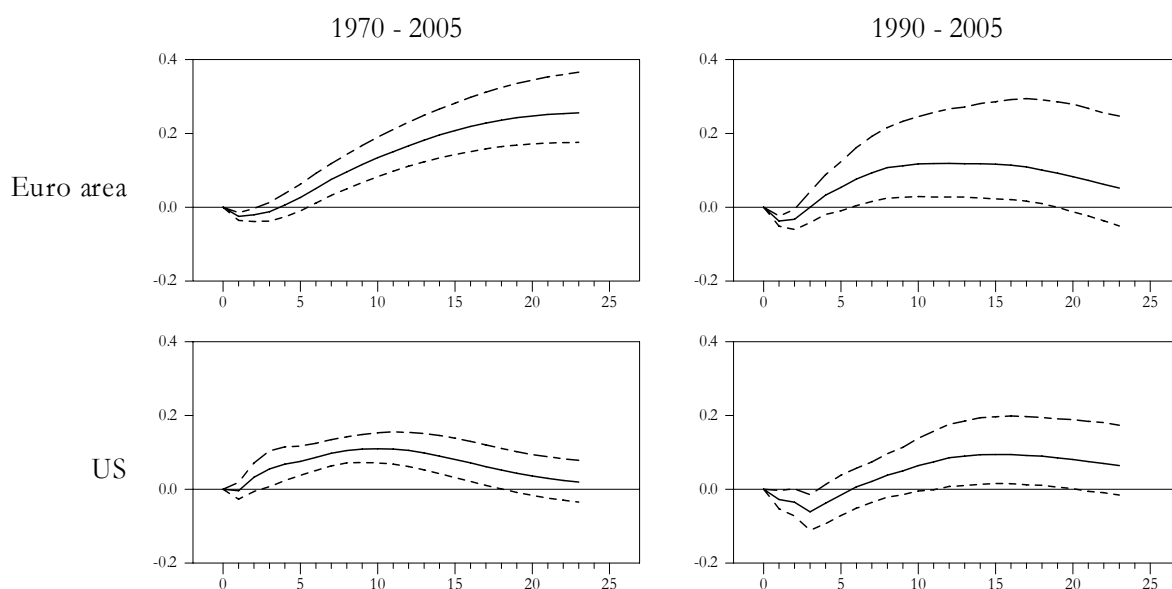
As a benchmark, Figure 3 illustrates the responses of unemployment to an unexpected increase in interest rates, in a typical recursive four-variable BVAR, where the order of the variables is the standard one: (1) current inflation, (2) unemployment, (3) interest rate and (4) exchange rate, for both the US and the euro area, over two samples, 1970-2005 and 1990-2005. We also report a 68% confidence interval for each response.³ Interestingly, for both the US and the euro area, there seems to be a change in the response in the last 15 years. A surprising common feature, for instance, is that the effect becomes positive and significant only after four to eight quarters, whereas it is negative and significant for the first two to four quarters. This is true for both the US and the euro area in the 1990s, but only for the latter if we consider the entire sample.

Although inconsistent with our *a priori* beliefs, this pattern can be justified from a theoretical point of view. Suppose, for example, that monetary authorities increase the nominal interest rate, leading to a negative impact on

³ In Appendix B we report all the impulse responses. Apart from the usual price puzzle, all other responses are in line with the expected benchmarks.

output. When a recession occurs, people in the labour force, who are not working, can react in three different ways. First, they can keep looking for a job in the area, thus remaining unemployed; second, they can migrate to another area; or third they can stop looking for a job, thereby exiting the labour force (and becoming “discouraged workers”). The concept of discouraged workers was first introduced by Long (1953). The discouraged worker hypothesis assumes that since searching for a job is a very expensive activity, a persistent period of unemployment reduce the probability of finding a job and may induce a group of secondary workers not to enter in the labour market. A large number of empirical studies covering various countries report evidence consistent with this hypothesis (Benati (2001); Darby et al. (2001); Blundell et al. (1998); Clark and Summers (1982)). Our preliminary findings appear to confirm this hypothesis, which in the US would be sample-dependent and only valid in the 1990s, whereas in the euro area it holds over the whole sample.

Figure 3. Response of unemployment to an interest rate shock in a recursive VAR



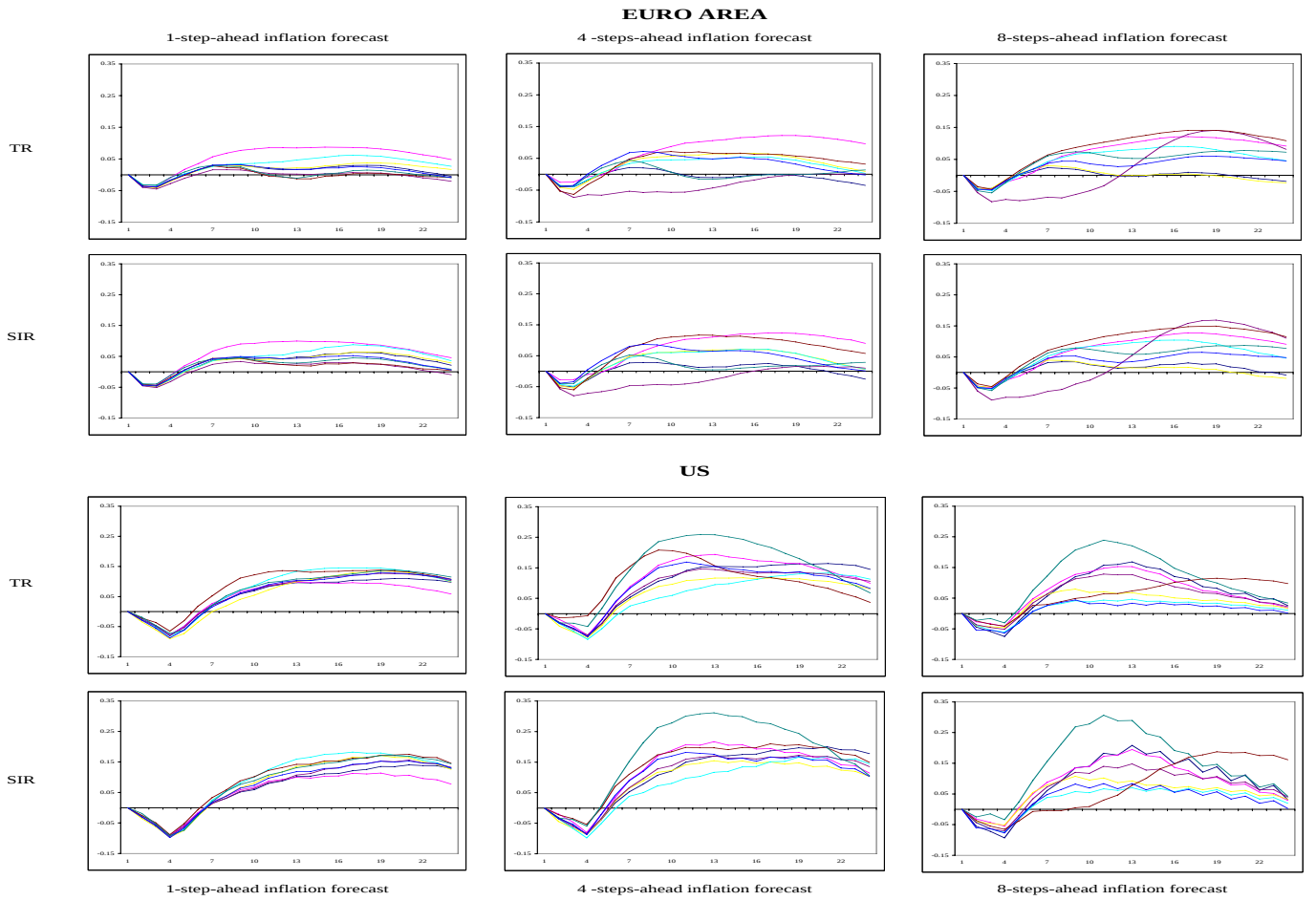
The different time pattern of unemployment responses can be explained by analysing the monetary policy transmission channels. Particularly, the strength of the discouraged work effect mostly depends on the mechanisms through which monetary shocks influence unemployment. These mechanisms are characterised by the particular set of labour market institution adopted by each country. Different labour market institutions might generate different reactions in the unemployment rate to interest rate shocks. In Europe, for example, where the presence of institutions considerably influences labour market variables, the effect of a monetary policy shock is transmitted to the labour market through the participation rate; as a consequence, when the interest rate increases, the participation rate initially dampens, leading to a decrease in the unemployment rate. On the contrary, in the

US, where institutions do not significantly affect labour market dynamics, a negative shock directly influences unemployment, thereby reducing the possibility for the discouraged effect to emerge.⁴

3.2.2. Inflation Forecasts and Unemployment Responses to Monetary Policy Shocks

Figure 4 reports the responses of unemployment to a shock to the interest rate for each inflation forecast and each policy rule, for both the euro area and the US. The charts are only illustrative and provide a first qualitative and quantitative answer to our main questions. In particular a detailed visual inspection reveals at least four interesting aspects.

Figure 4. Inflation forecasts and unemployment responses to monetary shocks



⁴ The difference between the euro area and the US can be appreciated from the impulse responses in Appendix B, where the VAR has been enlarged with the growth rates of the labour force. The effect on the labour force of a shock to the interest rate is greater and more significant in the euro area than in the US. Also, the presence of the labour force in the VAR seems to reduce the initial negative impact on the euro area unemployment rate, thus confirming our intuition regarding the discouragement effect.

First, the estimated effect of interest rates on unemployment is indeed different if the monetary authority designs the policy based on different inflation forecasts, regardless of the country and of the adopted rule.⁵ This is more evident for higher forecast horizons, in particular at the typical horizons for policy decisions (one to two years). The charts give a good intuition on how different forecast models for inflation can influence both the estimated magnitude of the real effects of a policy decision and the uncertainty about these effects.

Second, responses are flatter under the TR than under the SIR, though this difference seems hardly significant. This evidence suggests that the transmission of monetary shocks – in particular the size of the real effects – is likely to be affected by the specific information set that the central bank uses to set interest rates. The relative weights that policymakers attach to unemployment and inflation, therefore, largely influence the transmission of monetary shocks to labour market variables. It is not surprising that the time pattern of the unemployment response is less sensitive to monetary shocks under a TR, when policymakers react to both unemployment developments and inflation expectations. If, on the other hand, central bank only focuses on inflation expectations, the estimated reaction of unemployment to monetary shocks is stronger.

Third, a discouraged worker effect could be in place here, as for the benchmark impulse responses, for both the US and the euro area. In the former, the initial negative impact is overall more prolonged than in the latter, though afterwards there is a higher average positive effect. This seems to be true for the three forecast horizons of inflation expectations, and is overall significant.

Fourth, the cumulative effects are higher in the US than in the euro area for all forecast horizons. In fact, average responses for US are around 0.15 pp, whereas those of the euro area are not above 0.05 pp. Table 4 reports the forecast error decompositions for unemployment, i.e. the percentage of variance of the error made in forecasting unemployment due to a specific shock at a given horizon. In principle we can report such a table for each of the inflation forecasts. Here we focus only on results relative to the forecast combination method at the medium-term horizon of one year.

Overall, our results do not show considerable interaction among the variables, both across countries and across policy rules. Two features are worth mentioning, though. First, in the euro area the dynamics of unemployment are largely dominated by its own shocks at most horizons. This result is hardly surprising given that the unemployment rate is more persistent in Europe than in the US. Second, from 12 to 24 quarters around 30-35 percent of the error in the forecast of the US unemployment rate can be attributed solely to interest rate shocks. This confirms that, at least in the US, monetary policy can have large and long-lasting effects on real activity, as recently argued by Blanchard (2003), for example.

⁵ This result mainly depends on the different model specifications we use when computing inflation forecast and should not be confused with a different functioning of the transmission mechanism.

Table 4. Variance decomposition of unemployment

<i>horizon</i>	Taylor Rule				Strict Inflation Rule			
	<i>u</i>	<i>i</i>	<i>e</i>	$\hat{\pi}$	<i>u</i>	<i>i</i>	<i>e</i>	$\hat{\pi}$
Euro area								
1	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
2	0.90	0.06	0.01	0.02	0.88	0.07	0.01	0.03
3	0.88	0.05	0.01	0.03	0.86	0.06	0.01	0.05
4	0.85	0.04	0.01	0.06	0.84	0.05	0.01	0.08
8	0.72	0.09	0.03	0.10	0.73	0.09	0.02	0.09
12	0.55	0.11	0.05	0.18	0.57	0.12	0.05	0.16
16	0.46	0.13	0.08	0.23	0.48	0.13	0.08	0.21
20	0.42	0.13	0.11	0.24	0.45	0.13	0.10	0.22
24	0.38	0.13	0.14	0.23	0.41	0.13	0.13	0.23
US								
1	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
2	0.85	0.02	0.10	0.01	0.83	0.03	0.10	0.01
3	0.76	0.06	0.13	0.02	0.71	0.09	0.13	0.03
4	0.65	0.11	0.15	0.04	0.56	0.17	0.16	0.05
8	0.40	0.20	0.17	0.19	0.38	0.21	0.15	0.20
12	0.20	0.27	0.23	0.22	0.25	0.27	0.20	0.20
16	0.16	0.30	0.25	0.20	0.20	0.31	0.21	0.18
20	0.15	0.34	0.24	0.19	0.18	0.35	0.20	0.18
24	0.14	0.34	0.23	0.20	0.17	0.38	0.20	0.18

As final evidence in this section, we report some results based on a counterfactual analysis. The question we ask is: what would have been the level of unemployment in the euro area and in the US if the economies had only faced an interest rate shock? The answer might clearly depend on the sample therefore we shut down all shocks but the interest rate over two different samples: 1992-1998 and 1999-2005.⁶ The idea is simply based on partitioning the variable of interest (unemployment) into two components: its forecast over 1992-98 and 1999-05 based on the information available respectively at 1991 and 1998; and the additional part due to innovations in the other shocks. By summing just the contribution of the interest rate shock to the forecast of unemployment, we obtain the counterfactual unemployment rate had the economy faced only this shock over the sample in analysis.

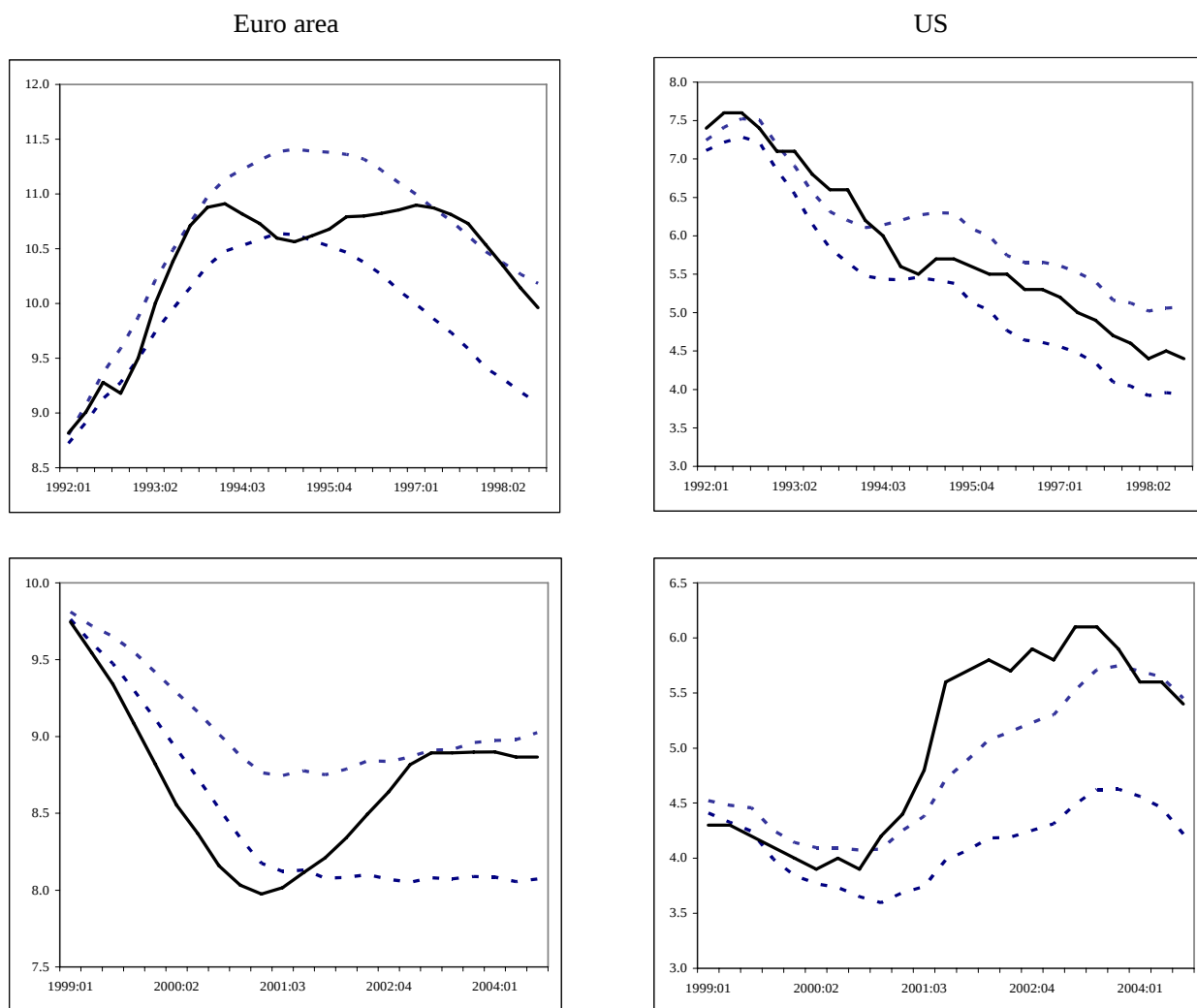
Figure 5 reports the experiment run in a VAR where the inflation forecast has been obtained with a TR, we have used the forecast combination (i.e. the best forecast on average) and the forecast horizon is four quarters (i.e. a typical central bank horizon). Results associated with other methods (or forecast horizons) show only minor differences which are not worth reporting. The charts plot the true level of unemployment and the 68% confidence bands of a counterfactual level of unemployment obtained had the economy faced only innovations in interest rate shocks.

Some differences between the euro area and the US are clear. As expected also from the variance decomposition and the higher degree of unemployment persistence, monetary policy innovations alone can hardly

⁶ The criteria for these sample choices are to be found in the creation of the EMU and the start of the euro economy. In this sense, though interesting from a European perspective, they are a bit ad hoc for the US, where none of such events have taken place.

explain the behaviour of the unemployment in the euro area. The downward trend between the mid 1990s and 2001 is certainly due to shocks other than monetary policy. The true level of unemployment falls in the bands only at the end of the second sample, when it stabilizes around 9%. On the other hand, US unemployment is almost always contained in the band over the sample 1992-1998, while it is over the bands in the recent five years. Both findings are hardly surprising: the downward trend of unemployment in the mid 1990s could have been predicted given the information up to 1992, regardless of other shocks; on the other hand, the level of unemployment in 2002-2004 – a period of historically low interest rates – is above the bands of what would have been produced if the only shock in the economy had been a monetary policy shock.

Figure 5. Historical decomposition



To conclude, the evidence provided so far suggests that the estimated effects of shocks to interest rates on unemployment might depend on both the method used to forecasting inflation and on the rule that the

policymaker uses. This result is independent of whether we consider the euro area or the US. In the latter, however, interest rate shocks can have larger and more significant effects on unemployment than in the former, the reason being the higher degree of persistence in European unemployment.

In the next section we look more closely at our results and quantify the uncertainty associated with rules and forecasting methods, making use of the posterior densities of the Bayesian estimation.

4. Quantifying Model Uncertainty

As mentioned at the beginning of the previous section, uncertainty is an integral element of the monetary policy decision process. A distinction is usually made between parameter and model uncertainty. Parameter uncertainty motivates our Bayesian choice in the estimation of the VAR.⁷ This section, instead, concentrates on model uncertainty. More precisely, starting from the impulse response function retrieved above, we directly measure the estimated uncertainty associated with monetary rules and forecasting models⁸.

The conclusions of Section 3 can be further quantified in Tables 5-6, where we report the posterior distribution of the responses of unemployment to interest rate shocks for methods, rules and countries, as summarised by the 16% and the 84% percentiles at relevant horizons. Uncertainty about the impulse response functions is therefore condensed in the distance between the two percentiles.

Notice first that US responses are overall more significant than those of the euro area, across methods, rules and inflation forecast horizons. This is clearly in line with the variance decomposition and the counterfactual analysis of the previous section. There does not seem to be any clear pattern across countries as forecasting methods are concerned. While for the euro area responses associated with the forecast methods SP and VAR are by and large the highest and the most significant, for the US the highest responses are associated with MSVAR and RW, and most methods give rise to significant responses, especially under the SIR and at a four-quarter inflation forecast horizon. Overall, the strict inflation rule is associated with the most significant responses.

⁷ A third source of uncertainty might come from the data and translate into a decision characterised by incompleteness and inadequacy of information on the economic variables. We do not tackle this issue here.

⁸ To provide a complete plot of the uncertainty, we should consider also the uncertainty around the inflation forecasts. However, we decided to take only a mean forecasts and not other quantiles of interest which would have highly complicated the presentation of the results, without greatly modifying the main conclusions.

Table 5. Impulse responses. Euro area.

Taylor rule																	
RW			SP		ESTAR		ARMA		MSAR		VAR		MSIHVAR		COMB		
horizon	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	
1-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.06	0.02	-0.05	0.03	-0.06	0.02	-0.06	0.02	-0.07	0.01	-0.05	0.02	-0.04	0.03	-0.06	0.02	
8	-0.03	0.10	0.01	0.14	-0.04	0.09	-0.03	0.09	-0.06	0.09	-0.04	0.09	-0.04	0.09	-0.04	0.10	
12	-0.06	0.10	0.01	0.16	-0.07	0.10	-0.06	0.12	-0.08	0.09	-0.08	0.06	-0.08	0.08	-0.07	0.10	
16	-0.06	0.12	0.02	0.17	-0.06	0.13	-0.05	0.14	-0.09	0.09	-0.07	0.06	-0.07	0.09	-0.07	0.11	
20	-0.06	0.12	0.00	0.16	-0.06	0.13	-0.05	0.15	-0.09	0.09	-0.06	0.07	-0.06	0.09	-0.06	0.11	
24	-0.09	0.10	-0.04	0.14	-0.07	0.11	-0.07	0.12	-0.11	0.06	-0.07	0.06	-0.07	0.06	-0.08	0.08	
4-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.06	0.02	-0.04	0.03	-0.07	0.02	-0.06	0.02	-0.11	-0.02	-0.07	0.01	-0.04	0.03	-0.05	0.05	
8	-0.05	0.09	0.01	0.12	-0.03	0.12	-0.03	0.11	-0.14	0.02	-0.02	0.14	-0.02	0.10	-0.01	0.15	
12	-0.09	0.07	0.04	0.18	-0.05	0.14	-0.05	0.13	-0.15	0.04	-0.01	0.16	-0.08	0.06	-0.04	0.14	
16	-0.10	0.09	0.06	0.20	-0.04	0.15	-0.05	0.15	-0.13	0.08	-0.01	0.16	-0.07	0.06	-0.04	0.13	
20	-0.11	0.09	0.05	0.22	-0.06	0.14	-0.06	0.14	-0.11	0.10	-0.02	0.15	-0.07	0.08	-0.06	0.10	
24	-0.15	0.06	0.02	0.21	-0.09	0.11	-0.09	0.11	-0.11	0.09	-0.04	0.13	-0.05	0.10	-0.09	0.08	
8-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.07	0.03	-0.07	0.02	-0.06	0.03	-0.07	0.02	-0.12	-0.04	-0.06	0.03	-0.07	0.02	-0.06	0.02	
8	-0.05	0.10	0.00	0.12	-0.05	0.10	-0.02	0.13	-0.16	0.01	0.00	0.15	0.00	0.15	-0.02	0.11	
12	-0.10	0.09	0.03	0.17	-0.10	0.09	-0.02	0.17	-0.14	0.11	0.02	0.22	-0.02	0.15	-0.04	0.10	
16	-0.10	0.11	0.05	0.20	-0.09	0.09	-0.01	0.19	-0.03	0.26	0.04	0.28	-0.02	0.16	-0.02	0.11	
20	-0.11	0.11	0.04	0.21	-0.10	0.08	-0.04	0.18	0.00	0.32	0.03	0.30	-0.01	0.19	-0.01	0.14	
24	-0.13	0.09	0.01	0.20	-0.11	0.06	-0.06	0.15	-0.07	0.29	0.00	0.30	-0.02	0.20	-0.03	0.13	

Strict inflation rule																	
RW			SP		ESTAR		ARMA		MSAR		VAR		MSIHVAR		COMB		
horizon	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	
1-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.07	0.01	-0.05	0.03	-0.06	0.01	-0.06	0.01	-0.07	0.01	-0.05	0.02	-0.05	0.03	-0.06	0.02	
8	-0.02	0.12	0.02	0.15	-0.02	0.11	-0.01	0.11	-0.04	0.11	-0.02	0.11	-0.01	0.11	-0.02	0.12	
12	-0.03	0.13	0.03	0.19	-0.04	0.12	-0.02	0.14	-0.06	0.11	-0.05	0.09	-0.04	0.11	-0.03	0.13	
16	-0.02	0.16	0.03	0.19	-0.02	0.14	0.00	0.18	-0.06	0.12	-0.04	0.10	-0.02	0.12	-0.02	0.14	
20	-0.03	0.16	0.01	0.18	-0.02	0.15	-0.01	0.18	-0.06	0.12	-0.04	0.09	-0.02	0.12	-0.03	0.13	
24	-0.07	0.12	-0.04	0.14	-0.05	0.12	-0.04	0.14	-0.10	0.08	-0.06	0.07	-0.05	0.09	-0.07	0.09	
4-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.07	0.01	-0.05	0.03	-0.07	0.01	-0.06	0.02	-0.11	-0.03	-0.06	0.02	-0.04	0.03	-0.04	0.05	
8	-0.03	0.10	0.01	0.13	-0.02	0.14	-0.02	0.13	-0.13	0.02	0.02	0.17	-0.01	0.12	0.01	0.17	
12	-0.07	0.10	0.05	0.19	-0.03	0.17	-0.03	0.15	-0.14	0.05	0.04	0.22	-0.06	0.08	-0.02	0.17	
16	-0.07	0.12	0.06	0.21	-0.03	0.17	-0.02	0.17	-0.12	0.10	0.04	0.22	-0.05	0.08	-0.02	0.16	
20	-0.09	0.11	0.04	0.22	-0.06	0.15	-0.05	0.15	-0.10	0.11	0.02	0.21	-0.04	0.08	-0.06	0.12	
24	-0.14	0.07	0.01	0.20	-0.10	0.11	-0.10	0.10	-0.11	0.11	-0.02	0.18	-0.03	0.10	-0.10	0.09	
8-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.07	0.02	-0.07	0.02	-0.06	0.03	-0.07	0.01	-0.12	-0.04	-0.06	0.02	-0.07	0.02	-0.06	0.02	
8	-0.04	0.12	0.00	0.13	-0.04	0.12	-0.01	0.15	-0.14	0.03	0.01	0.17	0.00	0.16	-0.01	0.12	
12	-0.08	0.11	0.03	0.18	-0.08	0.11	-0.01	0.19	-0.09	0.14	0.03	0.24	-0.01	0.17	-0.04	0.10	
16	-0.08	0.13	0.05	0.22	-0.08	0.11	0.00	0.22	0.02	0.30	0.06	0.28	-0.01	0.17	0.00	0.12	
20	-0.09	0.13	0.04	0.22	-0.09	0.09	-0.03	0.20	0.03	0.38	0.04	0.32	0.01	0.20	0.00	0.14	
24	-0.13	0.10	0.01	0.20	-0.12	0.06	-0.05	0.17	-0.04	0.34	0.00	0.33	0.00	0.21	-0.02	0.13	

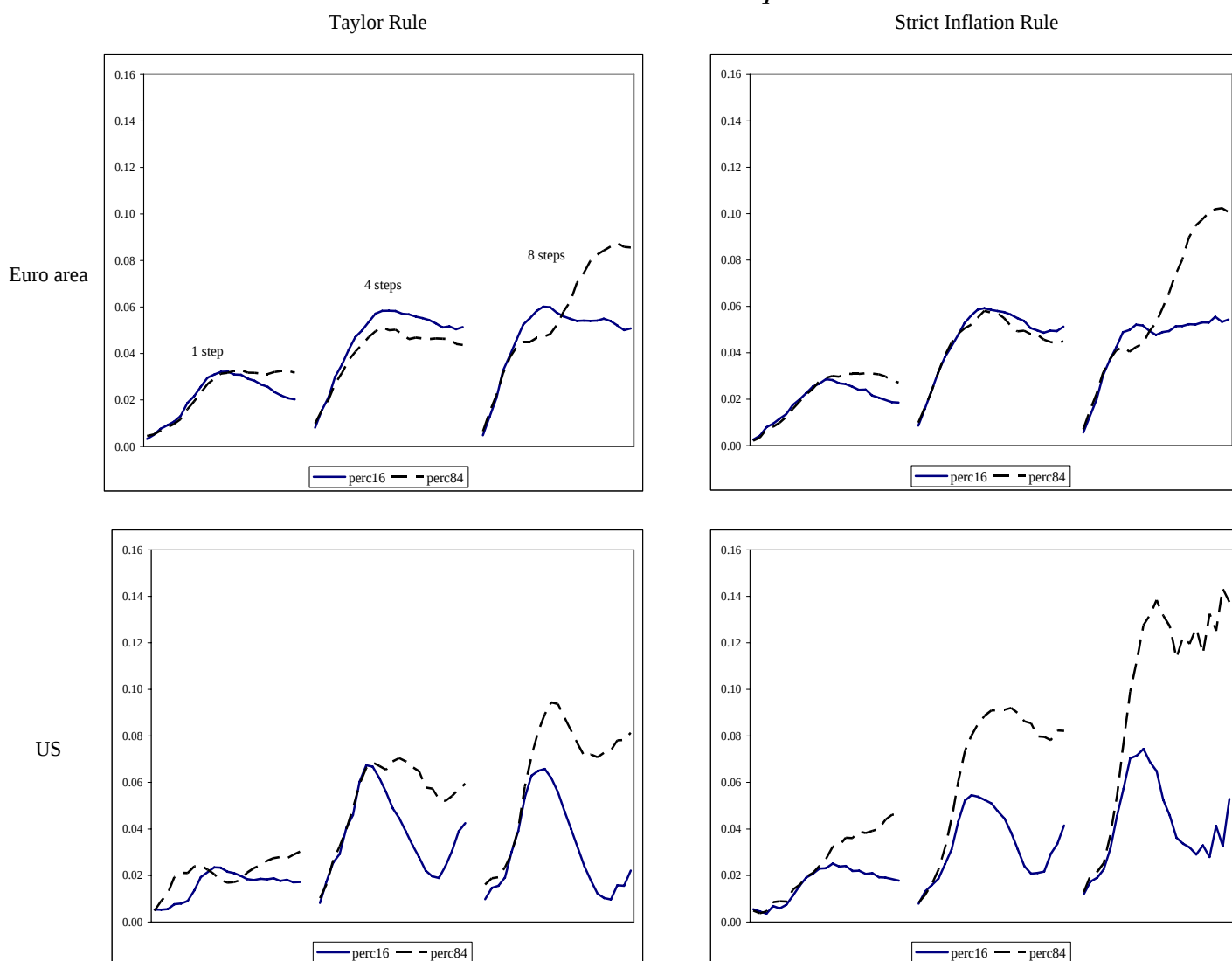
Table 6. Impulse responses. US.

Taylor rule																	
RW			SP		ESTAR		ARMA		MSAR		VAR		MSIHVAR		COMB		
horizon	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	
1-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.14	-0.02	-0.14	-0.01	-0.14	-0.04	-0.13	-0.03	-0.14	-0.02	-0.13	0.00	-0.13	-0.02	-0.14	-0.03	
8	-0.09	0.14	-0.07	0.14	-0.06	0.10	-0.05	0.13	-0.07	0.14	-0.04	0.18	-0.05	0.15	-0.06	0.12	
12	-0.05	0.21	-0.04	0.21	-0.01	0.19	0.00	0.23	-0.03	0.21	0.02	0.25	-0.01	0.22	-0.01	0.21	
16	0.00	0.21	0.00	0.21	0.03	0.24	0.05	0.27	0.02	0.24	0.04	0.25	0.03	0.25	0.03	0.23	
20	0.01	0.24	-0.01	0.21	0.04	0.26	0.05	0.29	0.03	0.27	0.04	0.29	0.04	0.27	0.04	0.26	
24	-0.01	0.26	-0.04	0.19	0.02	0.24	0.01	0.27	0.01	0.26	0.00	0.28	0.01	0.27	0.01	0.26	
4-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.13	-0.02	-0.13	-0.01	-0.13	-0.03	-0.14	-0.03	-0.13	-0.01	-0.06	0.04	-0.10	0.01	-0.13	-0.03	
8	-0.03	0.18	-0.01	0.24	-0.01	0.15	-0.06	0.13	-0.02	0.17	0.10	0.27	0.10	0.30	0.03	0.20	
12	0.02	0.29	0.06	0.35	0.00	0.25	-0.04	0.22	0.02	0.27	0.08	0.29	0.14	0.43	0.05	0.30	
16	0.04	0.33	0.05	0.36	0.00	0.27	0.00	0.26	0.02	0.28	0.02	0.26	0.10	0.45	0.03	0.29	
20	0.03	0.38	0.01	0.35	0.00	0.26	0.01	0.31	0.01	0.30	-0.03	0.25	0.02	0.39	0.02	0.29	
24	0.00	0.41	-0.05	0.32	-0.02	0.24	0.00	0.31	-0.02	0.30	-0.11	0.23	-0.10	0.32	-0.03	0.25	
8-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.14	-0.02	-0.11	0.02	-0.10	0.01	-0.12	-0.01	-0.11	0.00	-0.11	0.03	-0.09	0.02	-0.12	-0.02	
8	-0.04	0.19	-0.05	0.24	-0.01	0.17	-0.06	0.12	0.00	0.18	-0.13	0.19	0.05	0.30	-0.04	0.12	
12	0.00	0.32	-0.05	0.34	-0.05	0.21	-0.07	0.18	0.00	0.27	-0.10	0.20	0.10	0.42	-0.07	0.14	
16	0.00	0.31	-0.02	0.27	-0.06	0.18	-0.06	0.16	-0.01	0.23	-0.04	0.26	0.03	0.37	-0.06	0.14	
20	-0.05	0.27	-0.05	0.22	-0.06	0.16	-0.06	0.15	-0.03	0.19	-0.04	0.32	-0.05	0.29	-0.05	0.12	
24	-0.11	0.22	-0.11	0.16	-0.08	0.13	-0.07	0.11	-0.07	0.15	-0.05	0.34	-0.11	0.23	-0.07	0.09	
Strict inflation rule																	
RW			SP		ESTAR		ARMA		MSAR		VAR		MSIHVAR		COMB		
horizon	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	16%	84%	
1-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.15	-0.04	-0.15	-0.03	-0.16	-0.05	-0.15	-0.04	-0.15	-0.04	-0.15	-0.04	-0.15	-0.04	-0.15	-0.04	
8	-0.06	0.12	-0.05	0.12	-0.04	0.12	-0.03	0.14	-0.05	0.11	-0.04	0.14	-0.04	0.15	-0.04	0.13	
12	-0.02	0.21	-0.02	0.21	0.02	0.25	0.04	0.28	-0.01	0.21	0.03	0.26	0.00	0.25	0.01	0.23	
16	0.01	0.26	0.00	0.24	0.05	0.32	0.08	0.35	0.03	0.26	0.05	0.30	0.03	0.31	0.03	0.27	
20	0.02	0.31	0.01	0.25	0.06	0.34	0.07	0.37	0.05	0.31	0.06	0.36	0.05	0.37	0.05	0.31	
24	0.01	0.34	-0.03	0.23	0.02	0.32	0.02	0.35	0.03	0.31	0.02	0.38	0.03	0.37	0.02	0.32	
4-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.14	-0.04	-0.14	-0.02	-0.14	-0.03	-0.15	-0.05	-0.14	-0.03	-0.11	0.00	-0.11	0.00	-0.14	-0.04	
8	-0.02	0.17	0.02	0.23	0.01	0.18	-0.04	0.14	0.01	0.18	0.04	0.25	0.11	0.34	0.03	0.21	
12	0.04	0.31	0.07	0.39	0.02	0.31	-0.02	0.25	0.03	0.32	0.09	0.36	0.16	0.55	0.05	0.33	
16	0.05	0.38	0.05	0.40	0.00	0.35	0.00	0.33	0.04	0.36	0.08	0.40	0.12	0.61	0.04	0.33	
20	0.04	0.46	0.01	0.41	0.00	0.37	0.03	0.40	0.04	0.40	0.07	0.46	0.02	0.61	0.03	0.36	
24	0.01	0.53	-0.05	0.37	-0.03	0.32	0.01	0.43	0.01	0.41	0.00	0.45	-0.11	0.55	-0.03	0.35	
8-step-ahead																	
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	-0.16	-0.04	-0.12	0.00	-0.11	0.01	-0.14	-0.02	-0.13	-0.01	-0.13	-0.01	-0.10	0.03	-0.14	-0.02	
8	-0.01	0.21	0.00	0.24	0.00	0.21	-0.04	0.15	0.01	0.20	-0.12	0.12	0.09	0.37	-0.02	0.17	
12	0.04	0.39	0.02	0.37	-0.05	0.27	-0.07	0.23	0.01	0.32	-0.11	0.21	0.10	0.61	-0.06	0.24	
16	0.00	0.42	0.00	0.34	-0.07	0.27	-0.07	0.25	-0.01	0.33	0.00	0.35	0.01	0.58	-0.06	0.23	
20	-0.07	0.40	-0.05	0.28	-0.08	0.25	-0.08	0.23	-0.03	0.29	0.01	0.45	-0.08	0.52	-0.08	0.19	
24	-0.16	0.35	-0.12	0.22	-0.10	0.22	-0.10	0.20	-0.09	0.23	-0.01	0.50	-0.18	0.50	-0.11	0.15	

To quantify the uncertainty associated with model and rules, one could ask what is the degree of overlap between the posterior densities of the impulse response functions. Figure 6 plots the standard deviations of the two percentiles that characterise our posterior densities (16 and 84%) across the eight forecast methods for each step of the impulse responses.

The uncertainty in this chart is measured both by the absolute size of the standard deviation associated with each percentile and by the distance between the two standard deviations. Several comments are in order here.

Figure 6. Overall uncertainty across methods, rules and countries
Standard deviations across percentiles



First, uncertainty increases with the forecast horizon, as somehow expected. In particular, the dispersion among the 84% percentiles seems to increase more than the one among the 16% percentiles, which means that there is more uncertainty associated with the upper part of the distributions. Second, the typical pattern of the standard deviations consists of a steep increase and then a decrease over the steps of the impulse responses. This is true regardless of the rule, the country or the horizon of the inflation forecast. In other words, responses of

unemployment associated with the eight inflation forecasts are more dispersed around the peak value of the impulses, typically after 10-15 steps. Third, the uncertainty associated with the TR is slightly lower than the one associated with the SIR. This result confirms our previous conclusion that responses can be higher under the SIR than under the TR. Finally, the uncertainty associated with the US responses is higher than the one associated with the euro area, across rules and forecast methods. In particular, this is true for the upper part of the distribution and is consistent with higher responses of US unemployment to a shock to interest rate.

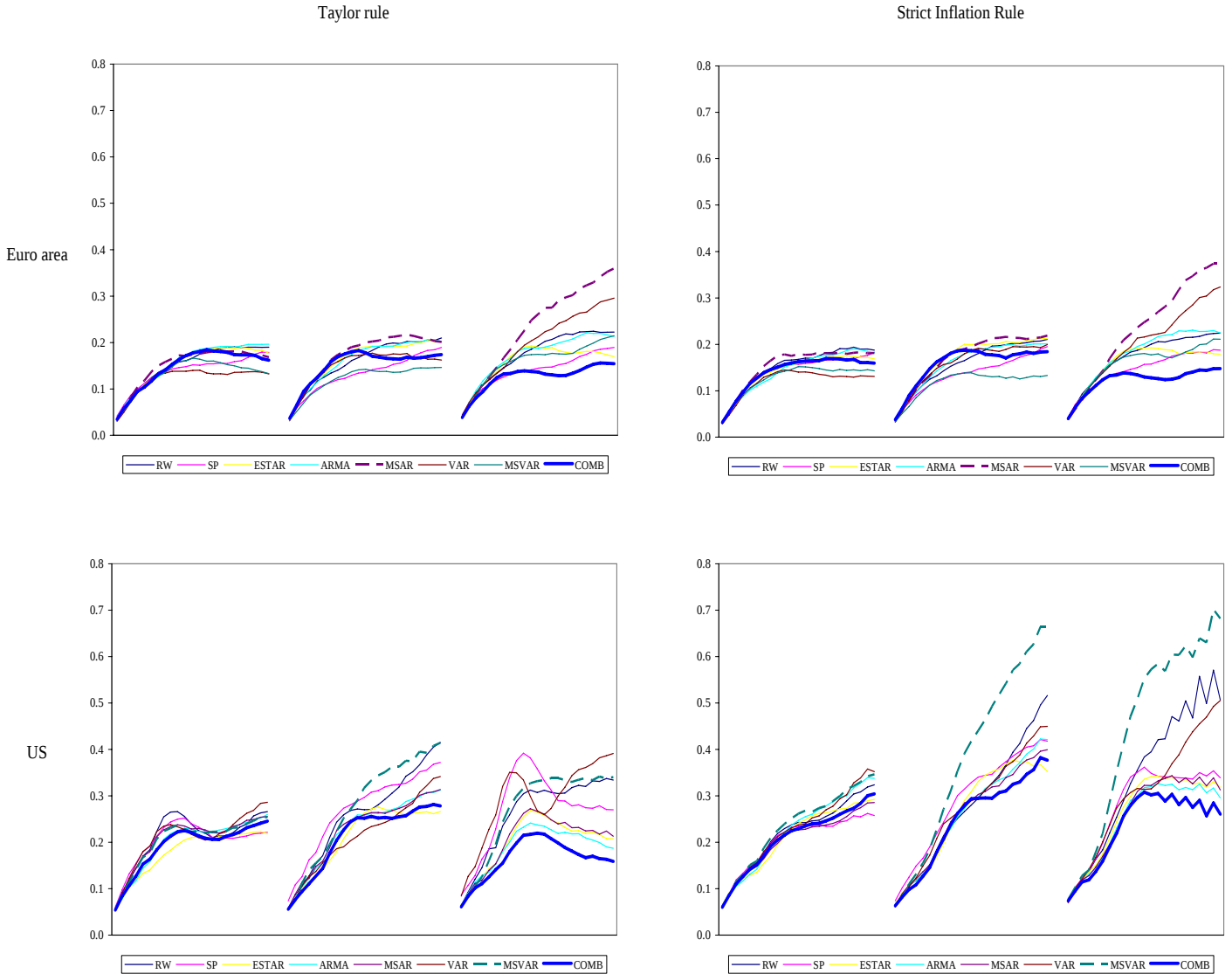
Overall, these findings support the idea of a high degree of uncertainty associated with the different inflation forecasts, especially around the peak impact of the interest rate on unemployment. The question now is: which inflation forecast has the highest level of uncertainty about the estimated responses of unemployment? This issue is important because the degree of uncertainty might significantly influence the accuracy of monetary actions. The identification of which forecasting model is likely to work most robustly across a range of possible methods decreases the uncertainty surrounding the future development of the target variable and the exact impact of the monetary policy instrument on labour market variables.

Figure 7 plots the distance between the 84% and the 16% percentile for each method, country and rule: the higher the difference, the more dispersed is the posterior distribution and the more uncertain is the estimated response of unemployment to an interest rate shock associated with a given forecasting method.

Although it is not possible to find clear and homogeneous patterns across methods, rules and countries, some recurring features are worth mentioning. First of all, it should be noted that the highest uncertainty is on average associated with non-linear methods, in particular the MSAR for the euro area and the MSVAR for the US (dashed lines). The intuition for this is to be found in the possible absence of clear structural breaks over the sample under analysis. Furthermore, the best method seems to depend on the forecasting horizon and on the specific country. Nevertheless, the lowest uncertainty on average is associated with the forecast combination method (bold line in the charts). In fact, while in the case of US the forecast combination beats all the other methods independently of the rule and the forecast horizon, the lowest uncertainty for the euro area is associated with the VAR for the one-quarter-ahead forecast, to the MSVAR for the four-quarters-ahead forecast and with the COMB for the eight-quarters-ahead forecast, independently of the policy rule.

Overall, the results suggest that central banks face considerable uncertainty about the future development of target variables and the impact of a given measure. Model uncertainty strengthens 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. This is because the dynamic underlying the price evolution might be surrounded by a high degree of uncertainty; as a consequence, fine-tuning monetary policy might amplify the business cycle.

Figure 7. Model uncertainty: distance between the 84% and the 16% percentile for each method, country and rule



The problem of model uncertainty suggests that, when evaluating risks to price stability, central banks should not concentrate on only one model, but instead should analyse as wide a range of models as possible. Overall, our results indicate that combining forecasts from many models not only yields more accurate forecasts than those of any specific model, but also reduces the uncertainty associated with the estimated effects of the policy decision. A monetary strategy that takes into account the information content of multiple models or multiple versions of models significantly improves the decision-making process. When various data-driven models (linear, nonlinear, univariate, multivariate) complement theoretical models, the uncertainty related to the effects of monetary actions

on real economy substantially dampens. These results are in line with the model-combination strategy that central banks already follow when assessing the risks to price stability.

5. Conclusions

In this paper we have shown how different models for forecasting inflation lead to different estimated effects of monetary policy on unemployment, beside the disparities that could be related to labour market institutions. Our evidence did suggest that the US might have a set of institutions which decreases the persistence of monetary shocks on unemployment, whereas euro area institutions could amplify the persistence of the reaction of unemployment to monetary shocks. However, regardless of the country and of the particular monetary policy rule adopted, a decision based on different inflation forecasts leads to considerable uncertainty regarding its real effects.

In order to forecast inflation, we have chosen eight competing models which differ not only in terms of the selected explicative variables and estimation methods, but also in terms of other core assumptions, such as their functional form. A ranking of the models in terms of forecasting performance suggests that there is no single model whose performance is clearly preferred; rather, a combination of forecasts appears most desirable.

The inflation forecasts have been used in a standard VAR to quantify the uncertain real effects of a shock to the interest rate under two different policy rules. Our results show that model uncertainty is a significant issue which strengthens the case for a more cautious policy strategy. In fact, the evidence provided here suggests that, when evaluating risks to price stability, central banks should not concentrate on one single model, but instead should analyse as wide a range of models as possible. Assessments of the price outlook based on different models, however, lead to different policy recommendations. Best practice, therefore, would be to combine results from different models as a device to reduce uncertainty. Our results indicate that combining inflation forecasts from many models not only yields more accurate forecasts than those of any specific model, but also seems to reduce the uncertainty associated with the estimated effects of policy decisions.

Appendix

A. Competing Models to forecast inflation

The empirical analysis presented in the paper analyzes the forecasting properties of eight competing models over horizons from one to eight quarters.

The first model consists of a driftless random walk process (RW). This simple framework is typically used as a benchmark against which inflation rate models are judged. The dynamics of the model is as follows:

$$\pi_t = \pi_{t-1} + \varepsilon_t \quad (\text{A.1})$$

where π_t represents the nominal inflation rate.

The second model is a univariate time series model that combines an autoregressive process with a moving average process. The length of the autoregressive term as well as the moving average term is chosen with standard selection criteria. The model we estimate is an $ARMA(1,1)$:

$$\pi_t = \alpha\pi_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1} \quad (\text{A.2})$$

The third model examined in the paper computes out-of-sample forecasts by using spectral analysis (*SP*). The time-domain representation may not necessarily be the most informative one. In particular, spectral analysis might be useful in detecting regular cyclical patterns or periodicities in transformed inflation rate data, or other significant pieces of information that are not visible in the time-domain of the series. Frequency-domain representation obtained through an appropriate transformation of the time series enable us to access this information.

In order to map the inflation rate from the time domain into the frequency domain we apply the Fourier transformation. Starting from the time series $\{\pi_t\}_1^T$ this transformation is based on the following equation:

$$\pi^{\text{inf}}(2\pi j/T) = \sum_{t=1}^T \pi_t^{\text{inf}} \exp(-2\pi ij(t-1)/T) \quad (\text{A.3})$$

where the frequencies range from zero to $(2\pi(t-1)/T)$ by increments of $2\pi/T$.⁹ Starting from the moving average representation of the selected time series we follow the procedure outlined in Koopmans (1974) to compute out-of sample forecasts using spectral techniques.

The fourth model is a four-variable vector autoregressive (VAR) model:

$$y_t = c + \sum_{i=1}^{k-1} \Gamma_i y_{t-i} + \varepsilon_t \quad (\text{A.4})$$

⁹ In equation A.3, π^{inf} is the inflation whereas the π has the usual mathematical meaning.

where $y_t = [\mu_t \ \pi_t \ i_t \ e_t]'$, and μ_t is the unemployment rate; π_t is inflation rate; i_t is the short-term interest rate, and e_t is the annual change of the nominal exchange rate.

The fifth model is a smooth transition autoregressive model (STAR). STAR models were originally introduced by Terasvirta and Anderson (1992). Their statistical properties are studied in Luukkonen et al. (1988), Luukkonen and Terasvirta (1991), Granger and Terasvirta (1993), Eitrheim and Terasvirta (1996). The general form of the STAR¹⁰ model is as follows:

$$\pi_t = \phi_{10} + \phi_1' \varpi_t + (\phi_{20} + \phi_2' \varpi_t) \Gamma(\pi_{t-d}; \gamma, \mu) + \varepsilon_t \quad (\text{A.5})$$

where $\varpi_t = (\pi_{t-1}, \dots, \pi_{t-p})$ is a vector of lagged values of inflation, and $\varepsilon_t \sim iid(0, \sigma^2)$. The transition function $\Gamma(\pi_{t-d}; \gamma, \mu)$ depends on a transition variable (π_{t-d}) , the speed of adjustment parameter $\gamma > 0$, and the equilibrium parameter μ . We test the specific form of the transition function by employing a battery of tests proposed in Granger and Teräsvirta (1993). In the final specification, data seem to suggest that for both the US and the euro area inflation rates are better modelled with an ESTAR form:

$$\pi_t = \mu + (\pi_{t-1} - \mu) + \left\{ 1 - \exp \left[-\gamma (\pi_{t-1} - \mu)^2 \right] \right\} \sum_{i=1}^4 \alpha_i^* (\pi_{t-i} - \mu) + \varepsilon_t \quad (\text{A.6})$$

where the transition function has an exponential form, $\Gamma(\pi_{t-d}; \gamma, \mu) = \left\{ 1 - \exp \left[-\gamma (\pi_{t-1} - \mu)^2 \right] \right\}$. This transition function has a minimum of zero at $\pi_{t-4} = \mu$. As a consequence, the ESTAR model is in the first regime when π_{t-4} is close to μ and in the second regime when deviations of π_{t-4} from its equilibrium value (in both direction) are large. Within each regime, the inflation rate reverts to a linear autoregressive representation, with different parameter values and asymmetric speeds of adjustment. The resulting ESTAR models are estimated on our data by nonlinear least squares (see Gallant, 1987; Gallant and White, 1988).

The sixth model is a univariate markov-switching model (MS-AR) similar to the one estimated by Engel and Hamilton (1990). In this model, the dynamic of discrete shifts follows a two-state Markov process with an AR component. Standard criteria (AIC, HQ and SC) favour an autoregressive structure of order four. The model therefore has the form:

$$\pi_t - \mu(s_t) = \sum_{i=1}^4 \alpha_i (\pi_{t-i} - \mu(s_{t-i})) + \varepsilon_t \quad (\text{A.7})$$

¹⁰ The ESTAR model is a particular class of the STAR model with the transition function having an exponential form. Note that the ESTAR can be viewed as a generalization of the double-threshold TAR model.

Where the residuals are conditionally Gaussian, $\varepsilon_t | s_t \sim NID(0, \sigma^2(s_t))$, the conditional mean $\mu(s_t)$ switches between two states, and s_t is a generic ergodic Markov chain defined by the transition probabilities:

$$p_{ij} = \Pr(s_{t+1} = j | s_t = i), \quad \sum_{j=1}^2 p_{ij} = 1 \quad \forall i, j \in \{1, 2\}.$$

The seventh model consists of a markov-switching VAR (MS-VAR). As in the linear case, it is made up of four variables (y , π , i and e). The hypothesis behind the specific form of the estimated model is that the dynamics of the inflation rate process follows a 2-state Markov chain. The idea is that the relation between the inflation rate and a set of explanatory variables is time-varying, but it is constant when we condition on the stochastic and unobservable regime variable. Concretely, the model allows for an unrestricted shift in the intercept and the variance-covariance matrix and for two lags in each variable ¹¹:

$$y_t = \ell(s_t) + \sum_{i=1}^{k-1} \Gamma_i y_{t-i} + \varepsilon_t \quad (\text{A.8})$$

where $\varepsilon_t | s_t \sim NID(0, \Sigma(s_t))$.

The last model accounts for the time-varying forecast ability of alternative models and combines all of them adapting the methodology proposed in Hong and Lee (2003), Yang (2004) and Yang and Zou (2004) and specified in Section 2. The idea behind the combination of forecasting techniques is that no forecasting method is fully appropriate for all situations. A single forecasting model might only be optimal conditional on given realizations, information set, model specification or sample period. By combining methods, we can compensate for the weakness of each forecasting model under particular conditions.

Denoted π_t the nominal inflation rate and $\hat{\pi}_t^k$ the inflation rate forecast series obtained from the seven models indicated before (i.e. $k = \text{RW, ARMA, SP, MS-AR, VAR, MS-VAR, ESTAR}$) the combined forecast, $\hat{\pi}_t^{COM}$, is obtained as:

$$\hat{\pi}_t^{COM} = \sum_{k=1}^7 \omega_{kt} \hat{\pi}_t^k \quad (\text{A.9})$$

where the weights (ω_{kt}) attached to each model are calculated as follows:

¹¹ We also estimated the model allowing for a shift in the mean of the variables. The results we obtained from the two specifications are very similar with respect to the regime classification as well as to the parameter values. As we expected, the differences between the two models mainly consist of the different pattern of the dynamic propagation of a permanent shift in regime. More precisely, in the MSIH model, the expected growth of the variables responds to a transition from one state to another in a smoother way. See Krolzig (1997) on the peculiarity of the two models.

$$\omega_{kt} = \frac{\exp\left[-\frac{1}{2} \frac{(\pi_{t-1} - \hat{\pi}_{t-1}^k)^2}{\sigma_t^2}\right]}{\sum_{k=1}^7 \exp\left[-\frac{1}{2} \frac{(\pi_{t-1} - \hat{\pi}_{t-1}^k)^2}{\sigma_t^2}\right]} \quad (\text{A.10})$$

and σ_t^2 is the sample variance of the inflation rate $\{\pi_{t-1}\}_{j=1}^{t-1}$. Precisely, $\sigma_t^2 = (t-2)^{-1} \sum_{j=1}^{t-1} (\pi_j - \mu_t)^2$ and

$$\mu_t = (t-1)^{-1} \sum_{j=1}^{t-1} \pi_j.$$

Yang (2004) examined the theoretical convergence properties of a generalisation of this combination method and find that it has a significant stability advantage in forecasting over some popular model selection criteria. In particular, as already mentioned, the specific relationship imposed insures that a weight attributed to a certain model at time t is larger the larger its ability to forecast the actual inflation rate in period $t-1$.

B. Data and impulse responses

Figure B.1 plots the variables used in the empirical analysis. The sources are DataStream and the AWM (see Fagan et al. 2001). The inflation rate in each country is calculated as the percentage change in the annual CPI inflation rate, i.e. $100(\log CPI_t - \log CPI_{t-4})$. US interest rate is the Federal Funds Rate. Euro area interest rate is the short-run rate of the AWM database.

Figure B.2 plot the impulse responses of the US and the euro area economies in a recursive VAR ordered as in section 3.1, with the addition of the labour force to verify the discouragement hypothesis.

Figure B.1: The data used in the analysis

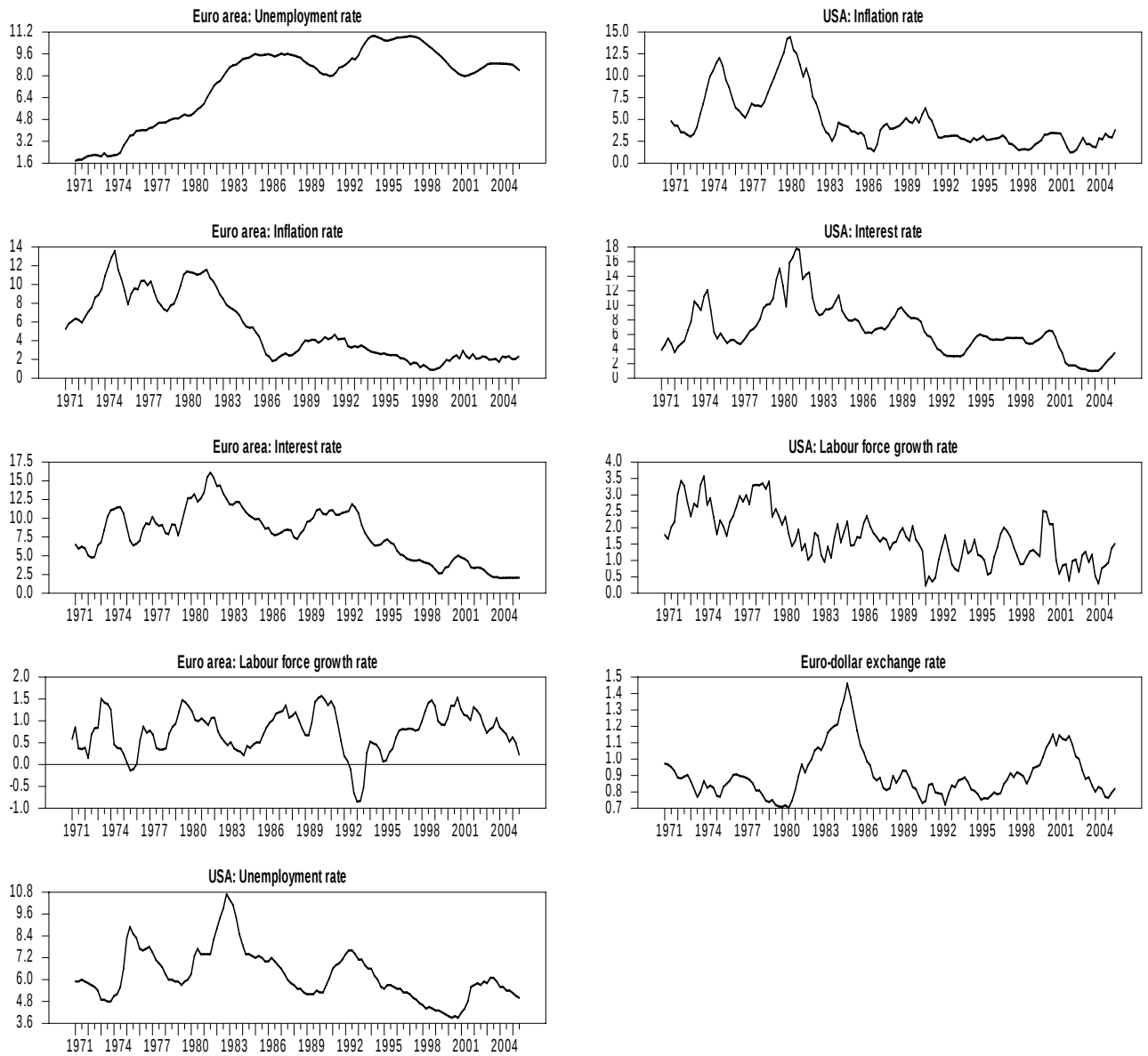
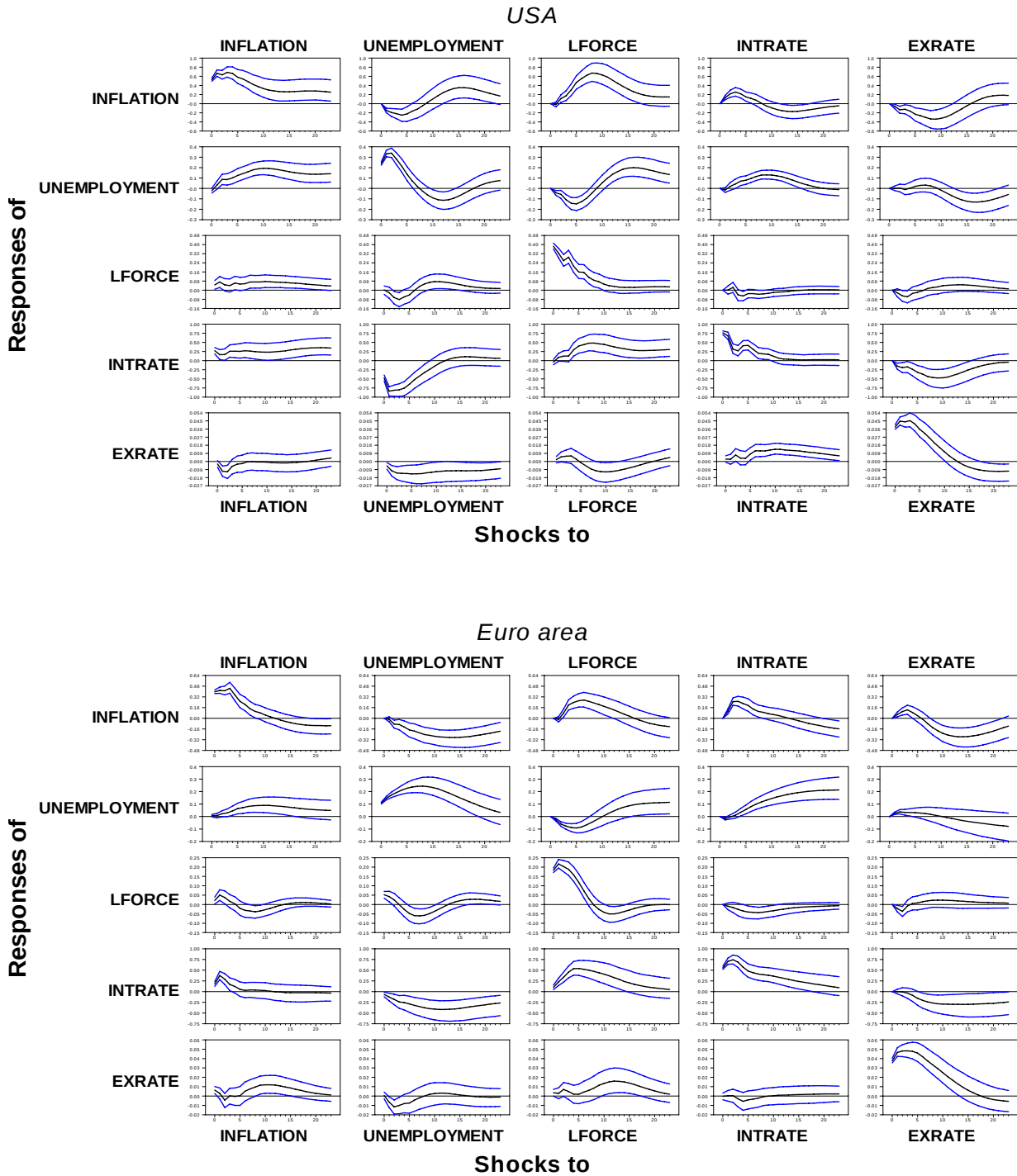


Figure B2. Impulse response functions in a recursive VAR with labour force



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