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Modelling and Forecasting Fiscal Variables for the euro Area[*]

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Abstract

In this paper we assess the possibility of producing unbiased forecasts for fiscal variables in the euro area by comparing a set of procedures that rely on different information sets and econometric techniques. In particular, we consider ARMA models, VARs, small scale semi-structural models at the national and euro area level, institutional forecasts (OECD), and pooling. Our small scale models are characterized by the joint modelling of fiscal and monetary policy using simple rules, combined with equations for the evolution of all the relevant fundamentals for the Maastricht Treaty and the Stability and Growth Pact. We rank models on the basis of their forecasting performance using the mean square and mean absolute error criteria at different horizons. Overall, simple time series methods and pooling work well and are able to deliver unbiased forecasts, or slightly upward biased forecast for the debt-GDP dynamics. This result is mostly due to the short sample available, the robustness of simple methods to structural breaks, and to the difficulty of modelling the joint behaviour of several variables in a period of substantial institutional and economic changes. A bootstrap experiment highlights that, even when the data are generated using the estimated small scale multi country model, simple time series models can produce more accurate forecasts, due to their parsimonious specification.

JEL Classification: C53, C30, E62

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1. Introduction

Forecasts for growth and fiscal variables are the key building blocks of all budgetary projections. In the European context fiscal forecasts have an additional function, in fact the submission of multiannual budget programmes is a central element of the surveillance process required by the Maastricht Treaty and the Stability and Growth pact. The available analysis of the performance of budgetary and growth forecasts in the euro area has shown some systematic over-optimistic bias (see, Artis and Marcellino(2001), Strauch et al.(2004)). This bias might reflect the fact that the loss function of the forecaster is not symmetric, or it might simply reflect forecasting errors given a symmetric loss function. The policy implications of the two alternative interpretations are very different[1] and hence it is important to assess the forecasting performance of different models to evaluate the possibility of achieving unbiased forecast errors for growth and fiscal variables.

In this paper, we consider forecasts for growth and fiscal variables for the largest countries in the euro area generated by a range of different models, which exploit different information sets and econometric techniques. In particular, we consider five different types of forecasts. First, standard ARMA models, which perform quite well from a forecasting point of view for several European macroeconomic variables, both on a country by country basis and at the euro area aggregate level, see e.g. Marcellino (2004a, 2005a), Marcellino, Stock and Watson (2003) and Banerjee, Marcellino and Masten (2006). Also, Artis and Marcellino (2001) found that even simple random walk forecasts sometimes outperform the leading international organizations such as the IMF, the EC or the OECD.

Second, VAR models, since VARs have been often used to model fiscal variables and their interaction with other macroeconomic variables, see e.g. Blanchard and Perotti (2002) for the US, Perotti (2002) for some OECD countries, and Marcellino (2005b) for the largest countries in the euro area.

Third, small scale models containing three types of variables: macroeconomic indicators, fiscal policy indicators and monetary policy indicators. We consider both national models, along the lines of Favero (2002) who used similar models to study the interaction between fiscal and monetary

[1] Jonung and Larch(2005) use the evidence of a systematic bias in growth and fiscal projections of EMU countries to make the case for independent fiscal forecasts, Fildes and Stekler(2002) after surveying the state of macroeconomic forecasting and the general improvement over time of the forecasting record of different forecasters reach the conclusion that researchers have paid too little attention to the issue of improving the forecasting accuracy record.

authorities, and a larger multi-country model, where the national models are linked up together to take into account the implications of the convergence process started by the adoption of the single currency, and in particular the presence of a single monetary policy with different fiscal policies.

Fourth, pooled forecasts obtained by taking either the mean or the median of the previous three types of forecasts. Since the pioneering work of Bates and Granger (1969) pooling has been found to be useful in improving the forecasting accuracy, see e.g. Clemen (1989) for an overview and Hendry and Clements (2004) for possible reasons underlying this result. Recent papers highlighting the good performance of pooling for forecasting macroeconomic variables include Stock and Watson (1999) for the US and Marcellino (2004b) for the euro area. Stock and Watson (2002) find that the simple average or median of the single forecasts perform well compared with more sophisticated pooling procedures.

Finally, we consider the OECD forecasts, as published in the World Economic Outlook. The forecasts in question are not directly derived from formal macroeconometric models but emerge from the iterative interplay between partial formal modelling, committee iteration and judgmental discretion. Moreover, they are produced by an independent forecaster so the political economy reasons that might induce euro area member countries in the temptation to issue biased forecasts do not apply to a supra-national entity such as the OECD.

Besides four key fiscal variables, i.e. government expenditures and receipts, the deficit and the government debt, we also consider forecasting the output gap, inflation and a nominal short term interest rate, since these are important variables to determine the evolution of the relevant fiscal aggregates for the Maastricht Treaty and the Growth and Stability Pact. All data are semi-annual and are extracted from the OECD dataset, with details provided below. We report results for one-step and two-step ahead forecasts, that can be used to derive current year and year ahead forecasts. We also summarize the findings for four-step ahead forecasts to evaluate whether the gains from using semi-structural models increase with the forecast horizon. Longer horizons are not worth evaluating because preliminary results indicates the presence of substantial uncertainty surrounding the forecasts and the presence of large biases.

We can anticipate some of the main results we obtain. First, for the macroeconomic variables the ARMA forecasts are often the best, with a slightly worse performance at the longer horizon. Second, for the fiscal variables the univariate time-series forecasts in general are the most accurate at the shorter horizon, while more mixed results are obtained at the longer horizon. Third, the good performance of the random walk forecasts mentioned before emerges also from our analysis, though in general it is possible to find a model that outperforms the random walk. Fourth, in general the semi-structural models do not yield any substantial forecasting gains, and a similar result holds for the OECD forecasts at the shortest horizon. Fifth, time-series forecasts show very little bias and, even when there is some bias, it goes in the direction of making the forecasted fiscal scenario worse than the realized one. This result is strengthened by the fact that naïve forecasts are generated under the null of a constant legislation scenario that does not take into account the potential role of announced future fiscal stabilization packages. In the light of this evidence, it is possible to attribute an eventual over-optimistic bias in government forecasts for fiscal variables to political economy considerations which make the loss function asymmetric (see, for example, Strauch et al.(2004)). Finally, substantial uncertainty surrounds the forecasts, so that the competing forecasts are seldom statistically different, and the size of the average forecast error for the fiscal balance, perhaps the most interesting fiscal variable from the policy point of view, is rather large.

Since the forecasting performance of our small scale semi-structural models is rather disappointing, not differently from the findings in other studies or using larger models (see, for example, Artis and Marcellino (2001) or the review in Fildes and Stekler (2002)), we have investigated whether such a result is due more to model mis-specification or to the substantial uncertainty that arises when estimating several parameters with a small sample. In particular, we have bootstrapped data with our multi-country model as the data generating process (DGP), and used this model, an ARMA(2,2) and a simple random walk to repeat the forecasting exercise on the simulated series. The results are very clear cut: the structural model is systematically beaten by the two simpler time series models even in this context where it coincides with the DGP. These findings support the adoption of simple time series models both to forecast fiscal variables and to provide a benchmark for the evaluation of official forecasts of the same variables. They also confirm the view that structural intepretability of the models is not necessarily a plus for forecasting performance (see Clements and Hendry (1996) in a related context).

The structure of the paper is the following. In section 2 we briefly describe the dataset. In section 3 we discuss the different forecasting methods we adopt. In section 4 we present the results of the forecast comparison exercise. In Section 5 we repeat the comparison exercise using bootstrapped series from the multi-country model. In section 6 we summarize and conclude.

2. Data

We focus on the four largest countries of the euro area, namely, Germany, France, Italy and Spain. For each country we consider the seven variables which determine the dynamics of debt-to-GDP and the deficit-to-GDP ratios : output growth and the output gap[2]; the CPI inflation rate; a monetary policy indicator (a nominal money market rate), which determines the cost of financing the debt; primary government deficits, also decomposed into revenues and expenditures; and total government debt. The fiscal variables are expressed as ratios to GDP.

The data source is the OECD and the frequency is half-yearly. This choice contrasts with the standard adoption of monthly or quarterly data for the analysis of macroeconomic variables. It is dictated first by data availability, and second by the fact that in most countries the major fiscal decisions are taken once a year, and possibly revised once. Perotti (2002) constructs a quarterly dataset, but Germany is the only country within the euro area for which such data are available.

For all countries the sample under analysis is 1981:1-2001:2, as in Marcellino (2005b). Though for some countries longer series are available, both Favero (2002) and Perotti (2002) found a clear indication of different behaviour of fiscal and monetary policy after the '70s, which suggests to focus on the most recent period.

The variables are graphed in Figure 1. There is a substantial co-movement of the business cycles of France, Germany, Spain and Italy, in line with the more detailed analysis in Artis, Marcellino and Proietti (2004). The convergence process in inflation and interest rates is also evident. Both features of the series should be taken into consideration in the model specification stage. Figure 1 also shows the working of the Maastricht Treaty in reducing the fiscal deficit and the government debt in all the four countries, a reduction that appears to be due more to expenditure cuts than to tax increases.

The figure does not highlight any non-stationary behaviour in the variables, possibly with the exception of the debt-to-GDP ratio. Since there are strong economic reasons to assume that all the seven variables are stationary, we will proceed under this assumption even though the outcome of

[2] In constructing the output gap we use the OECD measure of potential output, derived by the production function method (see Torres and Martin (1989) for a detailed description of this method).

ADF unit root tests is mixed, likely due to the low power of these tests in samples as short as ours (42 observations).

3. Models for fiscal variables

We now describe the four different approaches we consider in the forecasting competition, namely, ARMA, VAR, Simultaneous Equation Model (SEM), and forecast pooling. All models are specified using the full sample available, which is rather short (42 observations) so that recursive modelling is not suited.

For the specification of the ARMA models we start with an ARMA(2,2) for each variable and country, and select the combination of AR and MA length that minimizes the BIC. The resulting models are summarized in Table 1. Overall the fit is good, though this does not represent a reliable indication for forecasting, with lower values in the case of Germany. It is also interesting to point out the similarity of the models for Italy and Spain, and the fact that an MA component is always included in the model for inflation. In the subsequent analysis, following standard practice, we will also include a random walk based forecast.

For the (seven variable) VAR models, we can only include one or two lags because of the degrees of freedom constraint. Rather than selecting the lag length with an information criterion, we compute forecasts for both cases and compare their performance for each country and variable.

About the SEM, it is useful to distinguish between national models and the "euro area" model. The general specification of the national models follows Favero (2002) and is sketched below, with j indexing the countries, more details are provided in the Appendix.

$$\pi_t^j = c_1\pi_{t-1}^j + c_2 y_{t-1}^j + u_{1t}^j \qquad \text{(1-AD)}$$

$$y_t^j = c_3 + c_4 y_{t-1}^j + c_5\pi_{t-1}^j + c_6 i_{t-1}^j + c_7 g_{t-1}^j + c_8\tau_{t-1}^j + c_9 y_{t-1}^{US} + u_{2t}^j \qquad \text{(2-AS)}$$

$$i_t^j = c_{10} + c_{11} i_{t-1}^j + c_{12}\pi_t^j + c_{13} y_t^j + c_{14} i_t^{GER} + u_{3t}^j \qquad \text{(3-TR)}$$

$$g_t^j = c_{17} + c_{18} g_{t-1}^j + c_{19} y_t^j + c_{20} y_{t-1}^j + \frac{c_{21}}{\left(1+\Delta x_t^j + \pi_t^j\right)} avc_t^j * DY_t^j$$
$$+ c_{22} \frac{\Delta x_t^j + \pi_t^j}{\left(1+\Delta x_t^j + \pi_t^j\right)} DY_t^j + u_{4t}^j \qquad (4\text{-G})$$

$$\tau_t^j = c_{23} + c_{24} \tau_{t-1}^j + c_{25} y_t^j + c_{26} y_{t-1}^j + \frac{c_{27}}{\left(1+\Delta x_t^j + \pi_t^j\right)} avc_t^j * DY_t^j$$
$$+ c_{28} \frac{\Delta x_t^j + \pi_t^j}{\left(1+\Delta x_t^j + \pi_t^j\right)} DY_t^j + u_{5t}^j \qquad (5\text{-T})$$

The notation is as follows. π is annual inflation of the GDP deflator; y is the output gap, i.e., the percentage difference between real GDP and real potential GDP as measured by the OECD, i is the nominal monetary policy rate, measured by the three-month euro rate; *avc* is the average cost of financing the debt, i.e., the ratio of interest payment on government debt to debt; g is the ratio of government non-interest expenditure to GDP; τ is the ratio of government revenue to GDP; DY is the ratio of government debt to GDP; and Δx is real annual GDP growth.

We label this model semi-structural in that each equation has some economic interpretation although the model is not forward-looking.

Equations (1-AS) and (2-AD) represent aggregate supply and demand. The specification is similar to the one adopted in the recent strand of the empirical macroeconometric literature based on small scale models, see e.g. Rudebusch and Svensson (1999), Clarida, Gali and Gertler (2000). In the demand equation we introduce lagged government expenditures and revenues, to take into account the delays in the effects of fiscal policy and allow for a different elasticity of output to the two fiscal components. Demand can be also influenced by the corresponding US variables, and by the interest rate, possibly in real terms.

From the estimated models reported in the Appendix, in all countries the output gap enters with the proper sign into the specification of the aggregate demand (Phillips curve) equation, but it is significant only for France and Spain. Fiscal and monetary policy appear to have a limited effect on the evolution of the output gap in all countries, with often a negative coefficient for public expenditures. Instead, in all countries the output gap reacts positively and significantly to the US gap.

Equation (3-TR) is a monetary reaction function, in line with a Taylor-rule type of specification. It can be derived as the solution of the optimization problem of a central bank that has a quadratic objective function in the deviation of inflation from target, the output gap, and volatility in the policy rates, see e.g. Favero and Rovelli (2003). The inclusion of the German interest rate in the equation for the other countries captures the anchor role of Germany over this sample period, see e.g. Clarida, Gali and Gertler (1998).

From the Appendix, both inflation and the output gap have the proper sign and are significant for Germany, the output gap seems to matter less for the other countries (likely due to the overall marked decline of inflation over our sample period), while the German interest rate exerts an important role. To evaluate whether the monetary authority reacts to fiscal policy we have also included the government deficit and/or debt in the specification, but they were never statistically significant.

The evolution of government expenditures and receipts is determined by equations (4) and (5). The specification of these equations follows Bohn (1988), who allows for a smooth reaction of primary deficits to the output gap and to the debt to GDP ratio. Yet, we prefer to separately model the components of the primary balance since they separately enter the demand function. Moreover, our specification allows for a time-varying reaction of the primary deficit (and its components) to the debt to GDP ratio, which depends on the nominal rate of growth of output and the average cost of debt. In fact, the debt-stabilizing primary deficit-to-GDP ratio depends on the level of debt-to-GDP ratio and on the difference between the cost of finance the debt and output growth: if output growth is higher than the cost of financing the debt a stable debt-to-GDP ratio is compatible with a positive deficit-to-GDP ratio. Only dynamically efficient economies need surpluses to stabilize the debt-to-GDP ratio.

From the Appendix, in all countries there is substantial inertia in public expenditures, and they also increase in the presence of negative output gaps, but virtually without any long run effects. Taxes are also persistent, the effects of the output gap are minor (the output level matters more), while taxes increase significantly with the cost of public debt.

The model includes an equation for the evolution of the average cost of debt, which slowly adjust to the monetary policy rate,

$$avc_t^j = c_{15} avc_{t-1}^j + c_{16} i_t^j + u_{6t}^j \tag{6-AVC}$$

and for dynamic simulation purposes it is closed by the two equations below, describing the evolution of the debt to GDP ratio and the relationship between real GDP growth and the output gap.

$$DY_t^j = DY_{t-1}^j + \frac{avc_t^j - \Delta x_t^j - \pi_t^j}{\left(1 + \Delta x_t^j + \pi_t^j\right)} DY_{t-1}^j + \left(g_t^j - \tau_t^j\right) \tag{7-DY}$$

$$\Delta x_t^j = c_{29} + c_{30} y_t^j + u_{7t}^j \tag{8}$$

The parsimonious specification of the national models reflects the limited number of degrees of freedom. Though more complex dynamics or cross variable relationships might exist, they can be hardly detected and accurately estimated with such a short sample. On the other hand, the estimated equations (using SUR), reported in the Appendix, in general provide a good fit and diagnostic tests for no serial correlation (Lagrange Multiplier) and normality (Jarque-Bera) of residuals do not reject the null hypothesis in most cases. Moreover, parsimony is usually a benefit when forecasting is the goal of the analysis, as in our case. Similarly, the use of dummy variables could further improve the fit and diagnostic tests of the model, but it could weaken the forecasting performance of the model by making its specification too much sample dependent.

Since forecasting is our goal, we are also not interested in investigating whether the backward looking structure of the model is genuine or whether it is the reduced form of a forward looking model. Instead, it can be interesting to evaluate the dynamic behaviour of the model in equations (1)-(8) when all shocks are set to zero. The short run behaviour is of particular relevance for our short term forecasting exercise, but the long run behaviour is also important to evaluate the soundness of the economic hypothesis we made in specifying the model.

The dynamic behaviour of the national models is summarized in Figure 2, and overall it is quite satisfactory. The gap, inflation and interest rate tend to move together across countries. There are some differences in the long run values but stochastic simulations of the model have shown that these differences are not statistically significant. Actually, as expected, the standard errors around the point estimates tend to be quite large at the long horizon. About the fiscal variables, the expenditure and receipt ratios do not show any marked dynamics, while the government balance fluctuates in the range [-2.5%,0] and the debt ratio converges to values below 60%. The latter is an important finding since it indicates that we do not need to impose any restrictions on the model to guarantee that the Maastricht criteria are satisfied.

We can now discuss the multi-country model. This model links the national models together but also takes into account the convergence process associated with the monetary union that was already evident from the graphs of the macroeconomic variables. The euro area variables are constructed as averages of their national counterparts using real 1995 GDP weights.

The main characteristics of the model are the following. The national inflation rates can react also to the lagged euro area inflation and its change, and in general they do. The national output gap can react to its past difference with respect to the area gap. This term usually has a negative sign (except for Italy where it is not significant) supporting real convergence. The German interest rate can react not only to national but also to area wide inflation (positive and significant) and output gap (positive but not significant). The equations for expenditures and receipts are similar to those for the national models, since fiscal policy is not coordinated at the euro area level.

A detailed description of the multi-country model can be found in the Appendix. The dynamic simulation of the model is reported in Figure 3. The results show a closer convergence for macroeconomic variables, and on average higher government primary balances, but very similar debt-to-GDP dynamics. The (unreported) standard errors around the point estimates remain quite large, in particular at longer horizons.

Finally, we consider two forecast pooling procedures, the mean and the median of the forecasts we discussed so far, which notwithstanding their simplicity have performed quite well in previous analyses, as noted in the Introduction.

4. Forecasting fiscal variables

In this section we briefly review the forecasting methodology, which is rather standard, present the results, and finally discuss a comparison with the OECD fiscal forecasts.

4.1 Forecasting methodology

As we mentioned in the previous section, the specification of the forecasting models is based on the full sample. Yet, the chosen model is re-estimated over the forecast period, either recursively with the first sample ending in 1995:2, or with a 15 year rolling window, so that the first window ends again in 1995:2.

The estimated models are used to produce 1-, 2- and 4- semester ahead forecasts, where the latter are computed by forward iteration of the model rather than by means of dynamic estimation to avoid a further specification search. Moreover, the former approach empirically yields some forecasting gains for macroeconomic variables when the models are not severely mis-specified, see e.g. Marcellino, Stock and Watson (2005).

The resulting forecasts and the actual values are used to compute the forecast errors (forecast-actual), the root mean square error (RMSE), the mean absolute error (MAE) and the average forecast error (BIAS). Both the RMSE and the MAE of each model are expressed as a ratio of the corresponding values for the random walk forecasts, so that ratios smaller than one indicate a worse performance of the random walk forecasts. We have chosen the random walk as a benchmark since Artis and Marcellino (2001) have shown its good forecasting performance for fiscal variables. More sophisticated evaluation methods based on the full distribution of forecast errors are not applicable in our context, due to limited number of forecasts available.

Finally, we compute the Diebold and Mariano (1995, DM) test statistic to evaluate the statistical significance of the loss differentials. Two comments are in order on this topic. First, even though we apply the small sample corrections in Harvey, Leybourne and Newbold (1997), the very limited number of forecasts casts some doubts on the reliability of statistical testing in our context. Second, since models are pre-selected, some of them are nested, and their parameters are estimated, the asymptotic distribution of the DM test could be different from the standard normal, see e.g. Clark and McCracken (2001) and Giacomini and White (2005).

4.2 Results

Table 2 presents the RMSE of each forecasting method relative to the random walk, for h=1 and 2. Results for h=4 are available upon request.

ARMA models are clearly the best at the shortest horizon for most variables and countries (17 out of 28), with pooled forecasts ranked second (6 out of 28). The performance of the ARMA models deteriorates with the forecast horizon, ARMA produce the lowest RMSE in 12 out of 28 cases for h=2 and 9 out of 28 for h=4 (Table 6), while that of the pooling methods is basically unaffected (7 out of 28 best forecasts for h=2 and 8 out of 28 for h=4).

The structural models do slightly better at the longest horizon, they are the best in 6 out of 28 cases for h=4 and only in 3 out of 28 cases for h=1, but are still beaten often by the time series methods. These models perform best for output gap and government expenditure forecasts in Germany and for the interest rate in France.

As we mentioned before, because of the short sample size the forecasts are surrounded by a rather large uncertainty. As a consequence, the RMSEs are seldom statistically different from those of the random walk model, even though the latter is systematically beaten by the best forecast in terms of point RMSE values.

All these results are robust to changing the evaluation criterion from RMSE to MAE. This finding is related to the absence of major outliers in the distribution of the forecast errors.

Table 3 reports the bias of all forecasts. The results confirm that univariate ARMA models tend to outperform all other alternatives and they do not produce significant biases for all variables, with the only exception of the debt-to-GDP ratio. Interestingly, in this case the bias goes in the direction of making the forecasted fiscal scenario worse than the realized one. The bias increases with the forecasting horizon and the performance of the semi-structural model improves.

As a further robustness check, we recomputed all statistics using a rolling estimation window of fifteen years. Also in this case there are no major changes in the ranking of the forecasts, while no clear cut comparison of rolling and recursive estimation emerges.

4.3 Comparison with OECD forecasts

The OECD publishes current year forecasts in June and year ahead forecasts in December for some of the variables we consider. Also, the political economy related incentives that might generate some asymmetry in the loss function of forecasting errors for national countries should not apply to supra-national entities as the OECD. It is therefore interesting to compare their forecasts with ours, using the same methodology as above, but with an accurate choice of the timing (to reflect the availability of OECD forecasts), and forecast definition. Notice that our models are slightly advantaged by the full sample specification. We also include pooled OECD – structural model forecasts in the comparison.

The results in Table 4 indicate that pooled (mean) forecasts dominate OECD forecasts for the current year, with the OECD being the best for all countries only for Italian inflation and Spanish government primary balance. The OECD track record improves for the year ahead forecasts, but pooling or one of our models still dominates a number of macro and fiscal variables. Again the results are robust to the choice of loss function (MSE or MAE) and method of estimation (recursive or rolling). The good performance of the random walk is confirmed also with respect to the OECD, in particular one step ahead. This evidence casts some doubt on the political economy related intepretation of the bias in forecasts for growth and fiscal variables produced by countries in the euro area.

5. Forecasting bootstrapped variables

In this Section we use the estimated multi-country model, reported in the Appendix, to generate 2000 simulated time series with 42 observations (as in our sample) for each of the four fiscal variables and three macroeconomic variables of interest, and for each of the four countries. In particular, for each replication, we fix the values of the parameters in the multi-country model equations at their full sample estimates, and draw the random error series from a normal distribution centred on zero and with the full sample estimated standard deviation for each variable. Note that we could have drawn also the parameters from the distribution of the full sample estimators, but since the latter is characterized by substantial uncertainty many of the resulting simulated series could have undesirable economic properties.

For each simulated series, we consider recursive 1-step ahead forecasts, starting with observation 31 and ending with 42, which corresponds to the forecast period 1996:1-2001:2 used in the previous section. We compute the recursive forecasts for three models: the multi-country model, an ARMA(2,2), and a random walk. Since the multi-country model is used to generate the series, if the estimation sample is long enough to produce accurate estimates of its parameters, it should also produce the best forecasts. On the other hand, the ARMA(2,2) model is flexible enough to approximate well the fiscal and macroeconomic time series to our interests (see, for example, Artis and Marcellino (2001)) and it requires estimation of only four parameters (plus the error variance). With the random walk, no parameters have to be estimated to produce the forecast, and the model would be quite rapid in correcting forecast errors arising because of structural breaks. Therefore, on a priori grounds it is difficult to judge the expected relative short sample performance of the three competing models.

Table 5 can be used to run the comparison. As for the other empirical results, we report the RMSE and MAE of the MCM and ARMA relative to the random walk, for each country and variable, and the RMSE and MAE of the random walk model. The reported values are averages over the 2000 replications, together with their standard deviation. Five main comments can be made.

First, the MCM is systematically beaten by the random walk, the former outperforms the latter in only 2 out of 28 cases, and the gains are minor. On the other hand, the gains from the random walk are also minor, never larger than 10%. Second, the ARMA model is on average better than the random walk, it produces a lower MSFE for 16 out of 28 variables, and the gains can be very substantial. The ARMA model is the best for Germany, lower MSFE for 7 out of 7 variables, and the worst for France, lower MSFE for 2 out of 7 variables, with the cross-country differences depending on the different estimated MCM equations. Third, focusing on the macro variables, ARMA is best for inflation, lowest MSFE in 4 out of 4 countries, and worst for interest rate, lowest MSFE in 1 out of 4 countries. For the fiscal variables, ARMA is best for receipts and debt, lowest MSFE in 3 out of 4 countries, and worst for expenditures and deficit, lowest MSFE in 1 out of 4 countries. Finally, all the findings are basically unaffected by using the MAE criterion (the only changes are that ARMA is now better than random walk for expenditures in France, and MCM is worse than random walk also for the French receipts).

Overall, the results of this simulation experiment indicate that in short samples the ARMA model, and up to a certain extent the random walk, can substantially outperform the MCM model from a forecasting point of view even if the latter coincides with the data generation process. These findings reflect the estimation uncertainty when the sample size is small relative to the number of parameters to be estimated (see Clements and Hendry (1998), Chapter 7). Moreover, ARMA models provide good univariate representations for any weakly stationary variable and the use of an

MA(2) term is particularly helpful when the forecast horizon is up to two-period ahead, as in our case.

In the light of this evidence, the very good empirical performance of the ARMA model in Section 4 becomes less surprising. The results of the experiment are of more general interest for the interpretation of the comparisons of small scale time series models with larger scale econometric models. They also justify the adoption of ARMA models as benchmarks when evaluating the existence of bias in forecast for fiscal variables and macroeconomic variables relevant to determine the path of the indicators listed in the Maastricht Treaty and in the Stability and Growth Pact.

6. Conclusions

The main conclusion of our empirical exercise is that forecasting fiscal variables is hard and caution should be exercised in taking the observed bias in government forecasts for fiscal and fiscal-related macroeconomic variables as optimal, to then speculate on the incentives that could have generated the observed bias. Forecasts based on simple time-series models or pooled forecasts outperform forecasts based on multivariate time-series or semi-structural small models for fiscal variables and the macroeconomic variables relevant to determine the debt-to-GDP and the deficit-to-GDP dynamics for large countries in the euro area.

Our results can be due to several reasons, including the short sample available that makes the specification and estimation of structural models complicated, the robustness of simple methods to structural breaks (this is particularly so for random walk and pooled forecasts), and the difficulty of modelling the joint behaviour of several variables in a period of substantial institutional and economic changes. The results of a simulation experiment, where data are generated by our estimated Multi-Country Model with constant parameters, but simple ARMA models provide the best forecasts for most fiscal and macroeconomic generated variables, provide substantial support for the importance of parsimonious specification to limit the effects of estimation uncertainty and produce good forecasts when the size of the sample available is small .

Our results can be helpful to explain related findings in the literature: the good performance of the RW and simple univariate time-series models relative to institutional forecasts of fiscal variables by the IMF or the OECD in Artis and Marcellino (2001) or the systematic bias in forecasts provided by euro area country members in Jonung and Larch (2005) and Strauch et al.(2004).

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Figure 1: Macro and Fiscal variables – 1981:1 2002:2

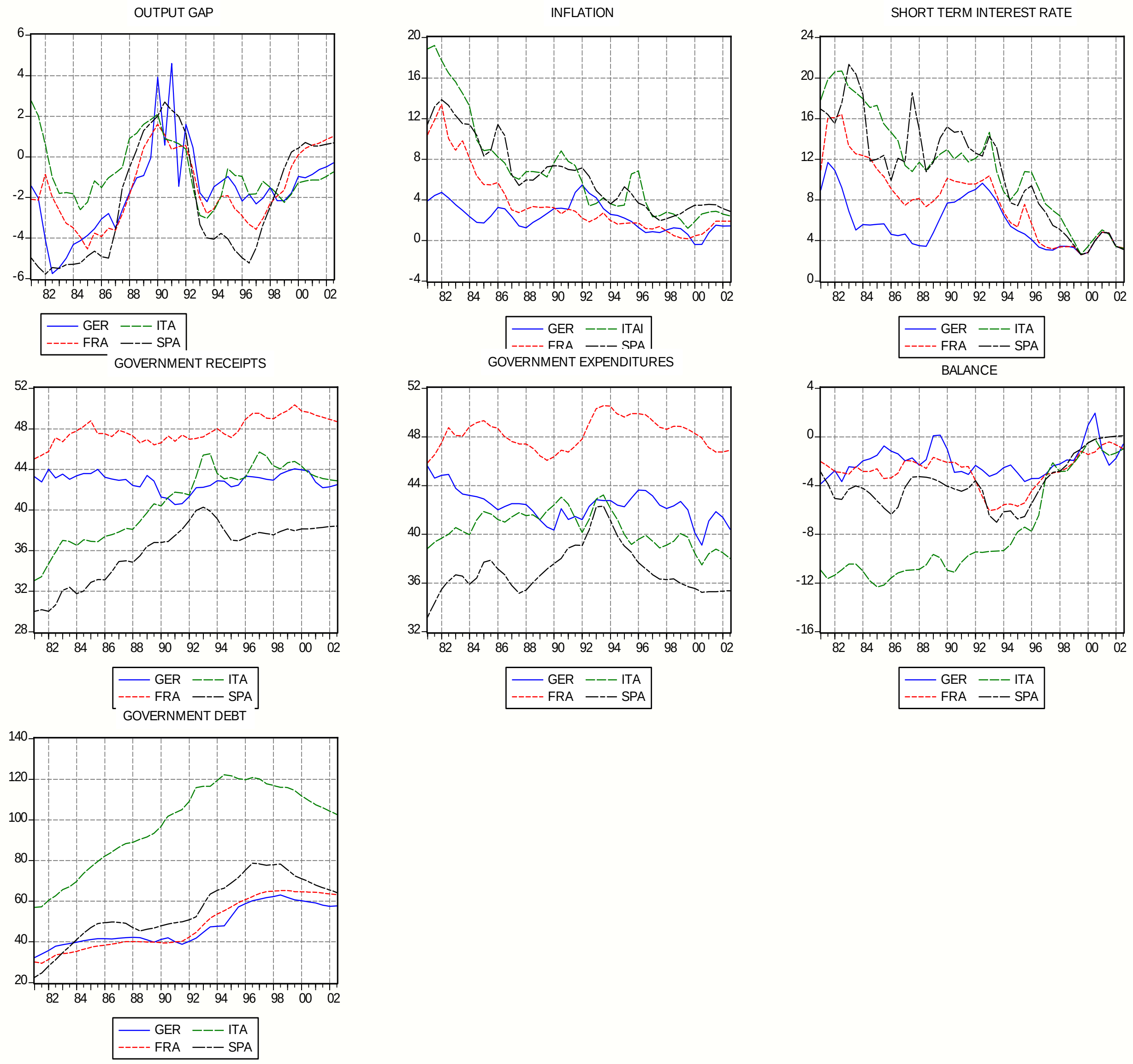
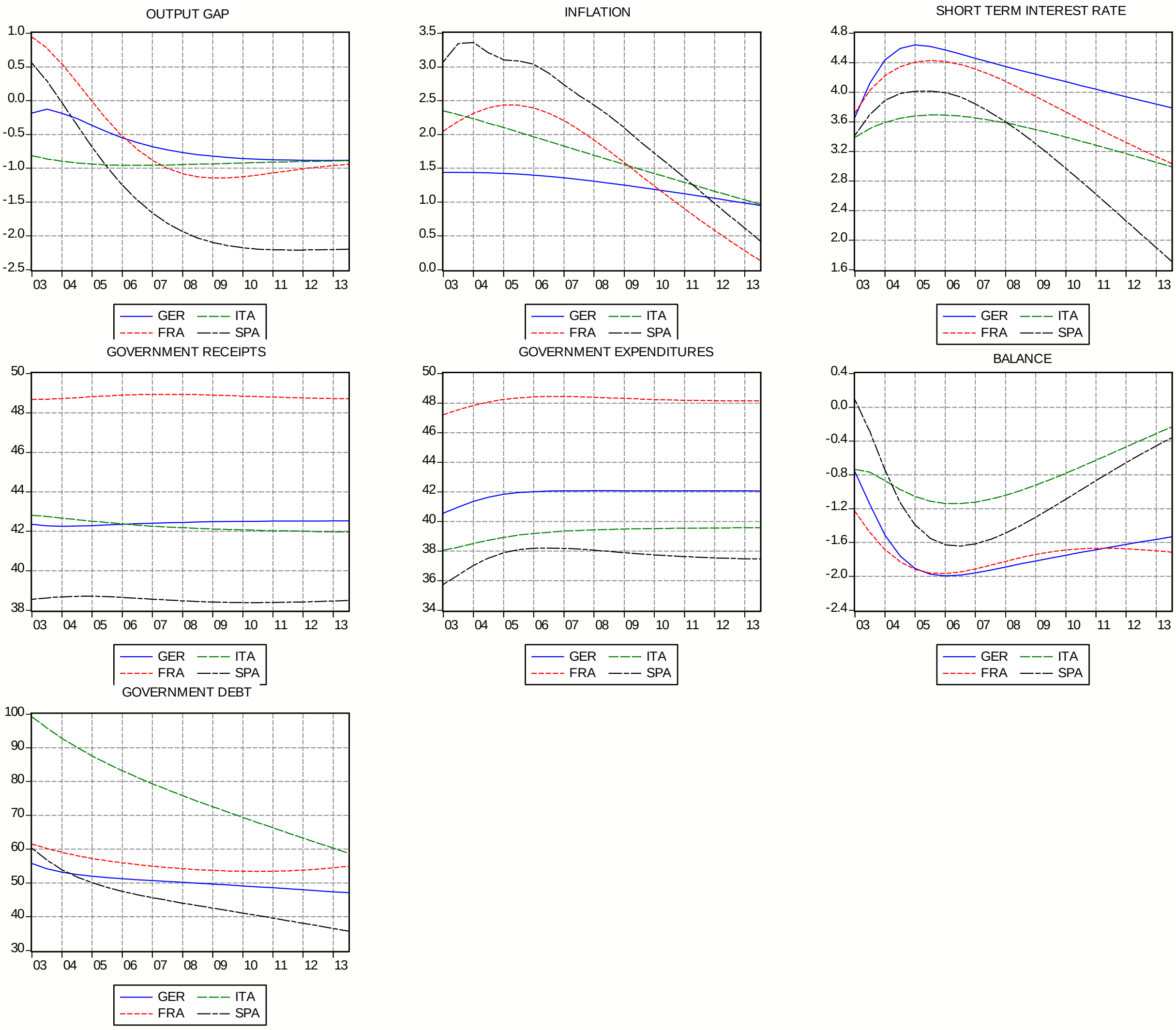
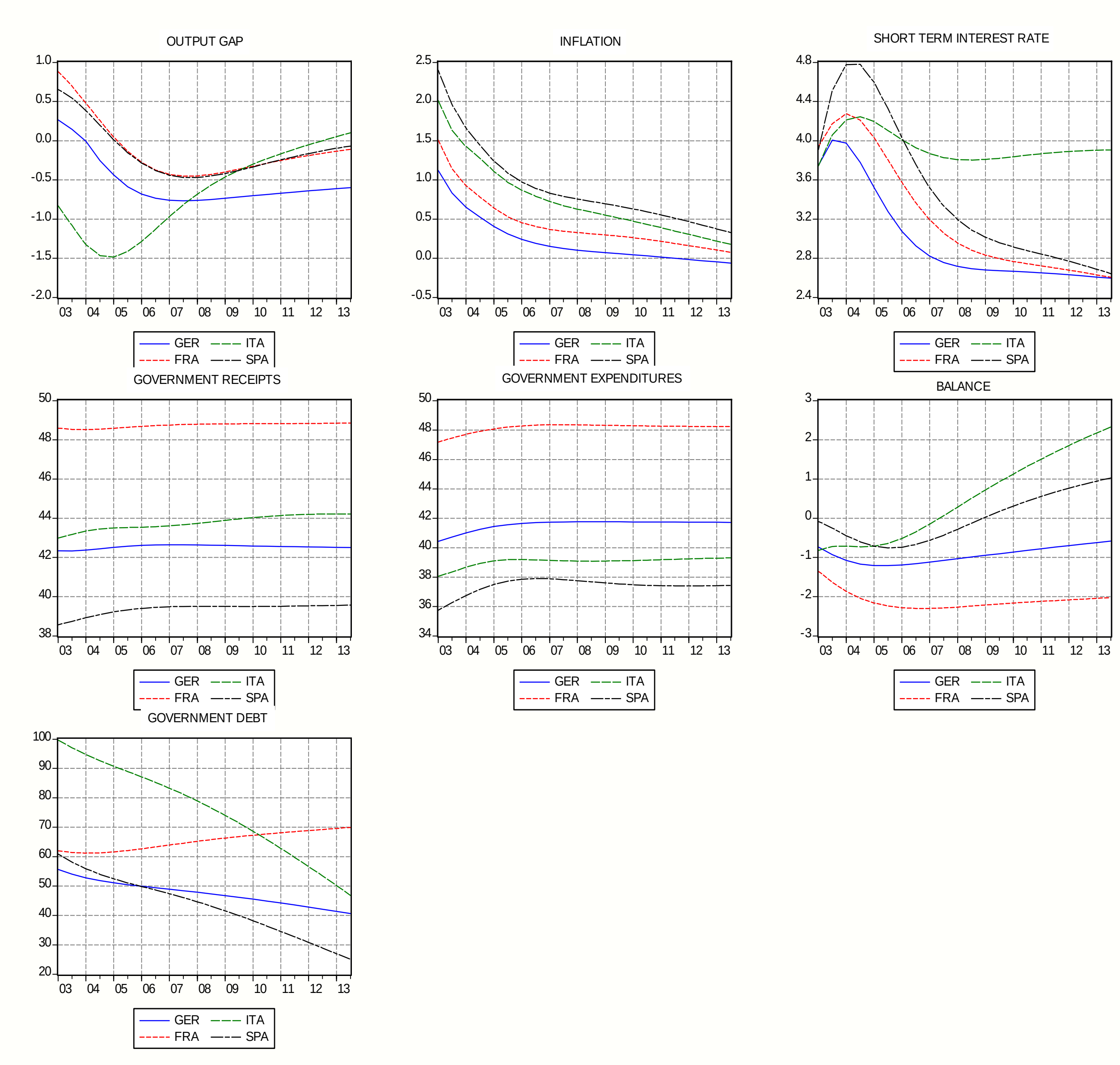


Figure 2: Simulation – Single Country Models – Estimation sample 1981:1 2002:2



Notes: the figures report dynamically simulated paths of macroeconomic and fiscal variables over the sample 2003:1 – 2013:2

Figure 3: Simulation – Multi-country model – Estimation sample 1981:1 2002:2



Notes: the figures report dynamically simulated paths of macroeconomic and fiscal variables over the sample 2003:1 – 2013:2

Table 1: Selection of ARMA models

			R^2	BIC	BIC_2_2
Germany	Gap	ARMA(1,2)	0.588	3.616	3.692
	Infl	ARMA(1,1)	0.905	1.312	1.530
	Intrate	ARMA(2,1)	0.892	2.592	2.606
	Bal	AR(1)	0.491	2.652	2.683
	Exp	AR(1)	0.684	2.262	2.391
	Rec	AR(1)	0.583	1.734	1.838
	Debt	ARMA(1,1)	0.989	2.962	3.129
France	Gap	ARMA(2,2)	0.924	1.694	1.694
	Infl	ARMA(1,2)	0.975	1.801	2.004
	Intrate	ARMA(2,1)	0.932	3.049	3.274
	Bal	AR(2)	0.872	1.690	1.755
	Exp	AR(2)	0.873	1.417	1.606
	Rec	AR(1)	0.822	1.615	1.799
	Debt	AR(2)	0.997	2.066	2.197
Italy	Gap	AR(2)	0.826	1.985	2.148
	Infl	ARMA(1,2)	0.971	2.702	2.835
	Intrate	ARMA(2,2)	0.960	3.232	3.232
	Bal	ARMA(1,2)	0.986	1.573	1.658
	Exp	ARMA(1,2)	0.824	2.079	2.089
	Rec	ARMA(1,1)	0.968	2.112	2.248
	Debt	AR(2)	0.994	3.930	4.114
Spain	Gap	AR(2)	0.968	1.616	1.688
	Infl	ARMA(1,1)	0.964	2.171	2.629
	Intrate	AR(1)	0.832	4.402	4.460
	Bal	ARMA(1,2)	0.956	1.332	1.418
	Exp	ARMA(1,2)	0.959	1.254	1.861
	Rec	ARMA(1,1)	0.986	0.874	1.009
	Debt	AR(2)	0.993	3.510	3.581

Notes: the table reports the “min-BIC” ARMA specification for each variable, along with its adjusted R-squared, BIC and the BIC of the ARMA(2,2) specification.

Table 2: Relative RMSE – Recursive estimates

	1-Step ahead								2-Step ahead							
	ARMA	VAR1	VAR2	S.C.M	MC.M	Mean	Med	RW RMSE	ARMA	VAR1	VAR2	S.C.M	MC.M	Mean	Med	RW RMSE
Germany																
Gap	1.331	1.386	2.608	1.403	**0.969**	1.158	1.054	0.420	1.003	1.737	3.129	1.215	**0.947**	1.201	1.011	0.525
Infl	**0.762**	0.947	1.075	0.890	0.987	0.801	0.835	0.509	0.894	**0.873**	1.316	1.054	0.934	0.849	0.889	0.874
Intrate	**0.853**	1.209 (*)	1.419 (*)	1.262	1.049	1.061	1.044	0.604	**0.941**	1.133	1.503	1.420	1.024	1.080	1.050	1.019
Bal	**0.959**	1.088	1.073	0.981	1.026	0.989	1.026	1.116	**0.930** (*)	1.037	1.113	0.988	0.994	0.985	1.011	1.809
Exp	0.997	1.124	1.129	0.979	0.976	0.989	**0.965**	0.904	1.002	1.139	1.341	**0.937**	0.956	1.023	0.968	1.447
Rec	1.015	1.060	1.424	1.205	1.148	**1.003**	1.068	0.438	1.025	0.886	1.317	1.079	0.986	**0.847**	0.955	0.689
Debt	**0.905**	1.351	1.468	1.162	1.174	0.911	1.183	0.893	1.253	1.381	1.479	1.026	1.132	**0.877**	1.107	1.615
France																
Gap	**0.715** (*)	0.837	1.041	0.799 (*)	0.769 (*)	0.797 (*)	0.793 (*)	0.466	**0.714**	0.761	1.186	0.803	0.876	0.823	0.830	0.878
Infl	1.287	2.685 (*)	2.314	1.045	2.470 (*)	1.081	**0.952**	0.347	1.353	2.621 (*)	1.975	1.049	2.508	1.150	**1.016**	0.604
Intrate	0.886	1.007	0.995	**0.835**	1.174	0.893	0.916	0.892	0.944	1.040	1.076	**0.707**	1.069	0.910	0.933	1.504
Bal	**0.823**	0.844	1.233	1.092	1.349 (*)	0.995	1.010	0.497	0.835	**0.802**	1.222	1.087	1.403 (*)	1.001	1.012	0.845
Exp	**0.821**	1.120	1.121	0.874	0.946	0.849	0.918	0.341	0.981	1.123	1.226	0.910	1.020	**0.896**	0.933	0.642
Rec	**1.008**	1.175	1.392 (*)	1.206	1.288	1.130	1.161	0.453	**1.045**	1.258	1.333 (*)	1.196	1.303	1.117	1.190	0.697
Debt	**0.566**	1.537 (*)	1.919 (*)	1.636 (*)	1.402	0.944	1.276	0.748	**0.794**	1.498	2.033	1.835 (*)	1.424	0.998	1.247	1.399
Italy																
Gap	1.072	1.431	1.926	1.362	1.489	1.074	**1.027**	0.371	1.210	1.253	1.935	1.440	1.490	**0.985**	1.008	0.569
Infl	**0.549**	0.974	1.265	0.972	1.394	0.932	0.965	0.968	**0.706**	0.961	1.208 (*)	0.974	1.283	0.943	0.947	1.603
Intrate	**0.836**	1.201	1.299	1.064	1.303 (*)	1.061	1.029	0.964	**0.837**	1.292 (*)	1.033	1.056	1.296 (*)	1.057	1.052	1.782
Bal	**0.651**	0.736	0.838	1.143	1.165	0.839	0.871	1.058	0.896	**0.794**	0.970	1.225	1.214	0.938	0.963	1.882
Exp	0.940	0.961	**0.783**	0.987	0.945	0.787	0.835	0.601	1.207	**0.773**	0.837	1.107	1.001	0.860	0.924	0.969
Rec	**0.854**	1.259	1.398	1.082	1.154	1.048	1.073	0.614	**1.089**	1.230	1.477 (*)	1.157	1.164	1.101	1.105	1.078
Debt	0.946	1.158	1.188	0.908	0.832	**0.583** (*)	0.821	1.550	1.190	1.242	1.306 (*)	0.930	0.834	**0.548**	0.770	2.934
Spain																
Gap	**0.470** (*)	0.685	0.586	0.695	0.566 (*)	0.529 (*)	0.524 (*)	0.604	**0.480**	0.609	0.681	0.809	0.622	0.525	0.518	1.184
Infl	**0.556**	1.051	1.552 (*)	0.823	2.299	0.895	0.851	0.427	**0.762**	1.152	1.334	0.943	2.329	1.005	0.972	0.733
Intrate	**0.903**	1.729 (*)	2.332 (*)	1.078	1.633 (*)	1.329	1.282	0.889	**0.843**	1.542	2.318 (*)	1.017	1.834 (*)	1.314	1.257	1.558
Bal	0.964	**0.632** (*)	0.647 (*)	1.167 (*)	1.293 (*)	0.812 (*)	0.838 (*)	0.585	0.948	**0.555**	0.698	1.253 (*)	1.402 (*)	0.864	0.897	1.102
Exp	**0.833**	1.032	1.159	1.308	1.209	0.913	1.073	0.330	**1.023**	1.147	1.345	1.781	1.543	1.104	1.296	0.574
Rec	1.373	2.388 (*)	2.048 (*)	**1.079**	1.738	1.311	1.236	0.193	1.335 (*)	2.832 (*)	2.585 (*)	**1.071**	2.336	1.492	1.398	0.299
Debt	0.732	1.105	1.015	0.953	0.863	**0.675**	0.856	1.886	0.963	1.122	0.972	0.880	0.796	**0.618**	0.791	3.355

Notes: The table entries are the RMSEs of different models, relative to the RMSE of a random walk model, for one and two-step ahead simulated forecasts. Estimation sample is 1981:1 – 1995:2. Forecasts are performed over the sample 1996:1 – 2002:2. Results are reported for ARMA models (ARMA – see table 1 for details), one and two-lag VARs (VAR1 and VAR2), single-country structural models (S.C. M – see text for details), a multi-country model (MC. M – see text for details), and for pooled forecasts (computed each period as the mean and the median of the forecasts of all models - MEAN and MED respectively), along with the RMSE of the random walk model (RW RMSE). A test (see Diebold and Mariano (1995) and Harvey at al. (1997) is also performed on the significance of the mean of the difference between the squared errors of the different models and those of the random walk. (*) denotes 5% significance.

Table 3: Forecast Bias – Recursive estimates

	1-step ahead							2-step ahead						
	ARMA	VAR1	VAR2	S.C.M	MC.M	Mean	Med	ARMA	VAR1	VAR2	S.C.M	MC.M	Mean	Med
Germany														
Gap	0.112	0.055	0.764 (*)	0.292	-0.007	0.19	0.123	0.07	0.211	1.014	0.291	-0.019	0.228	0.123
Infl	-0.015	0.266 (*)	0.375 (*)	-0.028	0.074	0.117	0.099	-0.074	0.494	0.928 (*)	-0.088	0.148	0.238	0.155
Intrate	-0.029	0.283	0.288	-0.071	-0.078	0.081	0.066	-0.063	0.492	0.768	-0.206	-0.114	0.171	0.137
Bal	-0.124	-0.135	-0.185	-0.423	-0.419	-0.248	-0.261	-0.191	-0.212	-0.341	-0.69	-0.643	-0.402	-0.43
Exp	0.097	-0.076	-0.232	0.143	0.189	0.049	0.098	0.197	-0.126	-0.29	0.341	0.353	0.136	0.2
Rec	-0.005	-0.211	-0.416 (*)	-0.289 (*)	-0.232	-0.193	-0.206	0.069	-0.338	-0.632 (*)	-0.391	-0.313	-0.256	-0.269
Debt	0.475 (*)	-0.09	-0.103	-0.259	-0.228	-0.04	-0.165	1.565 (*)	-0.253	-0.363	-0.195	-0.242	0.094	-0.132
France														
Gap	-0.085	0.008	-0.174	-0.141	-0.168	-0.133	-0.129	-0.221	0.08	-0.55 (*)	-0.316	-0.414 (*)	-0.324 (*)	-0.324 (*)
Infl	-0.168	-0.71 (*)	-0.47 (*)	-0.212 (*)	0.279	-0.215 (*)	-0.143	-0.311	-1.18 (*)	-0.69	-0.457 (*)	0.578	-0.348	-0.286
Intrate	0.173	0.266	0.237	0.515 (*)	0.635 (*)	0.352	0.342	0.304	0.331	0.44	0.72	0.954	0.536	0.498
Bal	-0.11	-0.086	-0.331 (*)	-0.366 (*)	-0.513 (*)	-0.283 (*)	-0.299 (*)	-0.259	-0.227	-0.687 (*)	-0.701 (*)	-1.003 (*)	-0.577 (*)	-0.597 (*)
Exp	0.117	-0.111	0.175	0.066	0.135	0.097	0.113	0.322	-0.211	0.42	0.164	0.324	0.243	0.276
Rec	0.049	-0.196	-0.156	-0.253	-0.328 (*)	-0.157	-0.167	0.157	-0.426	-0.25	-0.405	-0.551	-0.257	-0.303
Debt	0.322 (*)	0.049	0.15	0.297	0.206	0.127	0.067	0.945 (*)	0.528	0.78	1.157	0.765	0.617	0.53
Italy														
Gap	0.156	0.145	0.117	0.251 (*)	-0.018	0.106	0.103	0.381	0.119	0.408	0.498	0.033	0.238	0.235
Infl	0.114	-0.01	0.09	0.163	0.374	0.168	0.146	0.213	0.085	0.645	0.392	0.808	0.457	0.42
Intrate	0.379	0.721 (*)	0.575	0.705 (*)	0.825 (*)	0.618 (*)	0.606 (*)	0.855	1.51	1.183	1.361 (*)	1.583	1.259	1.229
Bal	-0.168	0.018	-0.153	-0.61 (*)	-0.627 (*)	-0.328	-0.387	-0.533	0.117	-0.342	-1.259	-1.358	-0.715	-0.788
Exp	0.021	-0.039	0.164	0.091	0.218	0.089	0.126	0.115	0.152	0.339	0.252	0.494	0.252	0.287
Rec	0.184	-0.021	0.01	-0.258	-0.137	-0.036	-0.052	0.501	0.185	-0.082	-0.457	-0.305	-0.023	-0.05
Debt	1.078 (*)	-1.444 (*)	-1.372 (*)	-0.861 (*)	-0.875 (*)	-0.383	-0.742 (*)	2.898 (*)	-3.059 (*)	-3.097 (*)	-1.262	-1.436	-0.6	-1.128
Spain														
Gap	-0.041	0.076	0.099	-0.214 (*)	-0.099	-0.089	-0.085	-0.128	0.186	0.29	-0.573 (*)	-0.267 (*)	-0.212	-0.215
Infl	-0.044	-0.288 (*)	-0.238	-0.087	0.244	-0.05	-0.053	-0.108	-0.482 (*)	-0.217	-0.221	0.438	-0.071	-0.125
Intrate	0.217	1.318 (*)	1.478 (*)	0.682 (*)	1.241 (*)	0.887 (*)	0.871 (*)	0.502	2.196 (*)	3.01 (*)	1.302 (*)	2.55 (*)	1.733 (*)	1.691 (*)
Bal	-0.154	-0.064	-0.252 (*)	-0.535 (*)	-0.614 (*)	-0.344 (*)	-0.365 (*)	-0.527 (*)	-0.088	-0.555 (*)	-1.199 (*)	-1.336 (*)	-0.762 (*)	-0.81 (*)
Exp	0.075	0.193 (*)	0.287 (*)	0.349 (*)	0.286 (*)	0.233 (*)	0.278 (*)	0.2	0.351	0.59 (*)	0.881 (*)	0.664	0.513 (*)	0.608 (*)
Rec	0.031	0.129	0.035	-0.037	-0.169 (*)	-0.018	-0.039	0.061 (*)	0.181	-0.044	-0.045	-0.383	-0.069	-0.09
Debt	0.5	-1.801 (*)	-1.65 (*)	-1.084 (*)	-1.163 (*)	-0.784 (*)	-1.141 (*)	1.587	-3.288 (*)	-2.885 (*)	-1.147	-1.559	-1.01	-1.558

Notes: The table entries are the average forecast errors of the different models, for one and two-step ahead simulated forecasts. Estimation sample is 1981:1 – 1995:2. Forecasts are performed over the sample 1996:1 – 2002:2. Results are reported for ARMA models (ARMA – see table 1 for details), one and two-lag VARs (VAR1 and VAR2), single-country structural models (S.C. M – see text for details), a multy-country model (MC. M – see text for details), and for pooled forecasts (computed each period as the mean and the median of the forecasts of all models - MEAN and MED respectively). An unbiasedness test is also performed as the (robust) t-test for the significance of the mean of the forecast errors. (*) denotes 5% significance.

Table 4: Relative RMSE – Recursive estimates – Comparison with OECD forecasts

	1-Step ahead						**2-Step ahead**					
	OECD	S.C.M	MC.M	Mean	Med	RW RMSE	OECD	S.C.M	MC.M	Mean	Med	RW RMSE
						Germany						
Gap	2.789	1.470	1.104	1.229	**1.056**	0.330	2.605	1.414	**0.941**	1.236	0.991	0.386
Infl	1.309	0.766	1.262	**0.778**	0.756	0.382	0.926	0.966	0.893	**0.824**	0.843	0.880
Bal	1.651	1.010	1.108	**0.914**	0.979	0.827	**0.665**	0.967	0.994	0.992	1.014	1.997
Debt	3.342	1.057	1.064	**0.841**	1.001	0.892	1.736	1.051	1.165	**0.890**	1.152	1.701
						France						
Gap	1.335	0.927	0.907	**0.903**	0.910	0.508	0.809	**0.669**	0.808	0.735	0.739	0.788
Infl	1.341	1.008	2.219	**0.792**	0.884	0.377	**0.938**	1.050	2.229	1.201	1.064	0.628
Bal	1.380	1.105	1.376	**0.940**	0.994	0.446	**0.638**	1.047	1.324	1.011	0.996	0.902
Debt	2.172	1.649	1.396	**0.935**	1.176	0.686	1.208	1.875	1.470	**1.061**	1.392	1.421
						Italy						
Gap	2.285	1.264	1.396	**0.995**	0.996	0.429	2.128	1.431	1.421	**0.953**	0.967	0.524
Infl	**0.397**	0.974	1.196	0.920	0.977	1.166	**0.447**	0.958	1.347	0.897	0.872	1.312
Bal	1.357	1.288	1.271	**0.883**	0.962	0.724	**0.533**	1.129	1.173	0.834	0.840	1.789
Debt	2.174	0.826	0.739	**0.543**	0.730	1.568	1.353	1.103	0.844	**0.623**	0.851	2.819
						Spain						
Gap	2.262	0.571	0.431	**0.401**	0.404	0.605	1.188	0.904	0.738	0.634	**0.622**	1.155
Infl	1.002	**0.762**	3.109	1.003	0.889	0.313	**0.849**	0.920	2.149	0.914	0.878	0.776
Bal	**0.730**	1.128	1.350	0.748	0.785	0.478	**0.468**	1.269	1.381	0.887	0.905	1.088
Debt	1.897	0.945	0.858	**0.645**	0.856	1.814	1.034	0.903	0.801	**0.678**	0.804	3.649

Notes: The table entries are the RMSEs of different models, along with those of OECD forecasts (as reported in the *OECD Economic Outlook*), relative to the RMSE of a random walk model, for one and two-step ahead simulated forecasts. Estimation sample is 1981:1 – 1995:2. Forecasting sample is 1996:2 – 2002:2. Results are reported for single-country structural models (S.C. M – see text for details), a multi-country model (MC. M – see text for details), and for pooled forecasts (computed each period as the mean and the median of the forecasts of all models - MEAN and MED respectively), along with the RMSE of the random walk model (RW RMSE).

Table 5: Monte Carlo Simulations

	RMSE						MAE					
	ARMA		MC.M		RW RMSE		ARMA		MC.M		RW MAE	
	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.
Germany												
Gap	0.648	0.21	1.055	0.11	1.144	0.37	0.660	0.21	1.051	0.11	1.456	0.47
Infl	0.517	0.17	1.072	0.08	3.307	1.13	0.450	0.14	1.047	0.07	4.214	1.34
Intrate	0.612	0.26	1.078	0.09	3.535	1.48	0.524	0.22	1.054	0.09	4.479	1.78
Bal	0.790	0.26	1.070	0.14	1.462	0.53	0.794	0.25	1.041	0.13	1.950	0.65
Exp	0.830	0.23	1.048	0.14	1.127	0.31	0.848	0.23	1.036	0.13	1.458	0.40
Rec	0.904	0.28	1.016	0.13	0.881	0.26	0.893	0.27	1.026	0.13	1.098	0.34
Debt	0.691	0.44	1.086	0.10	6.622	3.89	0.736	0.47	1.076	0.10	8.280	4.89
France												
Gap	1.397	0.68	1.046	0.17	1.311	0.53	1.417	0.68	1.036	0.16	1.633	0.66
Infl	0.148	0.05	1.088	0.07	5.201	1.93	0.130	0.04	1.050	0.07	6.680	2.25
Intrate	1.243	0.61	1.056	0.08	5.098	2.54	1.047	0.50	1.051	0.08	6.251	2.96
Bal	1.222	0.72	0.981	0.08	2.560	1.21	1.136	0.63	0.996	0.08	2.995	1.41
Exp	1.045	0.46	1.072	0.18	0.838	0.32	0.891	0.38	1.034	0.15	1.090	0.40
Rec	1.870	0.85	0.992	0.09	1.314	0.71	1.660	0.69	1.003	0.09	1.544	0.81
Debt	0.180	0.16	1.151	0.10	21.087	21.43	0.168	0.15	1.119	0.11	27.456	28.82
Italy												
Gap	0.412	0.18	1.091	0.11	1.273	0.56	0.404	0.18	1.065	0.11	1.657	0.73
Infl	0.507	0.18	1.087	0.08	6.479	2.44	0.414	0.14	1.052	0.07	8.269	2.82
Intrate	1.620	0.92	1.088	0.14	4.454	2.46	1.400	0.76	1.054	0.12	5.541	2.86
Bal	1.563	1.14	1.096	0.12	5.862	3.83	1.389	0.97	1.070	0.11	7.233	4.80
Exp	2.238	0.78	1.056	0.13	1.164	0.41	1.946	0.68	1.045	0.12	1.484	0.51
Rec	0.359	0.26	1.111	0.10	5.595	4.38	0.378	0.27	1.082	0.10	7.018	5.57
Debt	1.877	1.07	1.145	0.12	13.039	6.98	1.730	0.97	1.112	0.12	16.851	9.00
Spain												
Gap	0.292	0.18	1.076	0.23	1.964	1.09	0.287	0.17	1.055	0.20	2.447	1.34
Infl	0.137	0.05	1.077	0.07	5.114	2.08	0.144	0.05	1.053	0.07	6.440	2.39
Intrate	1.675	0.87	1.096	0.10	5.982	3.05	1.399	0.70	1.066	0.10	7.506	3.62
Bal	1.374	0.81	1.004	0.13	2.934	1.68	1.310	0.75	1.015	0.12	3.486	1.95
Exp	1.912	0.82	1.031	0.12	1.106	0.43	1.767	0.75	1.052	0.12	1.359	0.54
Rec	0.073	0.05	1.090	0.09	1.996	1.26	0.083	0.05	1.069	0.09	2.466	1.54
Debt	0.750	0.41	1.090	0.13	8.742	4.24	0.777	0.42	1.093	0.13	10.788	5.32

Notes: The table entries are the average and standard deviation over 2000 replications of the RMSEs and MAEs of MCM and ARMA(2,2), relative to the random walk model, for one step ahead forecasts (along with the RMSE of the random walk model (RW RMSE)). Data have been generated using the estimated MCM as the DGP. Estimation sample is 1 – 30, and forecasts are performed recursively over the sample 31 – 42, to match the empirical analysis with real data.

Appendix

Single country models: Germany

$$\pi_t = \underset{(0.116)}{1.492}\pi_{t-1} - \underset{(0.116)}{0.492}\pi_{t-2} + \underset{(0.028)}{0.019}y_{t-1} + u_{1t}^{NP} \qquad (1)$$

$\overline{R}^2 = 0.879$ S.E. of reg = 0.486 J.B.=0.275 LM-test=7.792

$$\begin{aligned} y_t &= \underset{(10.337)}{37.341} - \underset{(0.138)}{0.259}y_{t-1} + \underset{(0.094)}{0.443}y_{t-2} + \underset{(0.096)}{0.199} + \underset{(0.126)}{0.174}\pi_{t-1} - \underset{(0.126)}{0.174}i_{t-1} + \\ &\quad - \underset{(0.130)}{0.261}g_{t-1} - \underset{(0.241)}{0.617}\tau_{t-1} + \underset{(0.107)}{0.373}y_{t-1}^{US} + u_{2t}^{NP} \end{aligned} \qquad (2)$$

$\overline{R}^2 = 0.824$ S.E. of reg = 0.856 J.B.=23.243* LM-test=6.636

$$i_t = \underset{(0.271)}{0.876} + \underset{(0.124)}{0.958}i_{t-1} - \underset{(0.104)}{0.287}i_{t-2} + \underset{(0.144)}{0.473}\pi_t + \underset{(0.051)}{0.115}y_t + u_{3t}^{M} \qquad (3)$$

$\overline{R}^2 = 0.898$ S.E. of reg = 0.764 J.B.=90.792* LM-test=5.670

$$g_t = \underset{(3.803)}{11.388} + \underset{(0.121)}{0.987}g_{t-1} - \underset{(0.131)}{0.259}g_{t-2} - \underset{(0.066)}{0.251}y_t + \underset{(0.057)}{0.215}y_{t-1} + u_{5t}^{g} \qquad (4)$$

$\overline{R}^2 = 0.777$ S.E. of reg = 0.610 J.B.=1.036 LM-test=10.849*

$$\begin{aligned} \tau_t &= \underset{(4.250)}{23.793} + \underset{(0.100)}{0.437}\tau_{t-1} - \underset{(0.042)}{0.107}y_t - \underset{(0.045)}{0.027}y_{t-1} + \\ &\quad + \underset{(0.058)}{0.203}\left[DY_t\left(\frac{avc_t - \Delta x_t - \pi_t}{1 + \Delta x_t + \pi_t}\right)\right] + u_{6t}^{\tau} \end{aligned} \qquad (5)$$

$\overline{R}^2 = 0.747$ S.E. of reg = 0.434 J.B.=1.565 LM-test=1.218

Single country models: France

$$\pi_t = \pi_{t-1} + \underset{(0.051)}{0.151}\, y_{t-1} + u_{1t}^{NP} \tag{1}$$

$\overline{R}^2 = 0.934$ S.E. of reg = 0.855 J.B.=29.782* LM-test=16.665*

$$\begin{aligned} y_t &= \underset{(3.099)}{5.583} + \underset{(0.113)}{1.122}\, y_{t-1} - \underset{(0.169)}{0.252}\, y_{t-2} - \underset{(0.043)}{0.027}\, \pi_{t-1} + \underset{(0.043)}{0.027}\, i_{t-1} - \underset{(0.078)}{0.199}\, g_{t-1} + \\ &\quad + \underset{(0.075)}{0.078}\, \tau_{t-1} + \underset{(0.037)}{0.068}\, y_{t-1}^{US} + u_{2t}^{NP} \end{aligned} \tag{2}$$

$\overline{R}^2 = 0.904$ S.E. of reg = 0.540 J.B.=0.242 LM-test=2.136

$$i_t = -\underset{(0.416)}{0.186} + \underset{(0.077)}{0.577}\, i_{t-1} + \underset{(0.072)}{0.267}\, \pi_t + \underset{(0.092)}{0.057}\, y_t + \underset{(0.086)}{0.443}\, i_t^{GER} + u_{3t}^{M} \tag{3}$$

$\overline{R}^2 = 0.933$ S.E. of reg = 0.981 J.B.=1.527 LM-test=3.176

$$g_t = \underset{(2.236)}{10.251} + \underset{(0.115)}{1.123}\, g_{t-1} - \underset{(0.099)}{0.336}\, g_{t-2} - \underset{(0.091)}{0.313}\, y_t + \underset{(0.090)}{0.296}\, y_{t-1} + u_{5t}^{g} \tag{4}$$

$\overline{R}^2 = 0.898$ S.E. of reg = 0.407 J.B.=5.004 LM-test=4.326

$$\begin{aligned} \tau_t &= \underset{(2.919)}{4.062} + \underset{(0.061)}{0.916}\, \tau_{t-1} - \underset{(0.112)}{0.272}\, y_t + \underset{(0.117)}{0.259}\, y_{t-1} + \\ &\quad + \underset{(0.060)}{0.001}\left[DY_t \left(\frac{avc_t - \Delta x_t - \pi_t}{1 + \Delta x_t + \pi_t} \right) \right] + u_{6t}^{\tau} \end{aligned} \tag{5}$$

$\overline{R}^2 = 0.844$ S.E. of reg = 0.492 J.B.=0.545 LM-test=1.669

Single country models: Italy

$$\pi_t = \pi_{t-1} + \underset{(0.103)}{0.071} y_{t-1} + u_{1t}^{NP} \tag{1}$$

$\bar{R}^2 = 0.939$ S.E. of reg. = 1.206 J.B.=3.524 LM-test=5.193

$$y_t = \underset{(1.150)}{1.517} + \underset{(0.065)}{0.804} y_{t-1} - \underset{(0.030)}{0.004} \pi_{t-1} + \underset{(0.030)}{0.004} i_{t-1} - \underset{(0.028)}{0.039} \tau_{t-1} + \underset{(0.041)}{0.105} y_{t-1}^{US} + u_{2t}^{NP} \tag{2}$$

$\bar{R}^2 = 0.814$ S.E. of reg. =0.626 J.B.=0.739 LM-test=4.239

$$i_t = -\underset{(0.435)}{0.122} + \underset{(0.059)}{0.811} i_{t-1} + \underset{(0.065)}{0.181} \pi_t + \underset{(0.138)}{0.036} y_t + \underset{(0.178)}{0.457} i_t^{GER} - \underset{(0.177)}{0.304} i_{t-1}^{GER} + u_{3t}^{M} \tag{3}$$

$\bar{R}^2 = 0.963$ S.E. of reg. =0.987 J.B.=4.322 LM-test=5.092

$$g_t = \underset{(2.228)}{4.495} + \underset{(0.109)}{1.271} g_{t-1} - \underset{(0.098)}{0.383} g_{t-2} - \underset{(0.124)}{0.335} y_t + \underset{(0.116)}{0.406} y_{t-1} + u_{5t}^{g} \tag{4}$$

$\bar{R}^2 = 0.839$ S.E. of reg. =0.581 J.B.=1.712 LM-test=7.278

$$\begin{aligned} \tau_t &= \underset{(1.380)}{5.428} + \underset{(0.109)}{1.052} \tau_{t-1} - \underset{(0.095)}{0.182} \tau_{t-2} - \underset{(0.124)}{0.205} y_t + \underset{(0.112)}{0.311} y_{t-1} + \\ &\quad + \underset{(0.041)}{0.171} \left[DY_t \left(\frac{avc_t - \Delta x_t - \pi_t}{1 + \Delta x_t + \pi_t} \right) \right] + u_{6t}^{\tau} \end{aligned} \tag{5}$$

$\bar{R}^2$=0.979 S.E. of reg. =0.508 J.B.=31.227* LM-test=6.316

Single country models: Spain

$$\pi_t = \pi_{t-1} + \underset{(0.030)}{0.100}\, y_{t-1} + \underset{(0.090)}{0.383}(\pi_{t-1} - \pi_{t-2}) - \underset{(0.087)}{0.579}(\pi_{t-2} - \pi_{t-3}) + u_{1t}^{NP} \quad (1)$$

$\overline{R}^2 = 0.957$ S.E. of reg. =0.721 J.B.=0.157 LM-test=5.981

$$\begin{aligned} y_t &= \underset{(1.429)}{1.647} + \underset{(0.127)}{1.586}\, y_{t-1} - \underset{(0.219)}{0.779}\, y_{t-2} + \underset{(0.130)}{0.122}\, y_{t-3} - \underset{(0.022)}{0.012}\, \pi_{t-1} + \underset{(0.022)}{0.012}\, i_{t-1} + \\ &\quad - \underset{(0.052)}{0.023}\, g_{t-1} - \underset{(0.045)}{0.024}\, \tau_{t-1} + \underset{(0.040)}{0.078}\, y_{t-1}^{US} + u_{2t}^{NP} \end{aligned} \quad (2)$$

$\overline{R}^2 = 0.965$ S.E. of reg. =0.520 J.B.=0.106 LM-test=3.528

$$i_t = -\underset{(0.791)}{0.663} + \underset{(0.089)}{0.745}\, i_{t-1} + \underset{(0.145)}{0.252}\, \pi_t + \underset{(0.119)}{0.043}\, y_t + \underset{(0.159)}{0.294}\, i_t^{GER} + u_{3t}^{M} \quad (3)$$

$\overline{R}^2 = 0.836$ S.E. of reg. =2.085 J.B.=67.216* LM-test=6.373

$$g_t = \underset{(1.051)}{4.415} + \underset{(0.115)}{1.588}\, g_{t-1} - \underset{(0.182)}{0.926}\, g_{t-2} + \underset{(0.096)}{0.221}\, g_{t-3} - \underset{(0.076)}{0.233}\, y_t + \underset{(0.077)}{0.269}\, y_{t-1} + u_{5t}^{g} \quad (4)$$

$\overline{R}^2 = 0.957$ S.E. of reg. =0.407 J.B.= 3.593 LM-test=8.490

$$\begin{aligned} \tau_t &= \underset{(1.601)}{7.489} + \underset{(0.041)}{0.811}\, \tau_{t-1} + \underset{(0.077)}{0.007}\, y_t + \underset{(0.075)}{0.098}\, y_{t-1} + \\ &\quad + \underset{(0.063)}{0.152}\left[DY_t \left(\frac{avc_t - \Delta x_t - \pi_t}{1 + \Delta x_t + \pi_t} \right) \right] + u_{6t}^{\tau} \end{aligned} \quad (5)$$

$\overline{R}^2 = 0.978$ S.E. of reg. =0.433 J.B.=0.099 LM-test=12.612*

Multi-country model

$$\pi_t^{GER} = \underset{(0.018)}{0.892}\,\pi_{t-1}^{GER} - \underset{(0.015)}{0.084}\,\pi_{t-2}^{GER} + \underset{(0.064)}{0.647}\left(\pi_t^{EU} - \pi_{t-1}^{EU}\right) + \underset{(0.016)}{0.108}\,\pi_{t-1}^{EU} + \underset{(0.016)}{0.025}\,y_{t-1}^{GER} \tag{I.1}$$

$\overline{R}^2 = 0.930$ S.E. of reg. =0.368 J.B.=2.918 LM-test=10.310*

$$\pi_t^{FRA} = \underset{(0.041)}{0.851}\,\pi_{t-1}^{FRA} - \underset{(0.014)}{0.003}\,\pi_{t-2}^{FRA} + \underset{(0.106)}{1.039}\left(\pi_t^{EU} - \pi_{t-1}^{EU}\right) + \underset{(0.041)}{0.149}\,\pi_{t-1}^{EU} - \underset{(0.027)}{0.009}\,y_{t-1}^{FRA} \tag{I.2}$$

$\overline{R}^2 = 0.971$ S.E. of reg. =0.567 J.B.=4.092 LM-test=4.359

$$\pi_t^{ITA} = \underset{(0.035)}{0.789}\,\pi_{t-1}^{ITA} + \underset{(0.013)}{0.057}\,\pi_{t-3}^{ITA} + \underset{(0.117)}{1.269}\left(\pi_t^{EU} - \pi_{t-1}^{EU}\right) + \underset{(0.035)}{0.211}\,\pi_{t-1}^{EU} - \underset{(0.032)}{0.002}\,y_{t-1}^{ITA} \tag{I.3}$$

$\overline{R}^2 = 0.975$ S.E. of reg. =0.758 J.B.=3.452 LM-test=8.755

$$\pi_t^{SPA} = \underset{(0.037)}{0.906}\,\pi_{t-1}^{SPA} + \underset{(0.114)}{0.936}\left(\pi_t^{EU} - \pi_{t-1}^{EU}\right) + \underset{(0.037)}{0.094}\,\pi_{t-1}^{EU} - \underset{(0.028)}{0.059}\,y_{t-1}^{SPA} \tag{I.4}$$

$\overline{R}^2 = 0.952$ S.E. of reg. =0.763 J.B.=6.834* LM-test=12.780*

$$y_t^{GER} = \underset{(3.878)}{15.731} + \underset{(0.064)}{0.352}\,y_{t-1}^{GER} + \underset{(0.036)}{0.342}\,y_{t-2}^{GER} + \underset{(0.043)}{0.363}\,\pi_{t-1}^{GER} - \underset{(0.043)}{0.363}\,i_{t-1}^{GER} + - \underset{(0.053)}{0.306}\,g_{t-1}^{GER} - \underset{(0.073)}{0.051}\,\tau_{t-1}^{GER} - \underset{(0.102)}{0.233}\left(y_{t-1}^{GER} - y_{t-1}^{EU}\right) \tag{Y.1}$$

$\overline{R}^2 = 0.868$ S.E. of reg. =0.742 J.B.=3.697 LM-test=5.705

$$y_t^{FRA} = \underset{(3.010)}{0.602} + \underset{(0.064)}{1.248}\,y_{t-1}^{FRA} - \underset{(0.054)}{0.357}\,y_{t-2}^{FRA} - \underset{(0.026)}{0.027}\,\pi_{t-1}^{FRA} + \underset{(0.026)}{0.027}\,i_{t-1}^{FRA} + - \underset{(0.053)}{0.127}\,g_{t-1}^{FRA} + + \underset{(0.053)}{0.114}\,\tau_{t-1}^{FRA} - \underset{(0.031)}{0.032}\,i_y^{GER} - \underset{(0.061)}{0.202}\left(y_{t-1}^{FRA} - y_{t-1}^{EU}\right) \tag{Y.2}$$

$\overline{R}^2 = 0.902$ S.E. of reg. =0.544 J.B.=0.083 LM-test=0.895

$$y_t^{ITA} = -\underset{(2.097)}{10.716} + \underset{(0.073)}{0.757}\,y_{t-1}^{ITA} + \underset{(0.068)}{0.103}\,y_{t-2}^{ITA} + \underset{(0.025)}{0.110}\,\pi_{t-1}^{ITA} - \underset{(0.025)}{0.110}\,i_{t-1}^{ITA} + + \underset{(0.043)}{0.337}\,g_{t-1}^{ITA} - \underset{(0.023)}{0.033}\,\tau_{t-1}^{ITA} - \underset{(0.029)}{0.220}\,i_y^{GER} + \underset{(0.060)}{0.022}\left(y_{t-1}^{ITA} - y_{t-1}^{EU}\right) \tag{Y.3}$$

$\overline{R}^2 = 0.883$ S.E. of reg. =0.495 J.B.=0.139 LM-test=2.433

$$y_t^{SPA} = \underset{(0.947)}{0.752} + \underset{(0.077)}{1.568}\, y_{t-1}^{SPA} - \underset{(0.064)}{0.612}\, y_{t-2}^{SPA} - \underset{(0.012)}{0.009}\, \pi_{t-1}^{SPA} + \underset{(0.012)}{0.009}\, i_{t-1}^{SPA} + \\ - \underset{(0.034)}{0.007}\, g_{t-1}^{SPA} - \underset{(0.032)}{0.008}\, \tau_{t-1}^{SPA} - \underset{(0.029)}{0.054}\, i_y^{GER} - \underset{(0.058)}{0.049}\left(y_{t-1}^{SPA} - y_{t-1}^{EU}\right) \tag{Y.4}$$

$\overline{R}^2 = 0.964$ S.E. of reg. =0.525 J.B.=0.529 LM-test=4.941

$$i_t^{GER} = \underset{(0.226)}{1.182} + \underset{(0.048)}{0.165}\, \pi_t^{EU} + \underset{(0.117)}{0.064}\, y_t^{EU} + \underset{(0.086)}{0.787}\, i_{t-1}^{GER} - \underset{(0.073)}{0.193}\, i_{t-2}^{GER} + \\ + \underset{(0.102)}{0.312}\, \pi_t^{GER} + \underset{(0.092)}{0.188}\, y_t^{GER} \tag{R.1}$$

$\overline{R}^2 = 0.907$ S.E. of reg. =0.728 J.B.=24.840* LM-test=6.223

$$i_t^{FRA} = \underset{(0.299)}{0.075} + \underset{(0.062)}{0.389}\, i_{t-1}^{FRA} + \underset{(0.054)}{0.151}\, i_{t-2}^{FRA} + \underset{(0.043)}{0.301}\, \pi_t^{FRA} + \underset{(0.055)}{0.069}\, y_t^{FRA} + \underset{(0.054)}{0.419}\, i_t^{GER} \tag{R.2}$$

$\overline{R}^2 = 0.934$ S.E. of reg. =0.972 J.B.=0.681 LM-test=2.889

$$i_t^{ITA} = \underset{(0.343)}{0.481} + \underset{(0.035)}{0.758}\, i_{t-1}^{ITA} + \underset{(0.038)}{0.179}\, \pi_t^{ITA} + \underset{(0.070)}{0.181}\, y_t^{ITA} + \underset{(0.056)}{0.160}\, i_t^{GER} \tag{R.3}$$

$\overline{R}^2 = 0.961$ S.E. of reg. =1.020 J.B.=2.849 LM-test=5.262

$$i_t^{SPA} = \underset{(0.607)}{0.053} + \underset{(0.068)}{0.813}\, i_{t-1}^{SPA} - \underset{(0.061)}{0.134}\, i_{t-2}^{SPA} + \underset{(0.087)}{0.310}\, \pi_t^{SPA} + \underset{(0.091)}{0.083}\, y_t^{SPA} + \underset{(0.109)}{0.260}\, i_t^{GER} \tag{R.4}$$

$\overline{R}^2 = 0.837$ S.E. of reg. =2.080 J.B.=74.728* LM-test=3.189

$$g_t^{GER} = \underset{(2.711)}{10.666} + \underset{(0.083)}{0.894}\, g_{t-1}^{GER} - \underset{(0.086)}{0.151}\, g_{t-2}^{GER} - \underset{(0.044)}{0.280}\, y_t^{GER} + \underset{(0.042)}{0.197}\, y_{t-1}^{GER} \tag{G.1}$$

$\overline{R}^2 = 0.764$ S.E. of reg. =0.627 J.B.=0.809 LM-test=11.989*

$$g_t^{FRA} = \underset{(1.540)}{7.269} + \underset{(0.053)}{1.115}\, g_{t-1}^{FRA} - \underset{(0.047)}{0.265}\, g_{t-2}^{FRA} - \underset{(0.044)}{0.273}\, y_t^{FRA} + \underset{(0.047)}{0.262}\, y_{t-1}^{FRA} \tag{G.2}$$

$\overline{R}^2 = 0.899$ S.E. of reg. =0.406 J.B.=1.803 LM-test=3.394

$$g_t^{ITA} = \underset{(1.620)}{3.428} + \underset{(0.072)}{1.231}\, g_{t-1}^{ITA} - \underset{(0.066)}{0.317}\, g_{t-2}^{ITA} - \underset{(0.079)}{0.483}\, y_t^{ITA} + \underset{(0.074)}{0.480}\, y_{t-1}^{ITA} \tag{G.3}$$

$\overline{R}^2 = 0.842$ S.E. of reg. =0.575 J.B.=2.158 LM-test=5.967

$$g_t^{SPA} = \underset{(0.716)}{5.883} + \underset{(0.049)}{1.302}\, g_{t-1}^{SPA} - \underset{(0.045)}{0.406}\, g_{t-2}^{SPA} - \underset{(0.022)}{0.049}\, \tau_{t-1}^{SPA} + \\ - \underset{(0.040)}{0.305}\, y_t^{SPA} + \underset{(0.042)}{0.396}\, y_{t-1}^{SPA} \tag{G.4}$$

$\overline{R}^2 = 0.953$ S.E. of reg. =0.427 J.B.=4.626 LM-test=12.723*

$$\tau_t^{GER} = \underset{(2.953)}{25.972} + \underset{(0.069)}{0.387}\,\tau_{t-1}^{GER} - \underset{(0.031)}{0.099}\,y_t^{GER} - \underset{(0.034)}{0.013}\,y_{t-1}^{GER} + + \underset{(0.043)}{0.217}\left[DY_t^{GER}\left(\frac{avc_t^{GER} - \Delta x_t^{GER} - \pi_t^{GER}}{1 + \Delta x_t^{GER} + \pi_t^{GER}}\right)\right] \tag{T.1}$$

$\overline{R}^2 = 0.740$ S.E. of reg. =0.440 J.B.=1.812 LM-test=0.675

$$\tau_t^{FRA} = -\underset{(2.529)}{0.694} + \underset{(0.041)}{0.816}\,\tau_{t-1}^{FRA} + \underset{(0.048)}{0.201}\,g_{t-2}^{FRA} - \underset{(0.067)}{0.221}\,y_t^{FRA} + \underset{(0.074)}{0.303}\,y_{t-1}^{FRA} + - \underset{(0.047)}{0.043}\left[DY_t^{FRA}\left(\frac{avc_t^{FRA} - \Delta x_t^{FRA} - \pi_t^{FRA}}{1 + \Delta x_t^{FRA} + \pi_t^{FRA}}\right)\right] \tag{T.2}$$

$\overline{R}^2 = 0.837$ S.E. of reg. =0.502 J.B.=0.778 LM-test=2.602

$$\tau_t^{ITA} = \underset{(0.980)}{4.902} + \underset{(0.069)}{0.987}\,\tau_{t-1}^{ITA} - \underset{(0.061)}{0.104}\,\tau_{t-2}^{ITA} - \underset{(0.084)}{0.235}\,y_t^{ITA} + \underset{(0.078)}{0.384}\,y_{t-1}^{ITA} + + \underset{(0.027)}{0.187}\left[DY_t^{ITA}\left(\frac{avc_t^{ITA} - \Delta x_t^{ITA} - \pi_t^{ITA}}{1 + \Delta x_t^{ITA} + \pi_t^{ITA}}\right)\right] \tag{T.3}$$

$\overline{R}^2 = 0.979$ S.E. of reg. =0.518 J.B.=30.094* LM-test=6.683

$$\tau_t^{SPA} = \underset{(1.192)}{6.037} + \underset{(0.075)}{1.065}\,\tau_{t-1}^{SPA} - \underset{(0.058)}{0.244}\,\tau_{t-2}^{SPA} + \underset{(0.026)}{0.027}\,g_{t-1}^{SPA} + \underset{(0.049)}{0.062}\,y_t^{SPA} + + \underset{(0.046)}{0.055}\,y_{t-1}^{SPA} + \underset{(0.040)}{0.138}\left[DY_t^{SPA}\left(\frac{avc_t^{SPA} - \Delta x_t^{SPA} - \pi_t^{SPA}}{1 + \Delta x_t^{SPA} + \pi_t^{SPA}}\right)\right] \tag{T.4}$$

$\overline{R}^2 = 0.979$ S.E. of reg. =0.422 J.B.=0.778 LM-test=11.487*