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Comment

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I. Introduction

There is very little empirical analysis on the countries of the euro area, partly because of lack of data, partly because of lack of tradition. Many institutional changes have been put in place since the 1990s, the most important of which is the introduction of the euro 10 years ago. All the interesting questions are about the effects of these changes, but, as is well known, econometric analysis is hard when too much is going on. Boivin, Giannoni, and Mojon face the challenge nonetheless: their paper is one of the first attempts to dig out stylized facts about the monetary transmission mechanism in the euro area and its changes since the introduction of the single currency.

The authors construct an impressive data set, including not only several key macroeconomic variables for the large countries of the Eurozone but also more than 200 auxiliary variables that, although not the focus of the analysis, are supposed to help to extract the signal from the data. With these data, they estimate a factor model that they use to estimate the transmission mechanism of a common monetary policy shock and an oil shock throughout the economy. The analysis is conducted on a sample including pre–European Monetary Union (EMU) data (1987–2006) and on the shorter EMU sample.

The key empirical results indicate that, in the period including pre-EMU data, a monetary shock in Germany had a larger effect on the long-term interest rate, consumption, and investment in Italy and Spain than in the other countries (the same heterogeneity results hold when conditioning on the oil shock). Moreover, conditionally on the same shocks, the real exchange rate appreciated in core countries such as Germany and France and depreciated in Italy and Spain, whereas consumption

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and investment reacted more strongly there than in the core. The heterogeneity disappears with the euro.

Boivin et al. also propose a model. This is a general equilibrium two-country model in which the foreign country represents Germany (F) and the home country represents a country of the periphery such as Italy and Spain (H). The relation between the econometric analysis and the model is loose. The latter is not estimated but just used to generate impulse responses that are then compared with those obtained from the empirical analysis, with the goal of understanding the mechanism that helps the matching.

The story the authors suggest is as follows. Before the EMU, in response to a German (the foreign country in the language of the paper) monetary policy shock, international investors required a higher return on domestic (internationally traded) bonds than they did on foreign securities, even after accounting for the rational expectation of nominal exchange rate changes. With the EMU, the premium disappears and so does the difference in the response to shocks.

My discussion will first focus on the econometric models. I will use an economic example to illustrate how to interpret the factors and discuss some issues of implementation. I will then use an alternative econometric approach to verify the robustness of the main results of the paper. Finally, I will briefly comment on the model.

II. Econometrics

The aim of the study is to capture the cross-country heterogeneity of the transmission mechanism of "common" monetary policy and its changes over time. Boivin et al. consider four countries and several key macroeconomic variables. Moreover, they exploit information in a large set of macroeconomic indicators that, although not the focus of the analysis, are supposed to help extract shocks common to all countries and variables. Overall the model includes 240 variables.

To cope with the so-called curse of dimensionality problem that is faced when estimating the parameters of such a large system, the authors regress all variables of interest on a small set of common factors. Under the hypothesis that there is strong comovement among the time series in the panel, a small number of common factors should capture the bulk of the dynamic correlations. The common shocks can then be extracted by running a vector autoregression (VAR) on these few factors. There are several applications of this approach in the literature. A standard reference is Bernanke, Boivin, and Eliasz (2005). The econometric foundations have been developed in Stock and Watson (2002, 2005), Bai (2003), and Forni et al. (2008).

In the present application, the common factors include both some observable variables, such as the euro area policy rate (the German rate before the euro) and the oil price, and some that are unobserved. The latter are principal components extracted from the panel of the 240 time series.

This approach is a clever way to perform estimation and structural analysis in large models. However, although the asymptotic analysis is well developed, there are several complicated issues related to the implementation of such methods.

In order to estimate the model, many choices have to be made: the selection of the number of common factors, the choice of the observable variables to include in the vector of common factors, the lag length of the VAR on the factors, and the choice of data transformation to induce stationarity.

To understand the role of the parameterization in such a model, it is useful to relate it to a standard economic model (for details, see Giannone, Reichlin, and Sala [2006]). Let us consider a generic dynamic stochastic general equilibrium model. Typically, its solution has the following recursive structure:

$$\Psi(L)s_t = \epsilon_t,$$

$$C(L)x_t = D(L)s_t,$$

and

$$y_t = \Lambda_1(L)x_t + \Lambda_2(L)s_t,$$

where x_t is the $m \times 1$ vector of endogenous predetermined variables, y_t is the $n \times 1$ vector of the endogenous nonpredetermined variables, and s_t is the $q \times 1$ vector of exogenous variables (the number of variables considered is therefore $N = m + n + q$); all variables are expressed in logs and in their deviation from the steady state.

Defining the vector of all the observable variables as $w_t = [y_t' \; x_t' \; s_t']'$, we can write the solution in its static state space representation, where the vector of state variables includes the lagged predetermined variables and current and lagged exogenous variables. The latter are defined as $F_t = [x_{t-1}' \cdots x_{t-p_x}' \quad s_t' \cdots s_{t-p_s}']'$, where $p_x = \max\{p_{\Lambda_1}, p_c\}$ and $p_s = \max\{p_{\Lambda_2}, p_d\}$, and the variables in the vector w_t are expressed as contemporaneous linear combinations of F_t:

$$w_t = \Lambda F_t, \tag{1}$$

with

$$H(L)F_t = K\epsilon_t. \tag{2}$$

If we add measurement error to such a model, we obtain a factor representation in which the states F_t are the factors. The number of factors to be included depends on the dimension of the vector of the state variables (the rank of the variance-covariance matrix). The latter is $r = mp_x + q(p_s + 1)$ and depends on the p_x and p_s lags included in the model as well as on q, the number of common shocks, and m, the number of endogenous variables.

When macroeconomists think of common shocks, they mention productivity, money, time preferences, or governments, and it is difficult to think of many other candidates. Typically, it is understood that the number of common shocks (q in our notation) is small. The q common shocks are the exogenous forces driving the economy, they are essential characteristics of the economy, and their economic origin can potentially be identified. However, the dimension of the state vector r is a "technical" parameter (it has the same role as the lag length in a VAR) that depends on the structure of the economy and its dynamic complexity. Even if the number of common shocks is small, the number of factors r may potentially be very large. When there are many factors, it is difficult to distinguish between the common and the idiosyncratic component by analyzing the covariance matrix.[1] However, if the number of common shocks is small, this can be easily identified from the eigenvalues of the spectral density matrix.[2]

Given this discussion we may ask whether, with five factors (the authors' parameterization), we are really capturing the dynamics of the macroeconomy. This choice suggests a small number of common shocks and a very simple dynamic structure. Is this reasonable? How robust are the results to this choice?

Let us look at other less parsimonious parameterizations. Figure 1 reports the response of consumption to the German monetary shock for a choice of number of factors from five to eight and for one to three lags. Clearly, results are quite sensitive to the parameterization of the model, and a more generous parameterization than what was adopted in the paper might be desirable.

Other features of the model are potentially problematic: How does one choose which of the key macroeconomic variables considered are to be treated as observed common factors rather than be aggregated with other variables to form principal components? Are results robust to the choice? Does data transformation matter? Why considering

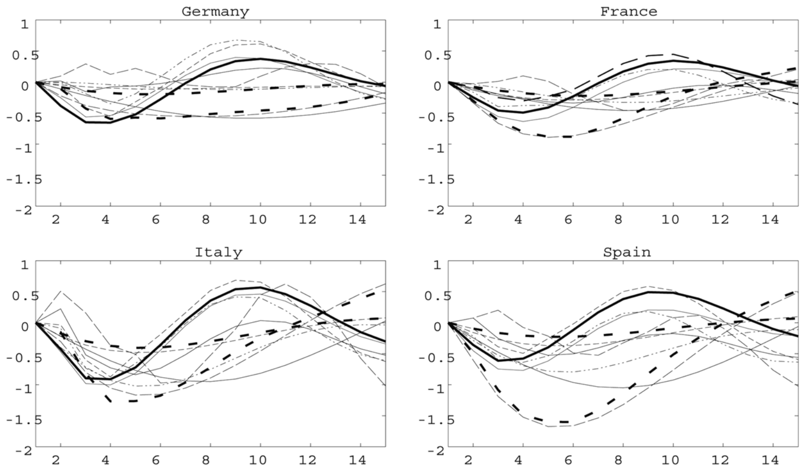

Fig. 1. Robustness: response to consumption to the German monetary policy shock. Each impulse response function is constructed with a different parameterization of the factor model (five to eight factors, one to three lags).

year-on-year growth rates? These choices touch on auxiliary features of the model, but they may affect results in important ways.

Because of these issues and to cross-check the key results of the paper, I propose below my own exercise. I will first estimate four VARs, each including euro area variables and variables for one of the four large countries (Germany, France, Italy, and Spain will be considered in turn). Then I will design a more complex exercise based on a large VAR, including variables of all countries.

In both approaches I will consider only key macroeconomic variables rather than the over 200 conjunctural indicators considered by the authors. My conjecture is that, while for real-time analysis, these auxiliary variables are relevant for a timely estimate of inflation and real output, for a historical analysis at the quarterly frequency, this extra information does not have a clear role, and the macro shocks can be successfully estimated on the basis of the key aggregate macro variables (for the United States this point has been made by Banbura, Giannone, and Reichlin [2008]). The models, however, are still very large, and parsimony will be attained via shrinkage.

III. Alternative Exercises: What Results Survive?

A. Euro Area and Single Countries' Bayesian Vector Autoregressions (BVARs)

I consider a VAR since this is a model that does not require an a priori assumption on the distinction between common and idiosyncratic components of the variables considered. Moreover, with a VAR I am able to consider variables in levels and retain possible cotrending relations while avoiding making arbitrary choices on data transformation.

I include the following variables: real exchange rate, consumption, real GDP, short- and long-term interest rates, inflation, and some control variables for external conditions (commodity prices, oil prices, short and long U.S. interest rates, and U.S. GDP). With 11 for the euro area as a whole and for the countries, each VAR includes 22 variables. Although this model is not as large as the factor model considered in the paper, it is too large for ordinary least squares estimation.

My way to cope with the curse of dimensionality is to apply Bayesian shrinkage. While, as we have seen, with the factor model we have to make many choices—number of factors, VAR lag length, and data transformation—here we can estimate the model on variables in levels and just select the degree of shrinkage.

De Mol, Giannone, and Reichlin (2008) and Banbura et al. (2008) have studied shrinkage in large models from the theoretical and empirical point of view and show that if the data are sufficiently collinear,[3] shrinkage can control for overfitting while retaining sample information from the large data set. For the purpose of this exercise I select the degree of shrinkage so as to obtain the same fit obtained by the policy rate in a three-variable VAR estimated with euro area GDP, inflation, and the short-term rate (see Giannone, Lenza, and Reichlin 2008). Figures 2, 3, 4, and 5 report selected results.

The BVAR results clearly show that the findings of Boivin et al. on the effect of the monetary shock on long interest rates, exchange rates, and consumption are robust. In Italy and Spain the response of those variables to the German monetary policy shock is outside the euro area's confidence bands. The asymmetry between the response of Germany and France and that of Italy and Spain is confirmed.

Having obtained these results on the basis of a different approach, which we know works under similar but more general conditions than the factor model, is indeed reassuring. There is something in their story.

B. Multicountry BVAR

To compare shocks and impulse response functions across countries as well as the uncertainty around the estimates, we have to go beyond the four VARs and consider a multicountry model. Therefore, I estimate a large VAR with all the variables included in the bivariate models for France, Germany, Italy, and Spain and the euro area aggregate (around

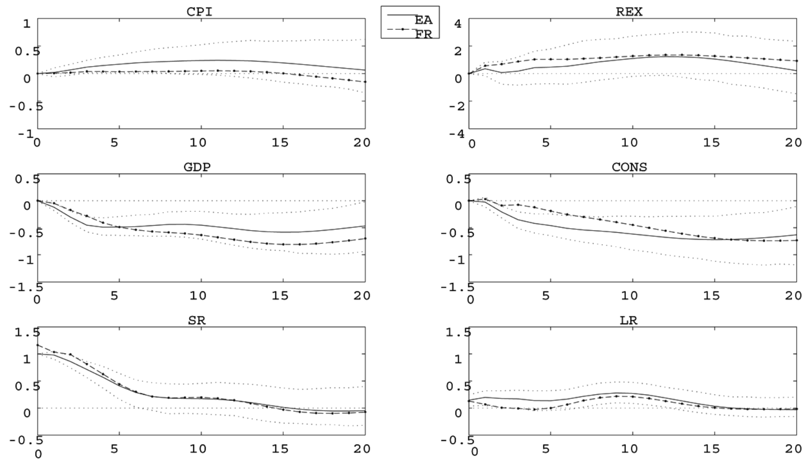

Fig. 2. France and the euro area: responses to the German monetary policy shock. The solid line represents the response of the euro area's variables, the dashed lines show the response of French variables, and the dotted lines indicate 68% confidence bands around the euro area's estimates. A dotted straight line corresponding to zero is added to facilitate the reading of the results.

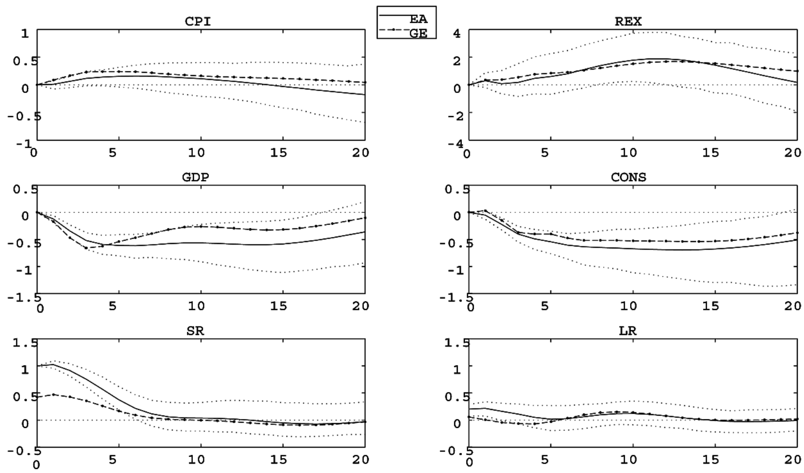

Fig. 3. Germany and the euro area: responses to the German monetary policy shock. The solid line represents the response of the euro area's variables, the dashed lines show the response of German variables, and the dotted lines indicate 68% confidence bands around the euro area's estimates. A dotted straight line corresponding to zero is added to facilitate the reading of the results.

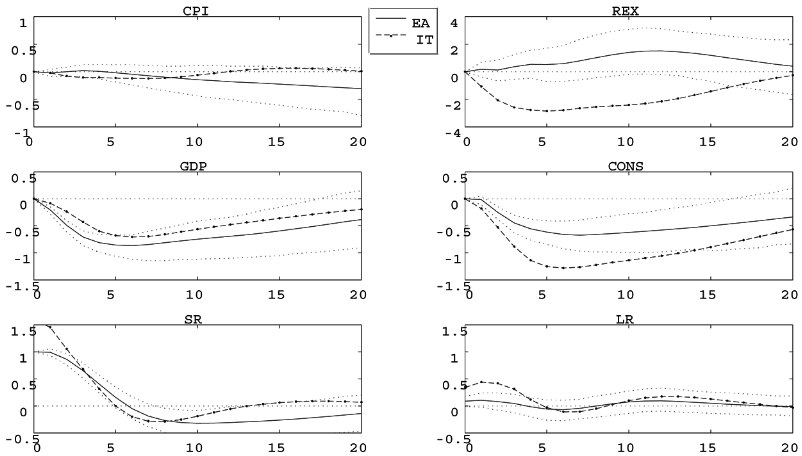

Fig. 4. Italy and the euro area: responses to the German monetary policy shock. The solid line represents the response of the euro area's variables, the dashed lines show the response of Italian variables, and the dotted lines indicate 68% confidence bands around the euro area's estimates. A dotted straight line corresponding to zero is added to facilitate the reading of the results.

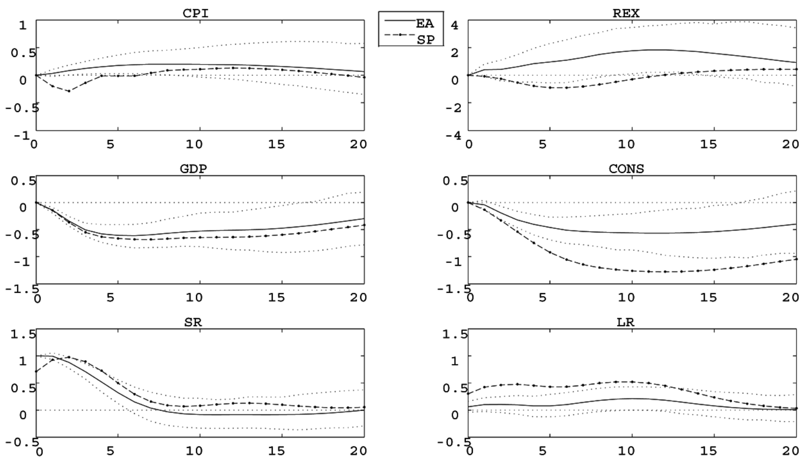

Fig. 5. Spain and the euro area: responses to the German monetary policy shock. The solid line represents the response of the euro area's variables, the dashed lines show the response of Spanish variables, and the dotted lines indicate 68% confidence bands around the euro area's estimates. A dotted straight line corresponding to zero is added to facilitate the reading of the results.

80 variables). The shrinkage parameter is set as explained in the previous subsection.

This time I will estimate the model on the long sample, 1987–2006, and on two subsamples, 1987–98 and 1999–2006. Results can be used to cross-check the other key result of the paper on the effect of the EMU on the transmission mechanism.

Figure 6 reports results for the six key variables (median response), the four countries, and the euro area. Again, results are confirmed. The median response of the exchange rate, interest rates, and consumption for Italy and Spain is outside the confidence bands of the euro area's estimates and therefore are significantly different from the euro area's average responses.

Let us now turn to the subsample analysis. Figures 7, 8, and 9 report results over two periods (pre-EMU on the left and EMU on the right) for long rates, consumption, and exchange rates.

For the pre-EMU sample, the results obtained by both the factor model and the euro area and single-country VARs are confirmed. For the EMU sample, we observe, as expected, more homogeneous responses of the long rates, but, contrary to the authors' results, the heterogeneity in the response of consumption increases rather than decreases whereas

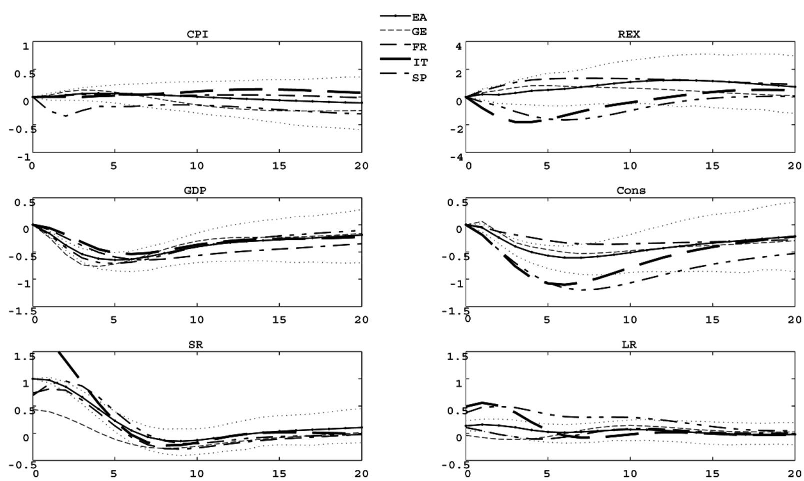

Fig. 6. Multicountry VAR: responses to the German monetary policy shock. The thin solid line corresponds to the response of the euro area aggregate, and the dotted lines are the 68% confidence bands around those estimates. Dashed lines and dashed-dot lines correspond to the responses of, respectively, Germany and France. Italian and Spanish responses are, respectively, bold dashed and double dot-dashed line.

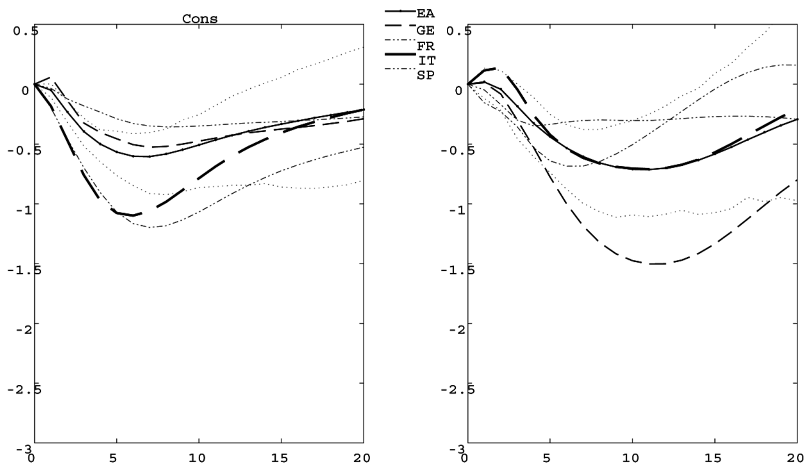

Fig. 7. Countries' response of consumption to the German monetary shock: pre-EMU (left) and EMU (right). The thin solid line corresponds to the response of the euro area aggregate, and the dotted lines are the 68% confidence bands around those estimates. Dashed lines and dashed-dot lines correspond to the responses of, respectively, Germany and France. Italian and Spanish responses are, respectively, bold dashed and double dot-dashed line.

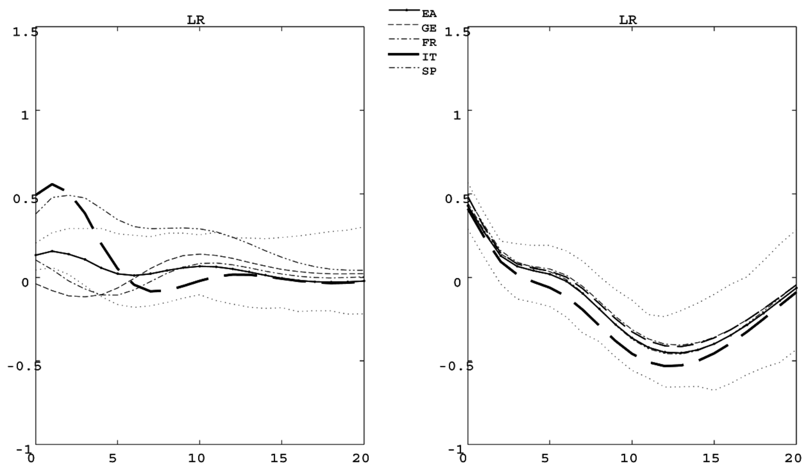

Fig. 8. Countries' response of the long rate to the German monetary shock: pre-EMU (left) and EMU (right). The thin solid line corresponds to the response of the euro area aggregate, and the dotted lines are the 68% confidence bands around those estimates. Dashed lines and dashed-dot lines correspond to the responses of, respectively, Germany and France. Italian and Spanish responses are, respectively, bold dashed and double dot-dashed line.

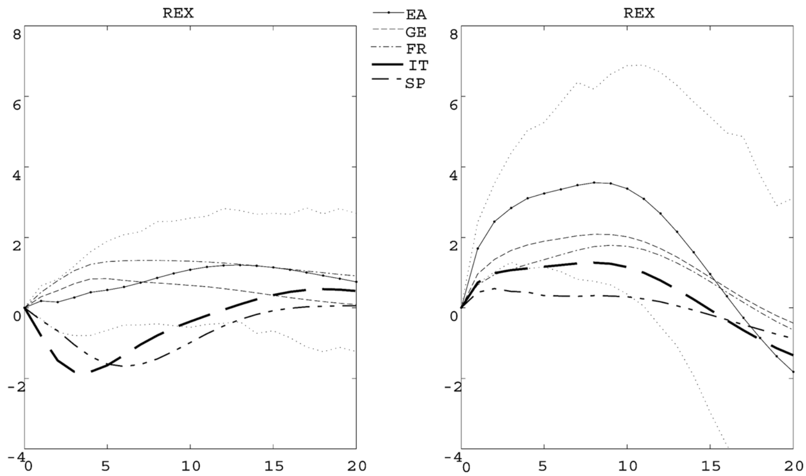

Fig. 9. Countries' response of the real exchange rate to the German monetary shock: pre-EMU (left) and EMU (right). The thin solid line corresponds to the response of the euro area aggregate, and the dotted lines are the 68% confidence bands around those estimates. Dashed lines and dashed-dot lines correspond to the responses of, respectively, Germany and France. Italian and Spanish responses are, respectively, bold dashed and double dot-dashed line.

there is large uncertainty around the median responses of the real exchange rates.

These results suggest that the authors' findings on the changes induced by the EMU are far from being reliable. But the finding of those changes is a key pillar in their story. If the response of consumption has not become more homogeneous since the EMU, the exchange risk premium story, which is at the core of their model, may not capture the essential change induced by the single currency. Let us then turn to the model to develop this point.

IV. The Model and the Story

Having uncovered the differences in the response to a monetary policy shock in core and periphery countries from the empirical point of view, Boivin et al. then build a model that generates impulse response functions that can match the empirical responses and then try to tell a story that helps explain this mechanism.

Since the basic version of the model is unable to reproduce the results, the authors introduce an ad hoc mechanism. The mechanism consists of a shock on the wedge on the uncovered interest parity equation induced by the German monetary shock. With this trick, the German monetary policy shock acts not only on interest rates but also on the gap between home and foreign interest rates. This in turn creates the overresponse in consumption at home (Spain or Italy).

This is an exchange risk premium "story." Upon the foreign monetary shock, international investors require a higher return on domestic (internationally traded) bonds than they do on foreign securities, even after accounting for the rational expectation of nominal exchange rate changes. This is also very much a pro-euro story: the model predicts that common monetary policy reduces the cross-country heterogeneity in the response of consumption to a common monetary policy shock.

I am unconvinced. As we have seen, BVAR results on the EMU sample do not support this story and suggest that this is the least robust of the authors' findings.

Is the model really capturing the essential change? Something else maybe going on, but it may be hard to explain changes in the degree of heterogeneity in impulse responses with a model in which the only source of heterogeneity comes from the coefficients of the Taylor rule.

V. Conclusions

Boivin et al.'s paper performs a heroic empirical exercise! The authors dig out an interesting fact: before the EMU, the gap between the German and the Italian or Spanish short and long interest rates increased in response to a euro area (German) monetary tightening. This induced a larger contraction in consumption in Spain and Italy than it did in Germany. Moreover, in response to a tightening, the real exchange rate depreciated in Italy and Spain and appreciated in core countries.

By using a different econometric approach that relies on less strict assumptions on the data-generating process, I have shown that this finding survives. However, the other result of the paper, that is, the disappearance of the heterogeneity in the response of consumption to monetary policy since the EMU, does not survive my experiment. This tells us that the exchange rate premium story suggested by the model as the essential mechanism governing the changes in the transmission mechanism since the EMU may not be the key one to understand the effect of the single currency on the transmission mechanism of shocks throughout the euro area.

Endnotes

1. On this point, see Onatski (2005).
2. Technically, the number of common shocks corresponds to the rank of the spectral density matrix. A formal test on the number of common shocks based on frequency domain analysis has been proposed by Hallin and Liska (2007). For an empirical analysis based on U.S. data, see Giannone, Reichlin, and Sala (2004).
3. This assumption is a generalization of the assumption under which consistency has been proved for factor models.

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