Institutional Members: CEPR, NBER and Università Bocconi

WORKING PAPER SERIES

Principal components at work: The empirical analysis of monetary policy with large datasets

Carlo A. Favero, Massimiliano Marcellino,Francesca Neglia

Working Paper n. 223

August 2002

IGIER – Università Bocconi, Via Salasco 5, 20136 Milano –Italy
http://www.igier.uni-bocconi.it

The opinion expressed in the working papers are those the authors alone, and not those of the Institute which takes non institutional policy position, nor of CEPR, NBER or Università Bocconi.

Principal components at work: The empirical analysis of monetary policy with large datasets*

Carlo A. Favero   Massimiliano Marcellino
IEP - Bocconi University, IGIER and CEPR

Francesca Neglia
IGIER

August 2002

Abstract

Two competing methods have been recently developed to estimate large-scale dynamic factor models based, respectively, on static and dynamic principal components. In this paper we use two large datasets of macroeconomic variables for the US and for the Euro area to evaluate in practice the relative performance of the two approaches to factor model estimation. The comparison is based both on the relative goodness of fit of the models, and on the usefulness of the factors when used in the estimation of forward looking Taylor rules, and as additional regressors in monetary VARs. It turns out that dynamic principal components provide a more parsimonious summary of the information, but the overall performance of the two methods is very similar, in particular when a common information set is adopted. Moreover, the information extracted from the large datasets turns out to be quite useful for the empirical analysis of monetary policy.

JEL Classification: C32, E52, E58
Keywords: factor model, principal component, Taylor rule, monetary shock

*We are grateful to Jim Stock and seminar participants at the ECB for useful comments on a previous draft.

1. Introduction

Monetary policy makers actively monitor a huge number of economic time series, while most of the recent empirical analysis of monetary policy has been based on parsimonious small scale models. The validity of the analysis based on a limited information set requires that the loss of information generated by omitting a conspicuous part of the information set used by central banks is not relevant to the problem at hand. In this paper we wish to evaluate whether this is the case or whether a better understanding can be obtained by exploiting all the available information.

Two approaches have recently emerged for information extraction from large macroeconomic datasets. Both are based on representing the variables by dynamic factor models, but in Stock and Watson's (1998, SW) method static principal components are used to estimate the factors, while Forni et al. (2000, FHLR) rely on dynamic principal components.

We apply both methods to two large monthly datasets, one for the US that contains 146 macroeconomic time series, and the other for the four largest countries in the European monetary union, for a total of 105 variables. In both cases the explanatory performance of the estimated factors for the macroeconomic variables is good, slightly better when the FHLR methodology is adopted. The latter also appears to provide a more efficient summary of the information contained in the large datasets, since fewer factors are required to achieve the same average fit. But, overall, the fitted values resulting from the FHLR and SW methodologies are rather similar, with average correlations in the range $0.70 - 0.80$.

The good performance of the factor models supports the use of static and dynamic principal components as a summary of the information contained in the large datasets, and the relevant question becomes whether the components are useful for understanding monetary policy. Since Taylor rules have become a common tool for tracking the behavior of central banks, a first issue is whether and by how much the inclusion of the components in the instrument set used for estimation reduces uncertainty on parameter estimates. In turns out that in general there are gains, larger for the US than for the Euro area, and usually larger and obtained with fewer factors in the case of FHLR.

A second relevant issue is the role of principal components in the analysis of the transmission mechanism of monetary shocks. VAR models have become the standard tool in this context, mainly due to the fact that they easily allow dynamic simulations and forecasting. Moreover, these tasks are achievable without using theory-based identifying restrictions and therefore the evidence from VAR can be used to select the best theoretical model to be used for policy simulation analysis (see, for example, Christiano, L. J., Eichenbaum, M., e Evans, C.L,. 1998).

However, VAR models often produce a certain number of results which are difficult to interpret on the basis of economic theory. The price puzzle case is emblematical: VAR models lead to events such as an increase in prices after an interest rate hike. Puzzles can be the effect of the difference in the information set used by the ecometrician and the policy makers or of the choice of the wrong identifying assumption.

With respect to this important issue there have been two parallel developments in the literature. On the one hand, in the VAR camp a new identification strategy is spreading according to which monetary policy shocks are identified by restricting the shape of the dynamic response of macroeconomic variables to them. According to this new "agnostic" method the variables included in a VAR of the monetary transmission mechanism are partitioned in two subsets. Then sign restrictions are imposed on the impulse responses of a first subset of variables to monetary policy shocks, while no restrictions are imposed on the response of the second subset of variables. The response of the second subset of variables to monetary policy shocks is then used to answer the relevant empirical question on the monetary transmission mechanism (see, for example Uhlig,1997, Faust, 1999). This approach has clearly some merits but limits the potential role of mis-specification in the explanation of puzzle. In a counterfactual scenario were monetary policy shocks are always exclusively identified by imposing sign restrictions on the response of prices to monetary policy shocks the price puzzle would have never been observed.

The second reaction to the puzzles has been the enlargement of the information set, by including into the analysis variables such as the commodity prices or the reserves. Our approach is in line with this, but since several variables are potentially relevant and cannot all be modelled within a VAR, the idea is again to summarize the potentially relevant information with the principal components. The results we obtained are again encouraging. The larger number of regressors in the VAR has no negative effects on the precision of the estimated responses to shocks, instead it sometimes increases. More importantly, even with a simple Choleski identification scheme, the pattern of responses often becomes in line with economic theory. This is particularly true in the case of the US, and the FHLR method appears again to summarize more efficiently the large amount of available information.

The paper is organized as follows. Section 2 briefly reviews the dynamic factor model and the alternative estimation methods. Section 3 describes the datasets for the US and Euro area. Section 4 provides results on the fit of the factor models for these datasets. Section 5 evaluates the role of the static and dynamic principal components in Taylor rule estimation. Sections 6 studies the consequences of the inclusion of the components in monetary VARs . Section 7 provides a further evaluation of our comparative analysis based on the dating of the information set. Section 8 concludes.

2. The dynamic factor model and the alternative estimators

The rationale underlying dynamic factor models is that the behavior of several variables is driven by few common forces, the factors, plus idiosyncratic shocks. Hence, the factors can provide an exhaustive summary of the information in large datasets, and in this sense they are precious to alleviate omitted variable problems in empirical analysis using traditional small-scale models, see Bernanke and Boivin (2000), Favero and Marcellino (2001).

A general formulation of a dynamic factor model is

$$x_t = B(L)u_t + \xi_t, \tag{2.1}$$

where x_t is the $N \times 1$ vector of variables under analysis, u_t is the $q \times 1$ vector of common factors (with q much smaller than N), whose dynamic effects on x_t are grouped in $B(L) = I + B_1L + B_2L^2 + ... + +B_pL^p$ (where each B_i is a $N \times q$ matrix), and ξ_{it} is the $N \times 1$ vector of idiosyncratic shocks. When p is finite, an alternative formulation of the model is

$$x_t = \Lambda f_t + \xi_t, \tag{2.2}$$

where $f_t = (u_{1t}, ..., u_{1t-p}, ..., u_{qt}, ..., u_{qt-p})$, so that now $r = p * q$ factors drive the variables, but the factors have only a contemporaneous effect on x_t, with loadings grouped in the $N * r$ matrix Λ.

Note that in general the factors are not identified since, for example, for any invertible $r \times r$ matrix G, the model (2.2) can be rewritten as

$$x_t = \Lambda G G^{-1} f_t + \xi_t = \Psi p_t + \xi_t, \tag{2.3}$$

where p_t is an alternative set of factors. The identification issue complicates the structural interpretation of the factors, but not their use as a summary of the information contained in x_t, because for that aim f_t and p_t are equivalent (one is just a linear transformation of the other).

Frequency domain analysis of the dynamic factor model was recently proposed by Forni and Rechlin (1996, 1997, 1998), Forni and Lippi (1997, 1998), Forni, Hallin Lippi and Reichlin (2000, FHLR henceforth), who are in general more interested in the common component of the series, $\chi_t = x_t - \xi_t$, than in the factors themselves. The model they adopt is (2.1), with the additional hypotheses that u_t (the vector of factors) is an orthonormal white noise process, ξ_t is a wide sense stationary process, and $cov(\xi_{jt}, u_{st-k}) = 0$ for any j, s, t and k. Moreover, χ_t, ξ_t and x_t are required to have rational spectral density matrices, Σ_n^χ, Σ_n^ξ, and Σ_n^x, respectively. To achieve identification of the common and idiosyncratic components (i.e. to avoid leakages from ξ_t to χ_t and viceversa), they assume that the first (largest) idiosyncratic dynamic eigenvalue, λ_{n1}^ξ, is uniformly bounded, and that the first (largest) q common dynamic eigenvalues, $\lambda_{n1}^\chi, ..., \lambda_{nq}^\chi$, diverge, where dynamic eigenvalues are the eigenvalues of the spectral density matrix, see e.g. Brillinger (1981, Chap. 9). In words, the former condition limits the effects of ξ_{it} on other cross-sectional units. The latter, instead, requires u_t to affect infinitely many units.

Time domain analysis of the dynamic factor model based on the static principal components of x_t was developed by Stock and Watson (1998, SW henceforth), focusing on the specification in (2.2), while the static version of this model was analyzed, among others, by Chamberlain (1983), Chamberlain and Rothschild (1983), Connor and Korajczyk (1986, 1993). SW require the factors, f_t, to be orthogonal but they can be correlated in time, actually they can also be correlated with the idiosyncratic component, precise moment conditions on f_t and ξ_t, and requirements on the loading matrix Λ, are given in SW.

We now briefly describe the two estimation methods, more details can be found in FHLR and SW. Five elements are primarily of interest in a factor model: the number of factors, the factors themselves, their loadings, the common component, and the idiosyncratic component.

Let us assume for the moment that the number of common factors is known. Then, FHLR suggest to estimate the common component χ_{it} with the following step-wise procedure. (i) Estimate the spectral density matrix of x_t as

$$\Sigma^T(\theta_h) = \sum_{k=-M}^{M} \Gamma_k^T \omega_k e^{-ik\theta_h}, \quad \theta_h = 2\pi h/(2M+1), \quad h = 0, ..., 2M, \tag{2.4}$$

where Γ_k^T is the sample covariance matrix of x_t and x_{t-k}, ω_k is the Bartlett lag window of size M ($\omega_k = 1 - k/(M+1)$), and M diverges but M/T tends to zero. (ii) Calculate the first q eigenvectors of $\Sigma^T(\theta_h)$, $p_j^T(\theta_h)$, $j = 1, ..., q$, for $h = 0, ..., 2M$. (iii) Define $p_j^T(L)$ as

$$p_j^T(L) = \sum_{k=-M}^{M} p_{j,k}^T L^k, \quad p_{j,k}^T = \frac{1}{2M+1} \sum_{h=0}^{2M} p_j^T(\theta_h) e^{ik\theta_h}, \quad k = -M, ..., M. \tag{2.5}$$

$p_j^T(L)x_t$, $j = 1, .., q$, are the first q dynamic principal components of x_t. (iv) Run an OLS regression of x_t on present, past, and future dynamic principal components. The fitted value is the estimated common component of x_t, $\widehat{\chi}_t$. FHLR prove that, under mild conditions, $\widehat{\chi}_t$ is a consistent estimator of χ_t (consistency is for both N and T growing). Once the common component is estimated, the idiosyncratic one is obtained simply as a residual, namely, $\widehat{\xi}_{it} = x_{it} - \widehat{\chi}_{it}$. In practice, M and the number of leads (s) and lags (g) of $p_j^T(L)x_t$ to be included as regressors have to be chosen. In what follows, we report results for $M = 3$, $s = g = 2$, but we have verified that the outcome is rather robust to other choices of the parameters.

The starting point in SW's approach is instead the estimation of the factors, f_t, and the loadings Λ. They define the estimators $\widehat{f}_t$ as the minimizers of the objective function

$$V_{N,T}(f, \Lambda) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \Lambda_i f_t)^2. \tag{2.6}$$

Under the hypothesis of k common factors, it turns out that the optimal estimators of the factors are the k eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $N^{-1} \sum_{i=1}^{N} \underline{x}_i \underline{x}_i'$, where $\underline{x}_i = (x_{i1}, ..., x_{iT})$. Moreover, the k eigenvectors corresponding to the k largest eigenvalues of the $N \times N$ matrix $T^{-1} \sum_{t=1}^{T} x_t x_t'$ are the optimal estimators of Λ. These coincide with the principal components of x_t. They are also the OLS estimators of the coefficients in a regression of x_{it} on the k estimated factors $\widehat{f}_t$, $i = 1, ..., N$. SW prove that when

$k = r$, i.e. the exact number of common factors is assumed, $\widehat{f}_t$ converges in probability to f_t, a part from the full rank $r \times r$ transformation matrix, G. When $k > r$, $k-r$ estimated factors are redundant linear combinations of the elements of f_t, while even when $k < r$ consistency for the first k factors is preserved (because of the orthogonality hypothesis). As for FHLR, an estimator of the common component can be obtained as $\widehat{\chi}_t = \widehat{\Lambda}\widehat{f}_t$, while a natural choice for the estimator of the idiosyncratic component is $\widehat{\xi}_t = x_t - \widehat{\chi}_t$.

It is worth pointing out that both FHLR and SW, when analyzing the properties of the estimators, require the number of variables, N, to diverge, possibly at a faster rate than T. Hence, these methods are suited to analyze datasets whose cross-sectional dimension is very large, possibly larger than the temporal dimension. When N is smaller, Kalman filter techniques are available and can be more efficient, see e.g. Stock and Watson (1991), Quah and Sargent (1993).

Finally, we have to discuss the determination of the number of factors. No formal testing procedures are available at the moment. FHLR suggest: (i) to estimate recursively the spectral density matrix of a subset of x_t, increasing the number of variables at each step; (ii) to calculate the dynamic eigenvalues for a grid of frequencies, λ_θ^x; (iii) to chose q on the basis of two properties: (a) when the number of variables increases the average over frequencies of the first q dynamic eigenvalues diverges, while the average of the $q+1^{th}$ does not; (b) for the whole x_t there should be a big gap between the variance of x_t explained by the first q dynamic principal components and that explained by the $q+1^{th}$ principal component.

SW suggest to determine the number of factors by minimizing a particular information criterion but, from their simulation experiments, more standard criteria like the AIC or BIC perform better. Bai and Ng (2000) further developed the study of information criteria.

In what follows, since the small sample performance of all the criteria is still uncertain, we follow the sequential procedure suggested by FHLR, but also experiment with different values for the number of factors.

3. The data for the US and for the Euro area

We apply the dynamic factor model to two large monthly macroeconomic datasets, for the US and for the four largest countries in the Euro area, i.e., Germany, France, Italy and Spain. The series for the US come from Stock and Watson

(1998), those for the European countries from Marcellino, Stock and Watson (2000a, 2000b), to whom we refer for additional information and details on data transformations.

The datasets in these papers include, for each country, industrial production and sales (disaggregated by main sectors); new orders in the manufacturing sector; employment, unemployment, hours worked and unit labor costs; consumer, producer, and wholesale prices (disaggregated by type of goods); several monetary aggregates, savings and credit to the economy; short term and long term interest rates, and a share price index; the effective exchange rate and the exchange rate with the US dollar; several components of the balance of payments; and other miscellanea variables. The level of disaggregation of some of these variables, such as industrial production and price indices, is much finer for the US.

Some of the series, though, present missing observations, different starting or ending dates, and outliers. While SW developed an EM algorithm to deal with these types of data irregularities, FHLR require the dataset to be balanced and without outlying observations. Hence, we have only retained series that satisfy there requirements. We end up with 146 series over the period 1959:1-1998:12 for the US, so that $T = 480$, $N = 146$, and 105 series over the period 1982:1-1997:8 for the four European countries as a whole, that will be referred to as the Euro area, so that $T = 188$, $N = 105$. A list of the variables is reported in the Data Appendix.

To evaluate whether the additional series in the non balanced panel (69 for the US and 65 for the Euro area) contain useful information, we also compute and compare results for the SW methodology in this case. This is also relevant to evaluate the role of real variables in th Euro area, since several of them are excluded from the balanced panel.

4. Empirical modelling of the US and Euro area series

In this section we evaluate how well the factor model fits the data and how different the results are using the two estimation methods.[1]

Figure 1 graphs the average over frequencies of the first dynamic eigenvalues, when the number of variables increases, for the US and for the Euro area. From

[1]The SW factors are extracted using their GAUSS routines, while the dynamic principal components are computed with Forni et al.' MATLAB programme. Taylor rules and VARs in the following sections are estimated with E-Views 4.0.

the graphs, in both cases $q = 3$ could already be a good choice for the number of FHLR factors, since the first 3 eigenvalues diverge at a faster rate than the others. For safety, we set $q = 6$, but we will report results also for $q = 4$ (slightly worse figures are obtained with $q = 3$). We also set $r = 6$, the number of factors in the SW approach. This choice is also supported by the fact that SW found only one or two factors to be relevant for forecasting key US macroeconomic variables, and Marcellino et al. (2000a) obtained good forecasts for the Euro area with 3 factors.

The main results are summarized in Table 1. Here we report the average and standard deviation over all variables of the variability of each variable explained by the FHLR and SW common components (adjusted R^2), and the correlation among the FHLR and SW common components. In the case of SW, both the balanced (bp) and the non balanced (nbp) panels are considered.

For the US, with the same number of factors and for the bp, FHLR yields an higher value of the average R^2, 0.51 versus 0.43 for SW. The value for SW further decreases to 0.40 with the nbp, while that for FHLR becomes 0.45 with 4 factors, still slightly higher than SW with 6 factors. Overall, the values are remarkable, since we are always using the same six or four regressors to explain hundreds of quite different macroeconomic variables. Thus, the factor model appears to provide an efficient mean for summarizing information in large datasets.

As far as the average correlation among the common components is concerned, the values are always higher when the bp is used for SW, and higher with 4 FHLR factors, 0.80 in this case. This figure is also noticeable, since it indicates that on average the FHLR and SW methodologies, though rather different in theory, yield similar results in practice.

For the Euro area, a similar pattern emerges. SW yields on average higher values of R^2 with the bp than with the nbp (0.44 versus 0.39); the values are lower than FHLR (0.50) but become comparable when only 4 FHLR factors are used (0.44); the average correlation among the SW and FHLR common components is highest with bp factors for SW and 4 FHLR factors (about 0.78).

The results are also similar and homogenous for the European countries considered separately, with a slightly better fit in terms of average R^2 for France and Italy, the countries with the larger number of variables in the pooled Euro area dataset.

In summary, the performance of the estimated factors in explaining large sets of macroeconomic variables is good, slightly better when the FHLR methodology is adopted. The latter appears to provide a more efficient summary of the information contained in the large datasets, since fewer factors are required to achieve the same average fit. Moreover, the common components resulting from the FHLR and SW methodologies are rather similar, with average correlations in the range $0.70 - 0.80$. Finally, the additional information in the non balanced panel is not useful, or at least the EM algorithm developed by SW does not manage to capture it efficiently in these datasets. This is in line with the simulation results in Angelini et al. (2002), who show that the EM algorithm works only when a very limited number of observations are missing. For this reason, in the following sections we will only report results based on the balanced panel (those with the nbp are always slightly worse and are available upon request).

5. Tracking central banks' decisions

In this section we evaluate the role of static and dynamic principal components as instruments for the estimation of Taylor rules. We will refer to them as, respectively, SW and FHLR factors. Favero and Marcellino (2001) found that in the case of European countries the SW factors are quite useful in reducing the uncertainty in the estimated coefficients. The rationale is that central bankers rely on a large set of indicators in the conduct of monetary policy, and the factors can provide a proxy for this large amount of information. Here we compare the relative performance of FHLR and SW for the Euro area, and extend the analysis to the US case, which was analyzed in a related context by Bernanke and Boivin (2000) within the SW framework.

5.1. US

In the specification of the Taylor rules for the US, we follow Clarida, Gali and Gertler (1998 (CGG), 2000 (CGG2)). The starting point is the equation

$$r_t^* = \overline{r} + \beta(\pi_{t+12}^e - \pi_t^*) + \gamma(y_t - y_t^*), \tag{5.1}$$

where r_t^* is the target nominal interest rate, $\overline{r}$ is the equilibrium rate, π_{t+12}^e is the forecast of the one year inflation rate made in period t, y_t is real output, and π_t^* and y_t^* are the desired levels of inflation and output. The parameter β indicates whether the target real rate adjusts to stabilize inflation ($\beta > 1$) or to accommodate it ($\beta < 1$), while γ measures the concern of the central bank for output stabilization.

Following the literature, we then maintain a partial adjustment mechanism of the actual rate to the target rate r^*. In particular,

$$r_t = (1 - \rho_1 - \rho_2)r_t^* + \rho_1 r_{t-1} + \rho_2 r_{t-2} + v_t, \tag{5.2}$$

where the smoothing parameters ρ satisfy $0 \leq \rho_1 + \rho_2 \leq 1$, and v_t is an interest rate shock.

Combining (5.1) and (5.2), and substituting the forecasts with their realized values, we obtain

$$r_t = \alpha + (1-\rho_1-\rho_2)\beta(\pi_{t+12}-\pi_t^*) + (1-\rho_1-\rho_2)\gamma(y_t - y_t^*) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \epsilon_t, \tag{5.3}$$

where $\alpha = (1 - \rho_1 - \rho_2)\overline{r}$ and $\epsilon_t = (1 - \rho_1 - \rho_2)\beta(\pi_{t+12}^e - \pi_{t+12}) + v_t$. This equation is estimated by GMM, appropriately corrected for the presence of an MA component in the error ϵ_t, over the period 1979:1-1998:12. We use the federal funds rate for r_t, 2% as a measure of the inflation target π_t^*, while the potential output y_t^* is the Hodrick Prescott filtered version of the actual output series. We also experimented with the unemployment gap, as a measure of the status of the economy, obtaining similar results.

In the base case, the set of instruments used for GMM estimation is similar to CGG and CGG2.[2] Then we also include either the FHLR or the SW estimated factors. If they contain useful information, more precise estimates of the parameters should be obtained, as measured by the corresponding t-tests.

The results are reported in Table 2. For the base case, the estimated values for β and γ are, respectively, 0.77 and 0.91, and the fact that the output gap matters more than inflation is rather surprising. The uncertainty around the point estimates, though, is rather large. Actually, the hypothesis that the output gap is not significant in the Taylor rule, i.e. $\gamma = 0$, cannot be rejected at the 5% level. The inclusion of the FHLR factors in the regression substantially reduces the uncertainty. Even with only four factors, the values of the t-test more than doubles for γ, which becomes strongly significant, and is four times as large for β. Furthermore, more reasonable point estimates are obtained, 1.75 for β and 0.80 for γ. The SW factors perform worse, a negative estimate for γ is obtained,

[2] We had to exclude the lags of the interest rate and of the exchange rate from the instrument set, since their inclusion always yielded estimate of $\rho_1 + \rho_2$ equal to one, which makes the parameters β and γ unidentified, compare equation (5.3). Hence, the basic set of instruments includes lags of the output gap, inflation, and commodity price index.

which is against economic theory. Yet, increasing the number of included factors, the results improve. In particular, with 12 factors estimates of 0.65 and 1.49 are obtained for γ and β, though the former is not statistically significant from zero.

With FHLR the values for R^2 are slightly lower than in the base case, and the standard error of the regression slightly higher. This is due to the estimated adjustment parameters, whose sum is closer to one in the base case. Actually, a sum of ρ_1 and ρ_2 close to one is obtained when the SW factors are included as instruments, and in this case both the R^2 and the standard error of the regression are as in the base case. Finally, the J-tests for the validity of the instruments are of comparable size in all cases.

5.2. Euro area

In the specification of the Taylor rules for European countries, we follow Clarida, Gali and Gertler (1998, CGG). For Germany, we consider a specification similar to the US, namely,

$$r_t^* = \overline{r} + \beta(\pi_{t+12}^e - \pi_t^*) + \gamma(y_t - y_t^*). \tag{5.4}$$

In the case of France, Italy and Spain, the commitment to remain in the ERM and, later on, to join the EMU should be included in the specification of the reaction function of the central banks. Hence, we assume that the target inflation rate coincides with the German one, and there is a willingness to follow the Bundesbank's monetary policy. The resulting Taylor rules for the three countries take the form

$$r_{it}^* = r_t + \beta(\pi_{it+12}^e - \pi_t^*) + \gamma(y_{it} - y_{it}^*), \tag{5.5}$$

where i indexes the country and r_t is the actual German rate.

Following the literature, we then maintain a quicker partial adjustment mechanism of the actual rate to the target rate r^*, so that

$$r_t = (1-\rho)r_t^* + \rho r_{t-1} + v_t, \tag{5.6}$$

where the smoothing parameter ρ satisfies $0 \leq \rho \leq 1$,and v_t is an interest rate shock.

Combining (5.4) and (5.6), and substituting the forecasts with their realized values, for Germany we obtain

$$r_t = \alpha + (1-\rho)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho)\gamma(y_t - y_t^*) + \rho r_{t-1} + \epsilon_t, \tag{5.7}$$

where $\alpha = (1-\rho)\overline{r}$ and $\epsilon_t = (1-\rho)\beta(\pi^e_{t+12} - \pi_{t+12}) + v_t$. For the other countries

$$r_{it} = (1-\rho)r_t + (1-\rho)\beta(\pi_{it+12} - \pi^*_t) + (1-\rho)\gamma(y_{it} - y^*_{it}) + \rho r_{it-1} + \epsilon_{it}. \quad (5.8)$$

Following Favero and Marcellino (2001), as a measure of π^*_t we use the official inflation target for Germany, while the potential output y^*_t is the Hodrick Prescott filtered version of the actual output series. For the interest rate, we use 3-month rates, in particular the Fibor for Germany, the Pibor for France, and the interbank rate for Italy and Spain.

As for the US, the parameters α, β, γ, and ρ in (5.7) and (5.8) are estimated by GMM, appropriately corrected for the presence of an MA component in the errors, over the sample 1983:1-1997:8 for all countries, except for Spain where the starting date is 1984:1. The basic set of instruments is as in CGG, and includes lagged values of the regressors, of the dependent variable, of a raw material price index, and of the real exchange rate with the US dollar. We then add the SW or FHLR estimated factors to this set.[3]

Table 3 summarizes the results for the four European countries. Overall, the point estimates do not change substantially, and the inclusion of the FHLR factors in the instrument set improves the precision in the case of France and Germany, and of Spain for the SW factors. The performance with four FHLR is in general better than with six SW factors. The values of R^2 and of the standard error of the regressions are very similar in all cases, as well as those of the J-test for the validity of the instruments.

From an economic point of view, it emerges that inflation was a substantially more important determinant of monetary policy decisions in Germany and Spain than in France and Italy. If a stronger credibility of the central banks is associated with such a behavior, then it is possible to explain why unexpected monetary policy was often found to be more effective in Germany and Spain than in the other European countries, see e.g. Sala (2001).

It is also worth mentioning that Favero and Marcellino (2001) found larger efficiency gains because of the use of country specific factors, possibly combined with the pooled factors, extracted from non balanced panels. Yet, few series remain in the balanced panels for some countries, in particular Germany, which makes the principal component based estimators unsuited. We find that when a large enough number of series are available in the balanced panel, as in the case of

[3]We have also experimented with the inclusion of contemporaraneous values of all instruments, which did not substantially alter our results.

France, the results concerning the estimation of the Taylor rule further improve if the FHLR or SW country specific factors are included in the instrument set.

In summary, the inclusion of factors in the instrument set used for the estimation of Taylor rules in general improves the precision of the estimates. The gains are larger for the US than for the Euro area, likely because of the larger and more detailed dataset available, and usually larger and obtained with fewer factors in the case of FHLR. This is in line with the findings in the previous section, and provides further evidence that, for the datasets under analysis, the FHLR method yields a more efficient summary of the information.

6. Evaluating the effects of monetary shocks

In this section we evaluate whether the inclusion of factors in a VAR, the most common tool for the empirical analysis of monetary policy, improves our understanding of the effects of monetary policy, either by changing the shape of the responses of main macroeconomic variables to monetary shocks, or by decreasing the uncertainty about such responses.

The baseline VAR model can be written as:

$$\begin{bmatrix} \mathbf{X}_t \\ i_t \end{bmatrix} = A(L) \begin{bmatrix} \mathbf{X}_{t-1} \\ i_{t-1} \end{bmatrix} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t = \mathbf{B} \begin{bmatrix} \mathbf{u}_t \\ u_t^m \end{bmatrix},$$

where the vector $\mathbf{X}_t$ contains domestic output gap, domestic inflation, commodities price inflation, and either the effective exchange rate in the case of the US, or the US Dollar-Deutschemark exchange rate for Germany, or the exchange rate of the local currency vis-a-vis the Deutschemark and the German policy rates for the other three European countries. We then consider an alternative scenario based on the inclusion of the FHLR or SW factors in $\mathbf{X}_t$. In all cases, i_t is the domestic policy rate. The specification of the lag length is chosen consistently with the specification of instruments in the forward looking Taylor rules estimated in the previous section.

The monetary policy shock, u_t^m, the only one we are interested in, is identified with a Choleski decomposition. Favero and Marcellino (2001) adopt a structural identification consistent with the forward-looking Taylor rules, but we find that the results are very similar with the Choleski decomposition. We here adopt the latter to stress that the issue is not related to the particular identification scheme but to whether the factors are included or not in the VAR.

In Figure 2 we report the responses of the US output gap and inflation to a domestic monetary policy shock, and the response of the policy rate to an own shock, together with 95% analytical standard errors. In the baseline case, the price puzzle emerges in the short run, combined with an increase in the output gap notwithstanding the monetary restriction. The inclusion of the FHLR factors in the VAR solves both puzzles, now the reaction of inflation is negative or close to zero, and the impact on the output gap is negative, and significant after three quarters. The pattern is similar with four or six FHLR factors, while with six SW factors there are no improvements with respect to the baseline. To solve the puzzles exploiting the additional information in the large dataset as summarized by the SW factors, as in Bernanke and Boivin(2000), twelve SW factors are required. Finally, though there are no major gains in terms of smaller standard errors around the responses when the factors are included in the VARs, it is already remarkable that the standard errors do not increase notwithstanding the inclusion of several additional regressors.

It is worth to point out that the response of the output gap in the base case seems odd and not consistent with the impulse response functions obtained in the literature for output as a result of a positive shock to the interest rate. In fact, usually this impulse response function is a downward sloping and j-shaped curve, across different model specifications and identification schemes. The peculiarity of the curve obtained here is entirely due to the use of the HP-filter in the calculation of the output gap. We decided to estimate a VAR model with this variable instead of output for coherence with the analysis of the Taylor rules, which are estimated using the output gap. By re-estimating the model with the output in place of output gap, the base case model is consistent with the literature as we obtain the usual j-shaped curve as a response of output to a positive interest rate shock. Moreover, we still manage to solve the price puzzle by adding the factors to the model (see Figure 2a).

Figure 3 presents a similar analysis for Germany. In this case the inclusion of the factors is not helpful. This is not surprising since, as shown in Favero and Marcellino (2001), the fact that the Bundesbank was a monetary targeter for most of the sample period is not taken into consideration in this type of VAR analysis.

In the case of France, from Figure 4 the inclusion of the factors, in particular for FHLR, improves substantially the responses, even though the price puzzle cannot be completely eliminated. For Italy and Spain the baseline responses are already in line with economic theory, see Figures 5 and 6, and only minor changes result when the factors appear in the VAR.

In summary, the results we have obtained support the inclusion of the factors in monetary VAR. The larger number of regressors has no negative effects on the precision of the estimated responses, instead it sometimes increases, and, more importantly, the pattern of responses often becomes in line with economic theory. This is particularly true in the case of the US and, as in the previous sections, the FHLR method appears to summarize more efficiently the large amount of available information.

7. Understanding the relative performance of FHLR and SW

In this section we further investigate the relative performance of the two methods with particular reference to the adopted information set. In fact, as illustrated in Section 2, the dynamic principal components underlying the FHLR approach are linear combination of past present and *future* economic variables, while the static principal component underlying the SW approach are linear combination only of contemporaneous variables. More specifically, information up to two quarters ahead is included in the FHLR estimated components. While this is not problematic for ex-post evaluation, it is important to endow the two alternative methods with a common information set for pseudo-ex-ante analysis and forecasting. In fact, to construct a coincident indicator for the European economy (see http://www.cepr.org/data/eurocoin/) Altissimo et al.(2001) have constructed and developed a one-sided version of their methodology. To provide a simple assessment of the importance of the inclusion of future information we have re-run the analysis for the US case by lagging three quarters each dynamic principal component.

The estimated parameters for the Taylor rules reported in Table 4 indicate that only when six factors are considered the FHLR methods allows some substantial improvement on the no-factors scenario and the SW methods. However, when we look at impulse response functions in Figure 7, we note that the price puzzle does no longer disappear, even when six components are included in the VAR.

To summarize, the results reported over Table 4 and Figure 7 show that the performance of the two methods becomes much closer when a common information set is adopted.

8. Conclusions

In this paper we have used two large datasets of macroeconomic variables for the US and for the Euro area to evaluate in practice the relative performance of two alternative approaches to factor model estimation, based, respectively, on static and dynamic principal components, and their relevance for the empirical analysis of monetary policy. The comparison is based both on the relative goodness of fit of the models, and on the usefulness of the factors for the estimation of forward looking Taylor rules, and as additional regressors in structural VARs, to evaluate the effects of monetary policy.

It turns out that dynamic principal components provide a more parsimonious summary of the information, but the overall performance of the two methods is similar, very similar when a common information set is adopted. Moreover, the information extracted from the large datasets using any of the two principal component based methods turns out to be quite useful for the empirical analysis of monetary policy. It decreases the uncertainty about parameter estimates in Taylor rules, and it is capable of eliminating the main puzzle in the transmission mechanism of monetary policy.

References

[1] Altissimo F., A.Bassanetti , R. Cristadoro , M. Forni , M. Hallin , M. Lippi , L. Reichlin , G. Veronese (2001) "EuroCOIN: A Real Time Coincident Indicator of the Euro Area Business Cycle" CEPR Discussion Paper 3108

[2] Angelini, E., Henry, J. and Marcellino, M. (2002), "Interpolation with a large information set", mimeo.

[3] Bai, J. and S. Ng (2000), "Determining the number of factors in approximate factor models", *Econometrica*, 70.

[4] Brillinger, D.R. (1981), *Time Series: data analysis and theory*, Holden-Day, San Francisco.

[5] Chamberlain, G. and M. Rothschild (1983), "Arbitrage factor structure, and mean variance analysis of large asset markets", *Econometrica*, 51, 1281-1304.

[6] Christiano, L.J., Eichenbaum, M. and Evans, C. (1998) "Monetary policy shocks: What have we learned and to what end?", in Taylor and Woodford (eds.), *Handbook of Macroeconomics*, Elsevier.

[7] Clarida, R. Gali, J., Gertler, M. (1998), "Monetary policy rules in practice: Some international evidence", *European Economic Review*, 42, 1033-1067.

[8] Clarida, R. Gali, J., Gertler, M. (2000), "Monetary policy rules and macroeconomic stability: evidence and some theory", *Quarterly Journal of Economics*, 115, 147-180.

[9] Connor, G. and R.A. Korajczyk (1986), "Performance measurement with the arbitrage pricing theory", *Journal of Financial Economics*, 15, 373-394.

[10] Connor, G. and R.A. Korajczyk (1993), "A test for the number of factors in an approximate factor model", *Journal of Finance*, 48, 1263-1291.

[11] Faust, J. (1998), "On the robustness of the identified VAR conclusions about money", *Carnegie Rochester Conference Series on Public Policy*, 49, 207-244.

[12] Favero, C.A. and Marcellino, M. (2001), "Large datasets, small models and monetary policy in Europe", CEPR WP 3098.

[13] Forni, M. and L. Reichlin (1996), "Dynamic common factors in large cross-sections", *Empirical Economics*, 21, 27-42.

[14] Forni, M. and L. Reichlin (1997), "National policies and local economies: Europe and the United States", CEPR WP 1632.

[15] Forni, M. and L. Reichlin (1998), "Let's get real: A dynamic factor analytical approach to disaggregated business cycle", *Review of Economic Studies*, 65, 453-474.

[16] Forni, M., Hallin, M., Lippi, M. and L. Reichlin (2000), "The generalized factor model: identification and estimation", *The Review of Economic and Statistics*, forthcoming.

[17] Marcellino, M., Stock, J.H. and Watson, M.W. (2000a), "Macroeconomic forecasting in the Euro area: country specific versus euro wide information", *European Economic Review*, forthcoming.

[18] Marcellino, M., Stock, J.H. and Watson, M.W. (2000b), "A dynamic factor analysis of the EMU", mimeo.

[19] Quah, D. and T.J. Sargent (1993), "A dynamic index model for large cross-sections", ch. 7 in Stock, J.H. and M.W. Watson (eds.), *Business cycles, indicators and forecasting*, University of Chicago Press for the NBER.

[20] Sala, L. (2001), "Monetary transmission in the Euro area: A factor model approach", mimeo.

[21] Sargent, T.J. and C.A. Sims (1977), "Business cycle modelling without pretending to have too much a-priori economic theory", in Sims, C.A. (ed.), *New methods in business cycle research*, Minneapolis: Federal Reserve Bank of Minneapolis.

[22] Stock, J.H. and M.W. Watson (1991), "A probability model of the coincident economic indicators", ch.4 in Lahiri, K. and G.H. Moore (eds.), *Leading economic indicators: New approaches and forecasting records*, New York: Cambridge University Press.

[23] Stock, J.H. and M.W. Watson (1998), "Diffusion indexes", NBER WP 6702.

[24] Uhlig, H. (1997), "What are the effects of monetary policy? Results from an agnostic identification procedure", mimeo.

Table 1: Analysis of the common components

	R^2-adjusted				Correlations					
	sw (6)		fhlr (6)	fhlr (4)	fhlr(6)	fhlr(6)	fhlr(4)	fhlr(4)	N	T
	nbp	bp			sw(nbp)	sw(bp)	sw(nbp)	sw(bp)		
US	0.40 (0.26)	0.43 (0.25)	0.51 (0.26)	0.45 (0.25)	0.72 (0.20)	0.76 (0.17)	0.75 (0.20)	0.80 (0.16)	146	478
Euro4	0.39 (0.26)	0.44 (0.27)	0.50 (0.24)	0.44 (0.24)	0.69 (0.20)	0.74 (0.18)	0.72 (0.19)	0.78 (0.16)	105	186
Germany	0.35 (0.23)	0.41 (0.24)	0.50 (0.23)	0.45 (0.23)	0.63 (0.16)	0.68 (0.16)	0.63 (0.15)	0.70 (0.16)	14	186
France	0.43 (0.29)	0.51 (0.31)	0.53 (0.25)	0.48 (0.26)	0.70 (0.20)	0.76 (0.19)	0.73 (0.19)	0.78 (0.16)	26	186
Italy	0.39 (0.28)	0.44 (0.28)	0.51 (0.25)	0.45 (0.26)	0.70 (0.22)	0.75 (0.17)	0.73 (0.21)	0.80 (0.15)	40	186
Spain	0.37 (0.21)	0.38 (0.23)	0.45 (0.21)	0.38 (0.21)	0.70 (0.18)	0.72 (0.18)	0.74 (0.16)	0.77 (0.16)	25	186

Notes: the table shows average and standard deviation over all variables of the variability of each variable (adjusted R^2) explained by the FHLR and SW common components, and the correlation among the FHLR and SW common components. In the case of SW, both the balanced (bp) and the non balanced (nbp) panels are considered. The indicators are calculated for the four european countries and for the US.

Table 2: Forward-looking Taylor rules for the US

US	ρ_1	ρ_2	γ	β	R^2-adj	Se of reg	J-stat
no factors	1.06 (16.47)	-0.09 (-1.49)	0.91 (1.79)	0.77 (2.23)	0.96	0.75	9.95 (0.95)
fhlr (6)	0.36 (3.51)	0.55 (5.50)	1.57 (4.80)	1.41 (5.53)	0.92	0.99	11.01 (0.99)
fhlr(4)	0.29 (2.14)	0.53 (4.31)	0.81 (4.34)	1.75 (10.00)	0.90	1.14	9.43 (0.99)
sw (6, bp)	2.12 (38.22)	-1.17 (-21.51)	-0.95 (-3.47)	0.80 (3.85)	0.93	0.96	12.89 (0.98)
sw(12, bp)	1.13 (47.92)	-0.15 (-5.71)	0.65 (1.02)	1.49 (2.80)	0.96	0.75	12.71 (0.99)

Notes: The estimated equation for the US is $r_t = \alpha + (1-\rho_1-\rho_2)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho_1-\rho_2)\gamma(y_t - y_t^*) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \epsilon_t$ (see text for details). The parameters are estimated by GMM over 1979.01-1998.12. In the base case (scenario with no factors) the set of instruments is similar to the one used in CGG and CGG2 (see text for details). In the other models, different amounts of FHLR and SW factors are added to the instruments. In the SW case, both factors calculated from balanced (bp) and non balanced (nbp) panels are considered. The table entries are coefficient estimates (standard errors in brackets), R^2 -adjusted, standard error of the regressions and the j-test (associated p-values in brackets) for the validity of the instruments.

Table 3: Forward-looking Taylor rules for Germany, France, Italy and Spain

		ρ	γ	β	R2-adj	Se of reg	J-stat
Germany	no factors	0.99 (197.01)	1.54 (1.88)	4.88 (2.42)	0.98	0.24	15.21 (0.99)
	fhlr (6)	0.99 (234.63)	1.09 (3.12)	4.18 (4.24)	0.98	0.24	15.26 (0.99)
	fhlr(4)	0.99 (232.89)	1.01 (3.14)	4.26 (4.17)	0.98	0.24	15.24 (0.99)
	sw (6, bp)	1 (224.19)	6.51 (0.62)	9.43 (0.71)	0.98	0.24	15.42 (0.99)
France	no factors	0.96 (355.59)	1.15 (6.96)	0.73 (5.04)	0.97	0.42	14.67 (0.99)
	fhlr (6)	0.95 (340.19)	0.85 (6.18)	0.80 (7.40)	0.97	0.42	14.88 (0.99)
	fhlr(4)	0.96 (347.77)	1.01 (6.76)	0.80 (6.97)	0.97	0.42	14.84 (0.99)
	sw (6, bp)	0.95 (329,11)	0.97 (6.73)	0.75 (6.04)	0.97	0.42	14.86 (0.99)
Italy	no factors	0.98 (321.07)	1.42 (4.96)	1.71 (23.22)	0.96	0.58	14.51 (0.99)
	fhlr (6)	0.98 (351.55)	1.75 (4.58)	1.80 (20.51)	0.96	0.58	14.54 (0.99)
	fhlr(4)	0.98 (349.92)	1.73 (4.57)	1.79 (20.10)	0.96	0.58	14.54 (0.99)
	sw (6, bp)	0.99 (383,47)	2,26 (3,87)	1.99 (17.55)	0.96	0.58	14.56 (0.99)
Spain	no factors	0.97 (237.30)	0.30 (1.57)	1.96 (18.66)	0.96	0.64	14.58 (0.99)
	fhlr (6)	0.97 (281.55)	0.54 (2.81)	1.81 (16.81)	0.96	0.64	14.67 (0.99)
	fhlr(4)	0.97 (264.82)	0.56 (2.70)	1.85 (17.34)	0.96	0.64	14.68 (0.99)
	sw (6, bp)	0.97 (291.77)	0.44 (2.34)	1.81 (19.00)	0.96	0.64	14.72 (0.99)

Notes: The estimated equations are $r_t = \alpha + (1-\rho)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho)\gamma(y_t - y_t^*) + \rho r_{t-1} + \epsilon_t$ for Germany and $r_{it} = (1-\rho)r_t + (1-\rho)\beta(\pi_{it+12} - \pi_t^*) + (1-\rho)\gamma(y_{it} - y_{it}^*) + \rho r_{it-1} + \epsilon_{it}$ for the other countries (see text for details). The parameters are estimated by GMM over 1983.01-1997.08 for all countries except for Spain (1984.01-1997.08). In the base case (scenario with no factors) the set of instruments is the one used in CGG (see text for details). In the other models, different amounts of FHLR and SW pooled factors (factors extracted from the 4-country merged dataset) are added to the instruments. In the SW case, both factors calculated from balanced (bp) and non balanced (nbp) panels are considered. The table entries are coefficient estimates (standard errors in brackets), R^2-adjusted, standard error of the regressions and the j-test (associated p-values in brackets) for the validity of the instruments.

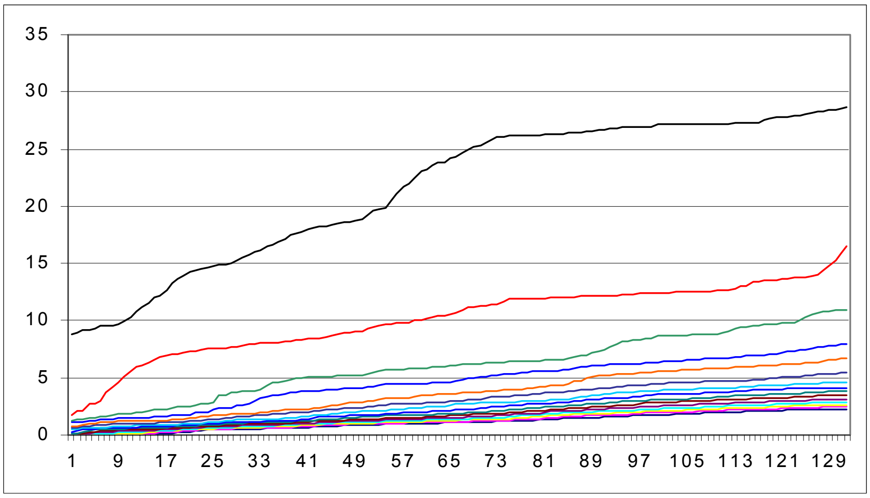
Table 4: Forward-looking Taylor rules for the US (using three-periods lagged FHLR factors)

US	ρ_1	ρ_2	γ	β	R^2-adj	Se of reg
no factors	1.06 (16.47)	-0.09 (-1.49)	0.91 (1.79)	0.77 (2.23)	0.96	0.75
fhlr (6)	0.36 (3.51)	0.55 (5.50)	1.57 (4.80)	1.41 (5.53)	0.92	0.99
fhlr(4)	0.29 (2.14)	0.53 (4.31)	0.81 (4.34)	1.75 (10.00)	0.90	1.14
fhlr (6) lagged	0.08 (0.48)	0.68 (4.74)	0.96 (5.48)	1.59 (12.12)	0.86	1.33
fhlr(4) lagged	1.23 (26.61)	-0.22 (-4.93)	-7.87 (-0.33)	-4.73 (-0.28)	0.96	0.75
sw (6, bp)	2.12 (38.22)	-1.17 (-21.51)	-0.95 (-3.47)	0.80 (3.85)	0.93	0.96
sw(12, bp)	1.13 (47.92)	-0.15 (-5.71)	0.65 (1.02)	1.49 (2.80)	0.96	0.75

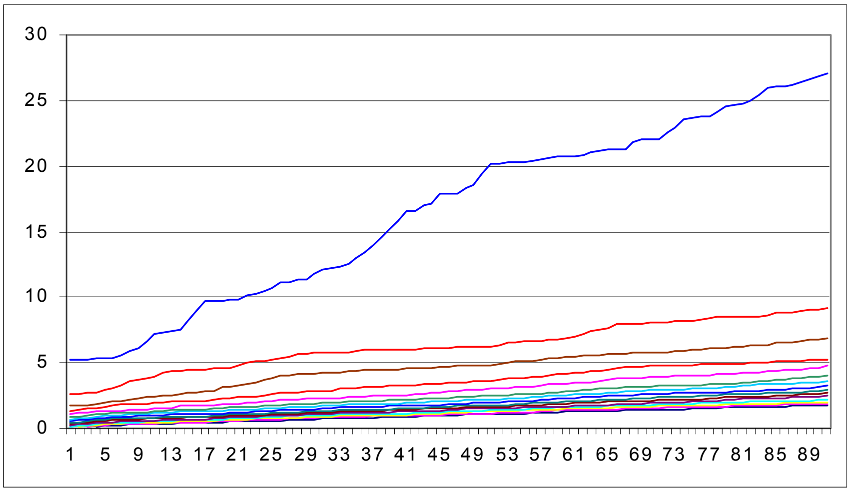
Notes: The estimated equation for the US is $r_t = \alpha + (1-\rho_1-\rho_2)\beta(\pi_{t+12}-\pi_t^*) + (1-\rho_1-\rho_2)\gamma(y_t-y_t^*) + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \epsilon_t$ (see text for details). The parameters are estimated by GMM over 1979.01-1998.12. In the base case (scenario with no factors) the set of instruments is similar to the one used in CGG and CGG2 (see text for details). In the other models, different amounts of FHLR (three-periods lagged factors when indicated) and SW factors are added to the instruments. In the SW case, both factors calculated from balanced (bp) and non balanced (nbp) panels are considered. The table entries are coefficient estimates (standard errors in brackets), R^2 -adjusted, standard error of the regressions and the j-test (associated p-values in brackets) for the validity of the instruments.

Figure 1: Choice of the number of factors

US:

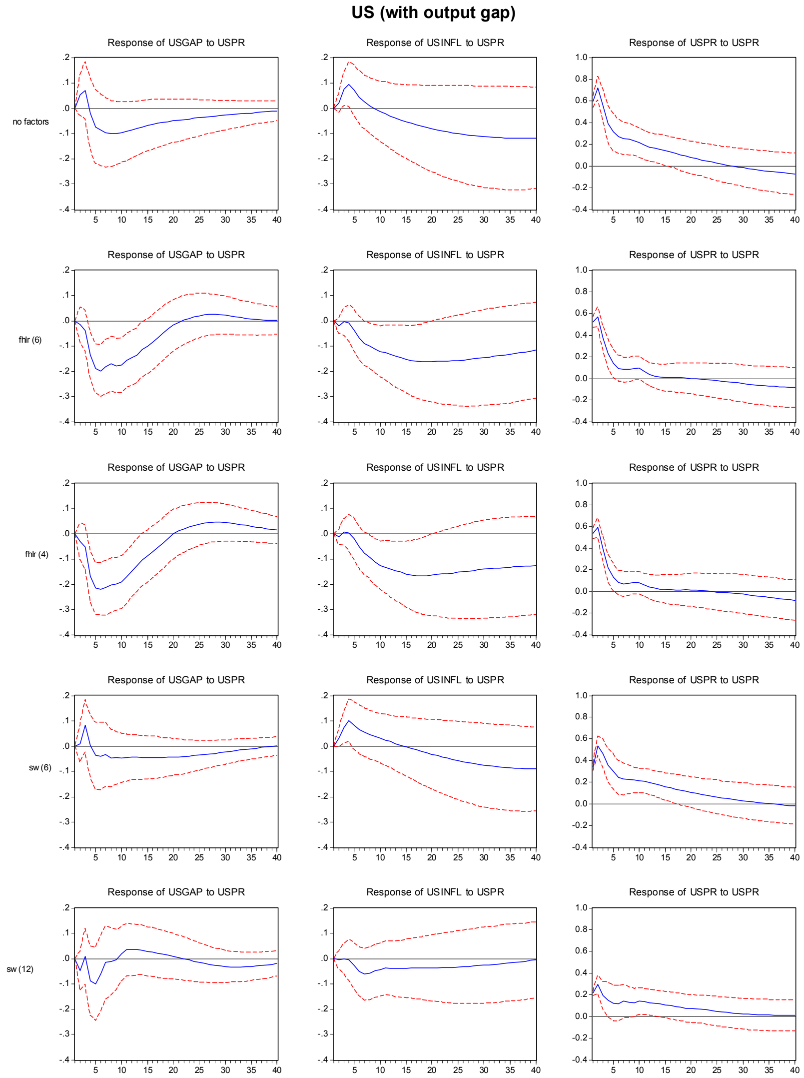


Euro4-area:



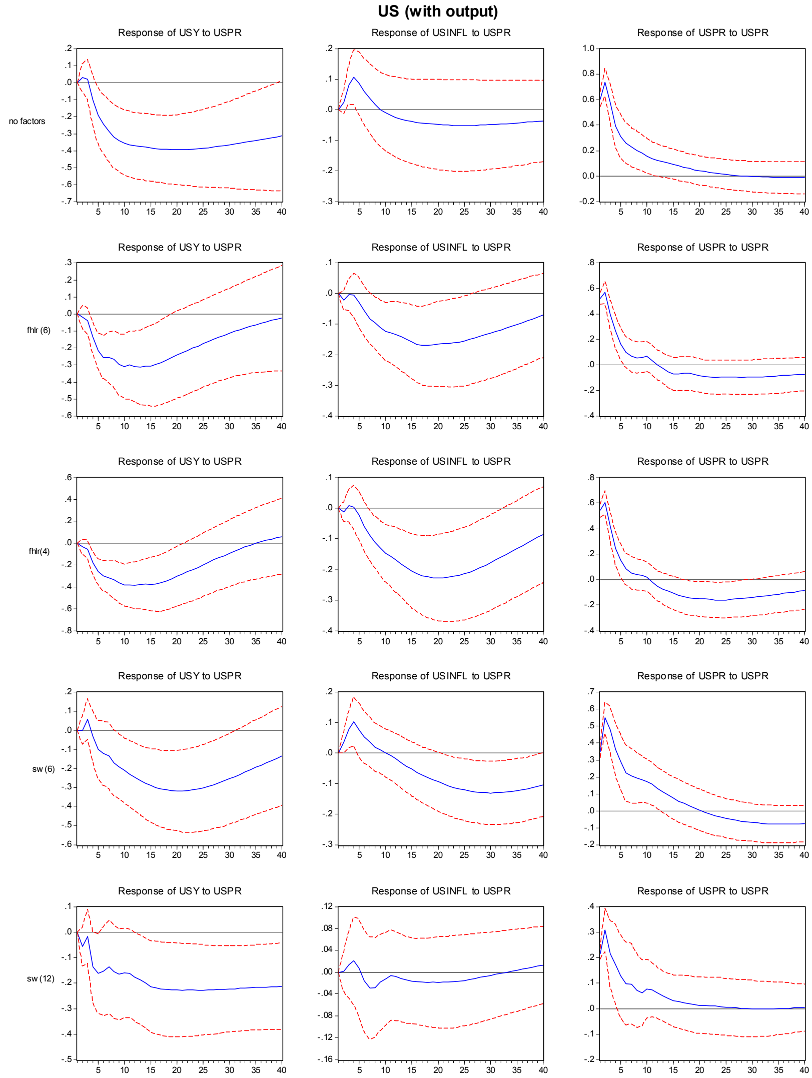
Notes: The number of factors to use is choosen according to a heuristic procedure suggested by FHLR (see Forni et Al. for details). The figures graph the average over frequencies of the dynamic eighenvalues as the number of series used to calculate them increases.

Figure 2: Responses to one S.D. shock to domestic policy rate for the US (in the model with output gap)



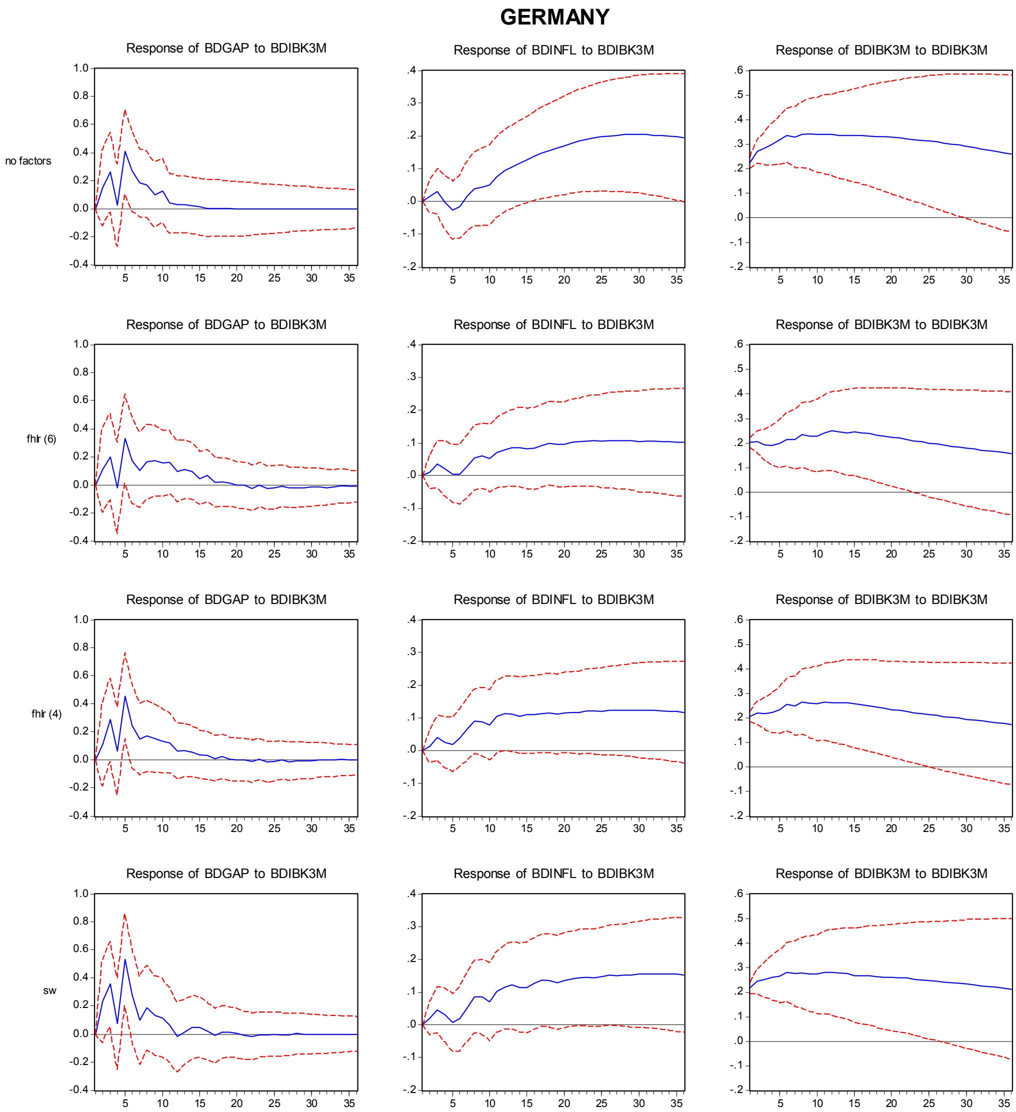
Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of SW and FHLR factors (indicated in brakets) are used as additional regressors in the VARs.

Figure 2a: Responses to one S.D. shock to domestic policy rate for the US (in the model with output)



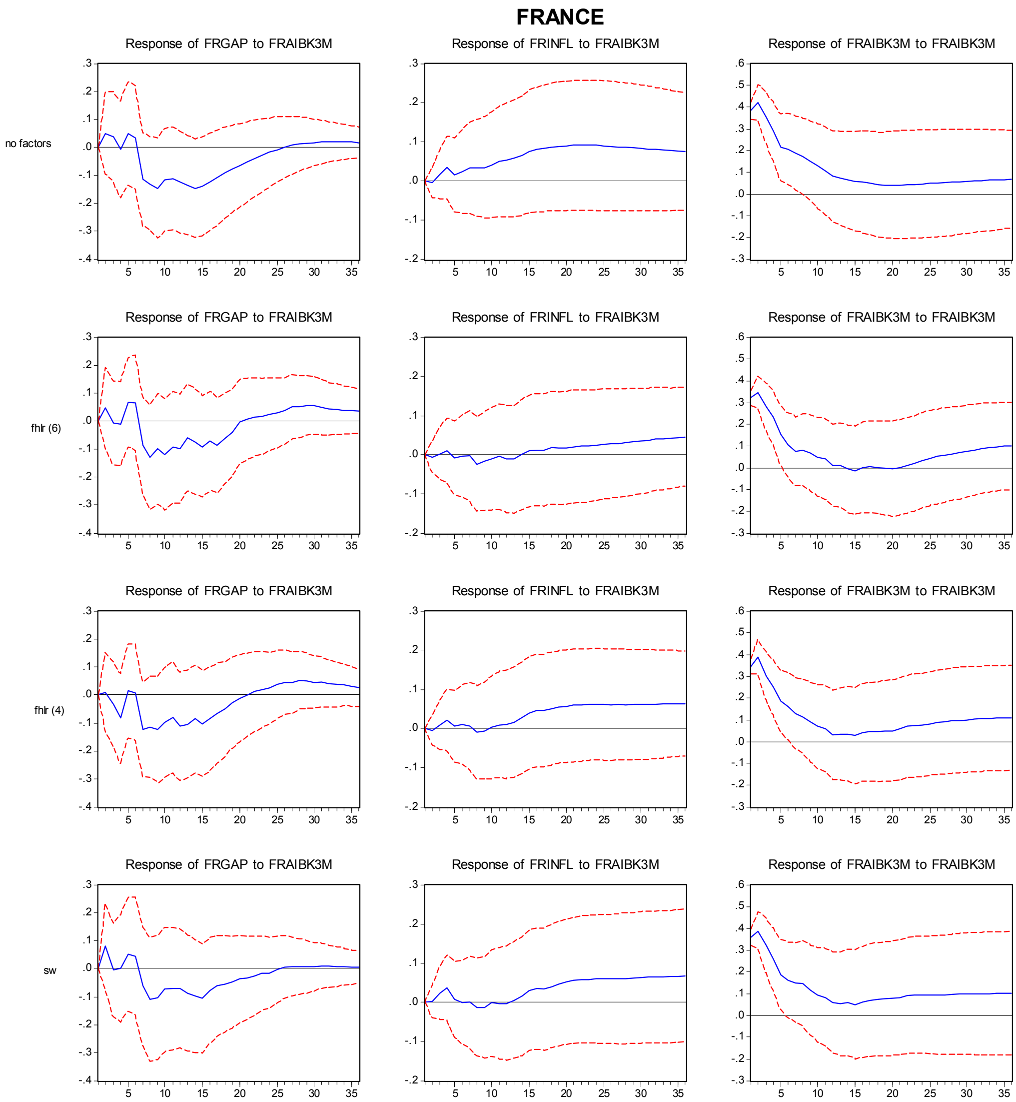
Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of SW and FHLR factors (indicated in brakets) are used as additional regressors in the VARs.

Figure 3: Responses to one S.D. shock to domestic policy rate for Germany



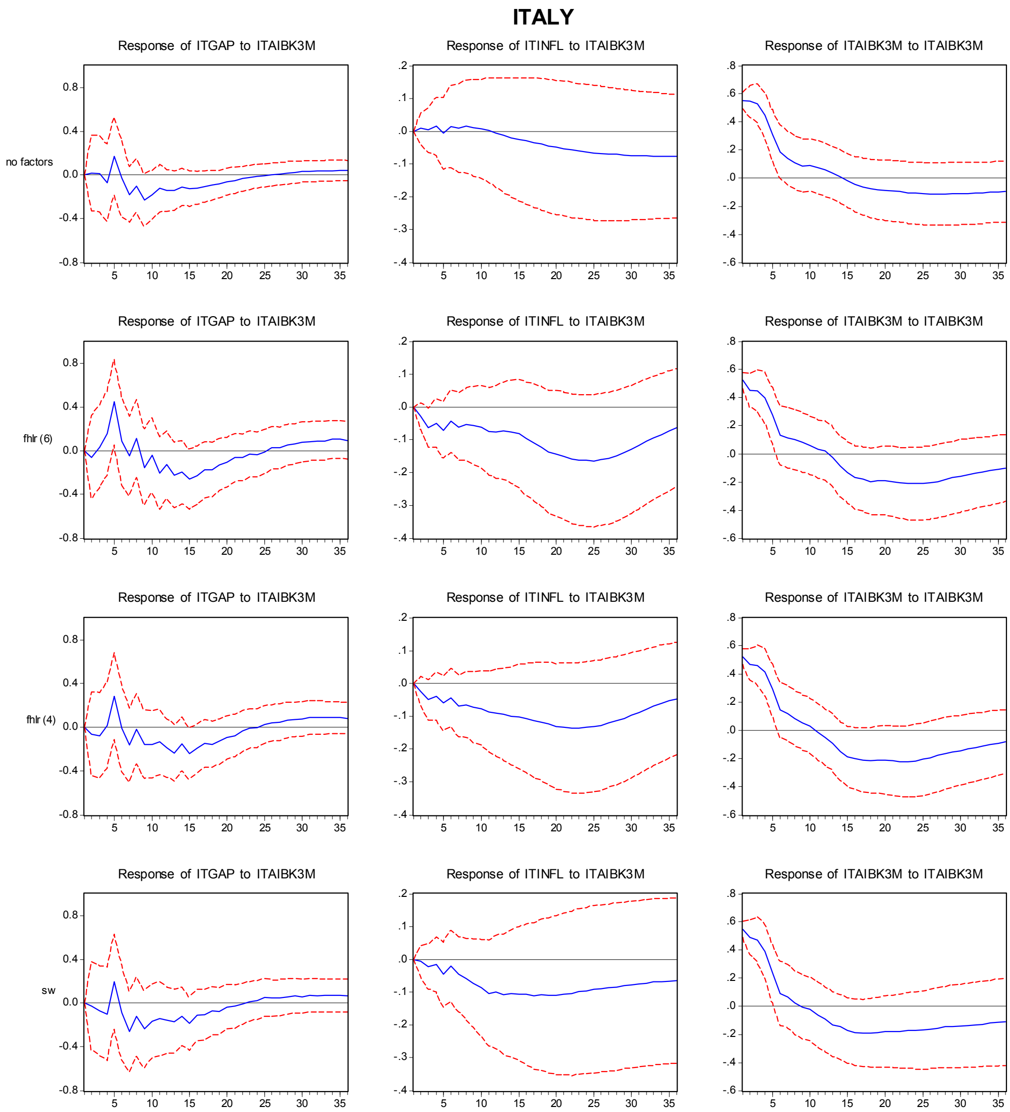
Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of FHLR factors (indicated in brakets) or six SW factors are used as additional regressors in the VARs.

Figure 4: Responses to one S.D. shock to domestic policy rate for France



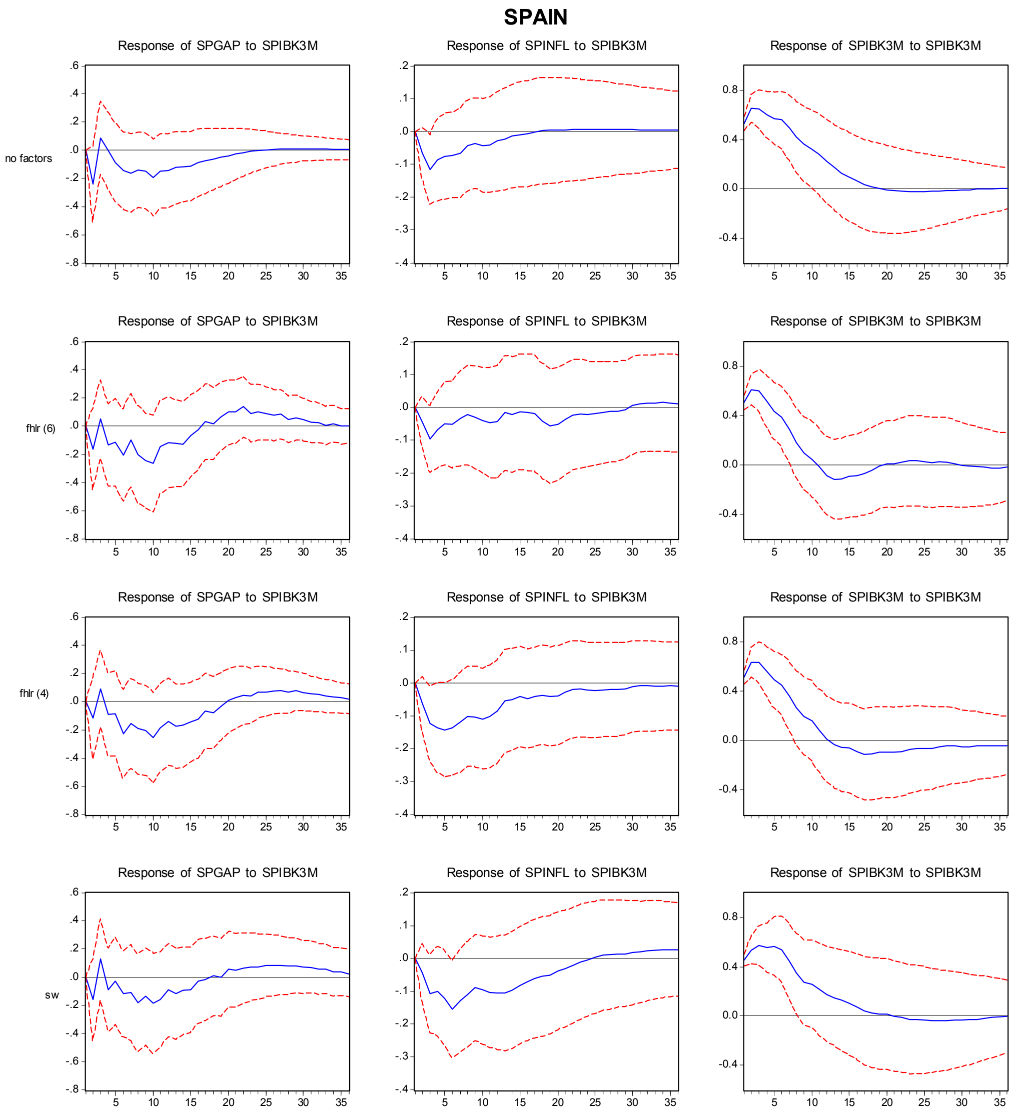
Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of FHLR factors (indicated in brakets) or six SW factors are used as additional regressors in the VARs.

Figure 5: Responses to one S.D. shock to domestic policy rate for Italy



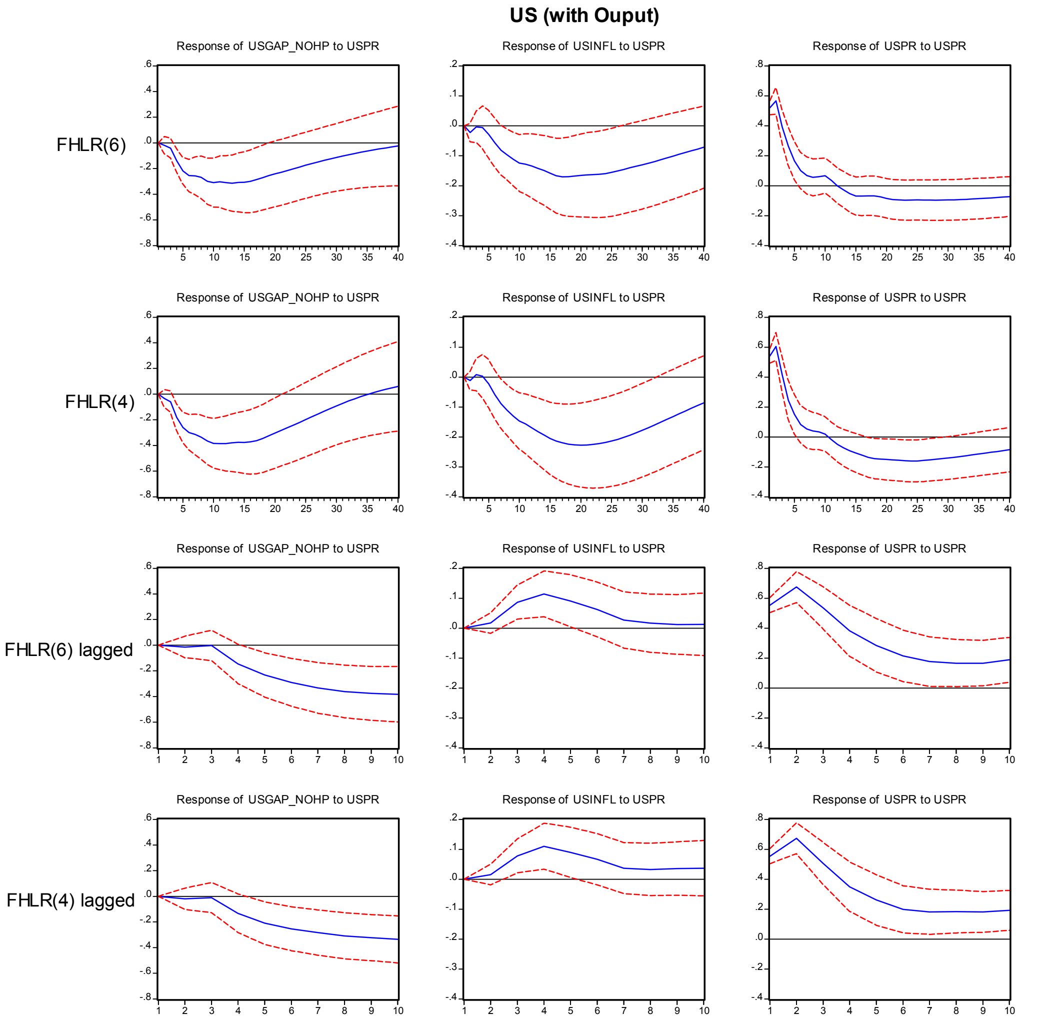
Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of FHLR factors (indicated in brakets) or six SW factors are used as additional regressors in the VARs.

Figure 6: Responses to one S.D. shock to domestic policy rate for Spain



Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of FHLR factors (indicated in brakets) or six SW factors are used as additional regressors in the VARs.

Figure 7: Responses to one S.D. shock to domestic policy rate for the US (in the model with output, using three-periods lagged FHLR factors)



Notes: each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analitically. In the augmented scenarios, different amounts of FHLR factors (three-periods lagged when specified) are used as additional regressors in the VARs.

DATA APPENDIX

This appendix lists the variables used in the empirical analysis, with a short description and the transformation applied. More details can be found in Stock and Watson (1998) for the US and Marcellino, Stock and Watson (2000a) for the European countries.
The transformation codes are: 1 = no transformation; 2 = first difference; 3= second difference; 4 = logarithm; 5 = first difference of logarithm; 6 = second difference of logarithm.

GERMANY

	Variable	*Transf*
1	Monthly hours of work /Labour - other /LABOUR	5
2	PRODUCER PRICES (manufacturing)	5
3	CONSUMER PRICES	5
4	Call money /Interest rates /INTEREST RATES - SHARE PRICES	1
5	3-month FIBOR /Interest rates /INTEREST RATES - SHARE PRICES	1
6	Public sector bond yield /Interest rates /INTEREST RATES SHARE PRICES	1
7	EFFECTIVE EXCHANGE RATES	5
8	Net foreign position /Foreign finance /FOREIGN FINANCE	2
9	Current account balance /Balance of payments /BALANCE OF PAYMENTS	2
10	FDR/DEU BOP CURRENT BALANCE/MN U	2
11	Net errors and omissions /Balance of payments /BALANCE OF PAYMENTS	2
12	FOREIGN TRADE - Ftr Trade Balance (fob-fob), sa Billions US dollars; monthly	2
13	FOREIGN TRADE - Ftr Imports (fob/cif) Total, sa Billions US dollars; monthly	5
14	FOREIGN TRADE - Ftr Exports Fob Total, sa Billions US dollars; monthly	5

ITALY

	Variable	*Transf*
1	Crude steel /Commodity output /PRODUCTION	5
2	RETAIL SALES (volume), sa	4
3	New passenger car registrations, sa /Domestic trade - other/DOMESTIC TRADE	5
4	Labour disputes: time lost /Labour - other /LABOUR	4
5	Hourly rates /Wages /WAGES	5
6	Machinery and equipment /Producer prices /PRICES	5
7	Chemical products /Producer prices /PRICES	5
8	Non-metallic mineral products /Producer prices /PRICES	5
9	Textiles and clothing /Producer prices /PRICES	5
10	Total /Producer prices /PRICES	5
11	Food /Consumer prices /PRICES	5
12	All items less food /Consumer prices /PRICES	5
13	Services less rent /Consumer prices /PRICES	5
14	All items /Consumer prices /PRICES	5
15	CONSUMER PRICES	5
16	Monetary aggregate (M1), sa /Domestic finance /DOMESTIC FINANCE Lit	5
17	ITA TOTAL LIQUIDITY/BN	5
18	Monetary aggregate (M2), sa /Domestic finance /DOMESTIC FINANCE Lit	5
19	3-month interbank deposits /Interest rates /INTEREST RATES	1
20	Gross bond issues: public sector /Domestic finance /DOMESTIC FINANCE Lit	5
21	Gross bond issues: banking sector /Domestic finance /DOMESTIC FINANCE Lit	5
22	Domestic credit /Domestic finance /DOMESTIC FINANCE Lit	5
23	Finance to the non state sector /Domestic finance /DOMESTIC FINANCE Lit	5
24	Bond yield /Interest rates /INTEREST RATES - SHARE PRICES	1
25	Long-term treasury bonds /Interest rates /INTEREST RATES - SHARE PRICES	1
26	ISE MIB Storico /Share prices /INTEREST RATES - SHARE PRICES	5
27	EXCHANGE RATES National currency units	5
28	Official reserves excluding gold /Foreign finance /FOREIGN FINANCE	5
29	Net foreign position /Foreign finance /FOREIGN FINANCE Lit	2

30	Trade balance /Balance of payments /BALANCE OF PAYMENTS Lit	2
31	Current account balance /Balance of payments /BALANCE OF PAYMENTS Lit	2
32	ITA BOP CURRENT BALANCE US $	2
33	Net services /Balance of payments /BALANCE OF PAYMENTS Lit	2
34	Net errors and omissions /Balance of payments /BALANCE OF PAYMENTS Lit	2
35	Net income /Balance of payments /BALANCE OF PAYMENTS Lit	2
36	Net trade (f.o.b.-c.i.f.), sa /Foreign trade /FOREIGN TRADE	2
37	FOREIGN TRADE - Ftr Trade Balance (fob-fob), sa Billions US dollars; monthly	2
38	FOREIGN TRADE - Ftr Imports (fob/cif) Total, sa Billions US dollars; monthly	5
39	Exports f.o.b., sa /Foreign trade /FOREIGN TRADE	5
40	FOREIGN TRADE - Ftr Exports Fob Total, sa Billions US dollars; monthly	5

SPAIN

	Variable	*Transf*
1	Investment goods /Industrial production /PRODUCTION	5
2	Building construction /Cost of construction /CONSTRUCTION	5
3	Registered unemployed, sa /Unemployment /LABOUR	5
4	Unfilled vacancies, sa /Labour - other /LABOUR	5
5	Agricultural products /Producer prices /PRICES	5
6	Consumer goods /Producer prices /PRICES	5
7	PRODUCER PRICES (manufacturing)	5
8	Investment goods /Producer prices /PRICES	5
9	Food /Consumer prices /PRICES	5
10	All items less food /Consumer prices /PRICES	5
11	Rent /Consumer prices /PRICES	5
12	Services less rent /Consumer prices /PRICES	5
13	All items /Consumer prices /PRICES	5
14	Monetary aggregate (M3) /Domestic finance - General /DOMESTIC FINANCE	5
15	ESP MONETARY AGGREGATE M3 SA	5
16	Total liquidity (ALP2) /Domestic finance - General /DOMESTIC FINANCE	5
17	Call money /Interest rates /INTEREST RATES - SHARE PRICES	1
18	3-month interbank loans /Interest rates /INTEREST RATES - SHARE PRICES	1
19	EXCHANGE RATES National currecy units	5
20	Official reserves excluding gold /Foreign finance /FOREIGN FINANCE	5
21	FOREIGN TRADE - Ftr Trade Balance (fob-fob), sa Billions US dollars; monthly	2
22	Imports c.i.f., sa /Foreign trade /FOREIGN TRADE	5
23	FOREIGN TRADE - Ftr Imports (fob/cif) Total, sa Billions US dollars; monthly	5
24	Exports f.o.b., sa /Foreign trade /FOREIGN TRADE	5
25	FOREIGN TRADE - Ftr Exports Fob Total, sa Billions US dollars; monthly	5

FRANCE

	Variable	*Transf*
1	Crude steel /Commodity output /PRODUCTION	5
2	CONSTRUCTION Thousands; monthly	5
3	New passenger car registrations, sa /Domestic trade - otther/ DOMESTIC TRADE	5
4	Registered unemployed, sa /Unemployment /LABOUR	5
5	Intermediate goods /Producer prices /PRICES	5
6	Food /Consumer prices /PRICES	5
7	All goods less food /Consumer prices /PRICES	5
8	All items less food /Consumer prices /PRICES	5
9	Rent /Consumer prices /PRICES	5
10	All items /Consumer prices /PRICES	5
11	Paris: all items /Consumer prices /PRICES	5
12	Monetary aggregate (M1), sa /Domestic finance /DOMESTIC FINANCE	5
13	Monetary aggregate (M3), sa /Domestic finance /DOMESTIC FINANCE	5
14	Investment aggregate (P1), sa /Domestic finance /DOMESTIC FINANCE	5

15	Call money /Interest rates /INTEREST RATES - SHARE PRICES	1
16	3-month PIBOR /Interest rates /INTEREST RATES - SHARE PRICES	1
17	Bonds: public and semi-public /Interest rates /INTEREST RATES - SHARE PRICES	1
18	Paris Stock Exchange: SBF 250 /Share prices /INTEREST RATES - SHARE PRICES	5
19	EXCHANGE RATES National currency units	5
20	Official reserves excluding gold /Foreign finance /FOREIGN FINANCE	5
21	Net trade (f.o.b.-f.o.b.), sa /Foreign trade /FOREIGN TRADE	2
22	FOREIGN TRADE - Ftr Trade Balance (fob-fob), sa Billions US dollars; monthly	2
23	Imports f.o.b., sa /Foreign trade /FOREIGN TRADE	5
24	FOREIGN TRADE - Ftr Imports (fob/cif) Total, sa Billions US dollars; monthly	5
25	Exports f.o.b., sa /Foreign trade /FOREIGN TRADE	5
26	FOREIGN TRADE - Ftr Exports Fob Total, sa Billions US dollars; monthly	5

US

Variable		*Transf*
1	INDUSTRIAL PRODUCTION: TOTAL INDEX(1992=100,SA)	5
2	INDUSTRIAL PRODUCTION: PRODUCTS,TOTAL(1992=100,SA)	5
3	INDUSTRIAL PRODUCTION: FINAL PRODUCTS(1992=100,SA)	5
4	INDUSTRIAL PRODUCTION: CONSUMER GOODS(1992=100,SA)	5
5	INDUSTRIAL PRODUCTION: DURABLE CONSUMER GOODS(1992=100,SA)	5
6	INDUSTRIAL PRODUCTION: NONDURABLE CONDSUMER GOODS(1992=100,SA)	5
7	INDUSTRIAL PRODUCTION: BUSINESS EQUIPMENT(1992=100,SA)	5
8	INDUSTRIAL PRODUCTION: INTERMEDIATE PRODUCTS(1992=100,SA)	5
9	INDUSTRIAL PRODUCTION: MATERIALS(1992=100,SA)	5
10	INDUSTRIAL PRODUCTION: NONDURABLE GOODS MATERIALS(1992=100,SA)	5
11	INDUSTRIAL PRODUCTION: MANUFACTURING(1992=100,SA)	5
12	INDUSTRIAL PRODUCTION: DURABLE MANUFACTURING(1992=100,SA)	5
13	INDUSTRIAL PRODUCTION: NONDURABLE MANUFACTURING(1992=100,SA)	5
14	INDUSTRIAL PRODUCTION: MINING(1992=100,SA)	5
15	INDUSTRIAL PRODUCTION: UTILITIES(1992-=100,SA)	5
16	CAPACITY UTIL RATE: MANUFACTURING,TOTAL(%OF CAPACITY,SA)(FRB)	1
17	PURCHASING MANAGERS' INDEX (SA)	1
18	NAPM PRODUCTION INDEX (PERCENT)	1
19	PERSONAL INCOME (CHAINED) (BIL 92$, SAAR)	5
20	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS "(1967=100;SA)"	5
21	EMPLOYMENT: "RATIO;" HELP-WANTED ADS:NO.UNEMPLOYED CLF	4
22	CIVILIAN LABOR FORCE:EMPLOYED,TOTAL (THOUS.,SA)	5
23	CIVILIAN LABOR FORCE:EMPLOYED,NONAGRIC.INDUSTRIES(THOUS.,SA)	5
24	UNEMPLOYMENT RATE:ALL WORKERS,16 YEARS & OVER(%,SA)	1
25	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS(SA)	1
26	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5WKS(THOUS.,SA)	1
27	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS(THOUS.,SA)	1
28	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS +(THOUS.,SA)	1
29	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS(THOUS.,SA)	1
30	EMPLOYEES ON NONAG.PAYROLLS:TOTAL(THOUS.,SA)	5
31	EMPLOYEES ON NONAG.PAYROLLS:TOTAL,PRIVATE (THOUS,SA)	5
32	EMPLOYEES ON NONAG.PAYROLLS:GOODS-PRODUCING(THOUS.,SA)	5
33	EMPLOYEES ON NONAG.PAYROLLS:CONTRACT CONSTRUCTION(THOUS.,SA)	5
34	EMPLOYEES ON NONAG.PAYROLLS:MANUFACTURING(THOUS.,SA)	5
35	EMPLOYEES ON NONAG.PAYROLLS:DURABLE GOODS(THOUS.,SA)	5
36	EMPLOYEES ON NONAG.PAYROLLS:NONDURABLE GOODS(THOUS.,SA)	5
37	EMPLOYEES ON NONAG.PAYROLLS:SERVICE-PRODUCING(THOUS.,SA)	5
38	EMPLOYEES ON NONAG.PAYROLLS:WHOLESALE & RETAIL TRADE (THOUS.,SA)	5
39	EMPLOYEES ON NONAG.PAYROLLS:FINANCE,INSUR.&REAL ESTATE (THOUS.,SA	5

40	EMPLOYEES ON NONAG.PAYROLLS:SERVICES(THOUS.,SA)	5
41	EMPLOYEES ON NONAG.PAYROLLS:GOVERNMENT(THOUS.,SA)	5
42	AVG. WEEKLY HRS. OF PRODUCTION WKRS.: MANUFACTURING (SA)	1
43	AVG. WEEKLY HRS. OF PROD. WKRS.:MFG., OVERTIME HRS. (SA)	1
44	NAPM employment index (percent)	1
45	MANUFACTURING & TRADE: TOTAL(MIL OF CHAINED 1992 DOLLARS)(SA)	5
46	MANUFACTURING & "TRADE: MANUFACTURING;TOTAL	5
47	MANUFACTURING & "TRADE: MFG;" DURABLE GOODS	5
48	MANUFACT.& "TRADE:MFG;NONDURABLE" GOODS	5
49	MERCHANT WHOLESALERS: TOTAL (MIL OF CHAINED 1992 DOLLARS)(SA)	5
50	MERCHANT WHOLESALERS:DURABLE GOODS TOTAL	5
51	MERCHANT WHOLESALERS:NONDURABLE GOODS	5
52	RETAILTRADE: TOTAL (MIL OF CHAINED 1992 DOLLARS)(SA)	5
53	RETAILTRADE: NONDURABLE GOODS (MIL OF 1992 DOLLARS)(SA)	5
54	PERSONAL CONSUMPTION EXPEND (CHAINED)-TOTAL(BIL 92$,SAAR)	5
55	PERSONAL CONSUMPTION EXPEND (CHAINED)-TOTAL DURABLES(BIL 92$,SAAR)	5
56	PERSONAL CONSUMPTION EXPEND (CHAINED)-NONDURABLES(BIL 92$,SAAR)	5
57	PERSONAL CONSUMPTION EXPEND (CHAINED)-SERVICES(BIL 92$,SAAR)	5
58	PERSONAL CONS EXPEND (CHAINED)-NEW CARS (BIL 92$,SAAR)	5
59	HOUSING "STARTS: NONFARM(1947-58);TOTAL" FARM&NONFARM(1959-)(THOUS.,SA	4
60	HOUSING STARTS: NORTHEAST (THOUS.U.)S.A.	4
61	HOUSING STARTS: MIDWEST (THOUS.U.)S.A.	4
62	HOUSING STARTS: SOUTH (THOUS.U.)S.A.	4
63	HOUSING STARTS: WEST (THOUS.U.)S.A.	4
64	HOUSING AUTHORIZED:TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)	4
65	MOBILE HOMES: MANUFACTURERS' SHIPMENTS(THOUS.OF UNITS,SAAR)	4
66	MANUFACTURING & TRADE INVENTORIES:TOTAL(MIL OF CHAINED 1992)(SA)	5
67	INVENTORIES,BUSINESS,MFG(MIL OF CHAINED 1992 DOLLARS, SA)	5
68	INVENTORIES,BUSINESS DURABLES(MIL OF CHAINED 1992 DOLLARS, SA)	5
69	INVENTORIES,BUSINESS,NONDURABLES(MIL OF CHAINED 1992 DOLLARS, SA)	5
70	MANUFACTURING & TRADE INV:MERCHANT WHOLESALERS	5
71	MANUFACTURING & TRADE INV:RETAIL TRADE (MIL OF CHAINED 1992 DOLLARS)(SA)	5
72	RATIO FOR MFG & TRADE:INVENTORY/SALES (CHAINED 1992 DOLLARS, SA)	2
73	RATIO FOR MFG & "TRADE:MFG;INVENTORY/SALES"(87$)(S.A.)	2
74	RATIO FOR MFG & "TRADE:WHOLESALER;INVENTORY/SALES(87$)(S.A.)"	2
75	RATIO FOR MFG & TRADE:RETAIL"TRADE;INVENTORY/SALES(87$)(S.A.)"	2
76	NAPM INVENTORIES INDEX (PERCENT)	1
77	NAPM NEW ORDERS INDEX (PERCENT)	1
78	NAPM VENDOR DELIVERIES INDEX (PERCENT)	1
79	NEW ORDERS (NET)-CONSUMER GOODS & MATERIALS, 1992 DOLLARS(BCI)	5
80	NEW ORDERS, DURABLE GOODS INDUSTRIES, 1992 DOLLARS(BCI)	5
81	NEW ORDERS, NONDEFENSE CAPITAL GOODS,IN 1992 DOLLARS(BCI)	5
82	MFG NEW ORDERS:ALL MANUFACTURING INDUSTRIES,TOTAL(MIL$,SA)	5
83	MFG NEW ORDERS:MFG INDUSTRIES WITH UNFILLED ORDERS(MIL$,SA)	5
84	MFG NEW ORDERS:DURABLE GOODS INDUSTRIES, TOTAL(MIL$,SA)	5
85	MFG NEW ORDERS:DURABLE GOODS INDUST WITH UNFILLED ORDERS(MIL$,SA)	5
86	MFG NEW ORDERS:NONDURABLE GOODS INDUSTRIES, TOTAL (MIL$,SA)	5
87	MFG NEW ORDERS:NONDURABLE GDS IND.WITH UNFILLED ORDERS(MIL$,SA)	5
88	MFG UNFILLED ORDERS: ALL MANUFACTURING INDUSTRIES,TOTAL(MIL$,SA)	5
89	MFG UNFILLED ORDERS: DURABLE GOODS INDUSTRIES,TOTAL(MIL$,SA)	5
90	MFG UNFILLED ORDERS: NONDURABLE GOODS INDUSTRIES, TOTAL(MIL$,SA)	5
91	CONTRACTS & ORDERS FOR PLANT & EQUIPMENT (BIL$,SA)	5
92	CONTRACTS & ORDERS FOR PLANT & EQUIPMENT IN 1992 DOLLARS(BCI)	5
93	NYSE COMMON STOCK PRICE INDEX: COMPOSITE (12/31/65=50)	5
94	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	5
95	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS(1941-43=10)	5

96	S&P'S COMMON STOCK PRICE INDEX: CAPITAL GOODS (1941-43=10)	5
97	S&P'S COMMON STOCK PRICE INDEX: UTILITIES (1941-43=10)	5
98	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD(% PER ANNUM)	1
99	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO(%,NSA)	1
100	UNITED "STATES;EFFECTIVE" EXCHANGE RATE(MERM)(INDEX NO.)	5
101	FOREIGN EXCHANGE RATE: GERMANY(DEUTSCHE MARK PER U.S.$)	5
102	FOREIGN EXCHANGE RATE: SWITZERLAND(SWISS FRANC PER U.S.$)	5
103	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	5
104	FOREIGN EXCHANGE RATE: CANADA(CANADIAN $ PER U.S.$)	5
105	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	2
106	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	2
107	BOND YIELD: MOODY'S AAA CORPORATE(%PER ANNUM)	2
108	BOND YIELD: MOODY'S BAA CORPORATE(%PER ANNUM)	2
109	SECONDARY MARKET YIELDS ON FHA MORTGAGES(%PER ANNUM)	2
110	Spread FYCP -FYFF	1
111	Spread FYGM3-FYFF	1
112	Spread FYGM6-FYFF	1
113	Spread FYGT1-FYFF	1
114	Spread FYGT5-FYFF	1
115	Spread FYGT10-FYFF	1
116	Spread FYAAAC-FYFF	1
117	Spread FYBAAC - FYFF	1
118	Spread FYFHA-FYFF	1
119	MONEY STOCK:M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	6
120	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP	6
121	MONEY STOCK:M3(M2+LG TIME DEP,TERM RP'S&INST ONLY MMMFS)(BIL$,SA)	6
122	MONEY SUPPLY-M2 IN 1992 DOLLARS (BCI)	5
123	MONETARY BASE,ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	6
124	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	6
125	DEPOSITORY INST RESERVES:NONBORROW+EXT CR,ADJ RES REQ CGS(MIL$,SA)	6
126	NAPM COMMODITY PRICES INDEX (PERCENT)	1
127	PRODUCER PRICE INDEX: FINISHED GOODS(82=100,SA)	6
128	PRODUCER PRICE INDEX: FINISHED CONSUMER GOODS(82=100,SA)	6
129	INDEX OF SENSITIVE MATERIALS PRICES (1990=100)(BCI-99A)	6
130	CPI-U: ALL ITEMS(82-84=100,SA)	6
131	CPI-U: APPAREL & UPKEEP(82-84=100,SA)	6
132	CPI-U: TRANSPORTATION(82-84=100,SA)	6
133	CPI-U: MEDICAL CARE(82-84=100,SA)	6
134	CPI-U: COMMODITIES(82-84=100,SA)	6
135	CPI-U: DURABLES(82-84=100,SA)	6
136	CPI-U: SERVICES(82-84=100,SA)	6
137	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)	6
138	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)	6
139	CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)	6
140	PCE,IMPL PR DEFL:PCE (1987=100)	6
141	PCE,IMPL PR "DEFL:PCE;" DURABLES (1987=100)	6
142	PCE,IMPL PR "DEFL:PCE;" NONDURABLES (1987=100)	6
143	PCE,IMPL PR "DEFL:PCE;" SERVICES (1987=100)	6
144	AVG HR EARNINGS OF CONSTR WKRS: CONSTRUCTION ($,SA)	6
145	AVG HR EARNINGS OF PROD WKRS: MANUFACTURING ($,SA)	6
146	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	1