JOURNAL OF APPLIED ECONOMETRICS
J. Appl. Econ. **19**: 0 (2004)
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/jae.815

JAE815

PRINCIPAL COMPONENTS AT WORK: THE EMPIRICAL ANALYSIS OF MONETARY POLICY WITH LARGE DATA SETS

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SUMMARY

The empirical analysis of monetary policy requires the construction of instruments for future expected inflation. Dynamic factor models have been applied rather successfully to inflation forecasting. In fact, two competing methods have recently been developed to estimate large-scale dynamic factor models based, respectively, on static and dynamic principal components. This paper combines the econometric literature on dynamic principal components and the empirical analysis of monetary policy. We assess the two competing methods for extracting factors on the basis of their success in instrumenting future expected inflation in the empirical analysis of monetary policy. We use two large data sets of macroeconomic variables for the USA and for the Euro area. Our results show that estimated factors do provide a useful parsimonious summary of the information used in designing monetary policy.

1. INTRODUCTION

The long and variable lags in the relation between instruments and targets in the monetary policy-making process imply that monetary decisions are based on future expected variables. Monetary policy makers typically monitor a very large number of time series to predict the future path of relevant macroeconomic variables. Most of the recent empirical analysis of monetary policy (see, for example, Christiano *et al*., 1998) has been based on parsimonious small-scale models. Using small-scale models at the theoretical level is important in that it helps tractability and the derivation of results. However, the validity of the empirical analysis based on a limited information set requires that the loss of information generated by omitting a conspicuous part of the information used by central banks is not relevant to the problem at hand. The omission of a relevant part of the truly adopted information set becomes an even more serious problem when expectations of future variables are an important argument of the policy maker's reaction function.

Recently developed econometric methods to extract a small number of factors from a large number of time series might help to close the gap between the actual process of monetary policy making and the econometric analysis of the monetary policy-making process.

Two approaches have recently emerged for information extraction from large macroeconomic data sets. 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 data sets, one for the USA that contains 146 macroeconomic time series, and the other for the four largest countries in the European monetary

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Received 26 September 2002
Revised 7 April 2004

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 data sets, 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 data sets, and the relevant question becomes whether the components are useful in the construction of parsimonious empirical models of the monetary policy process which are less affected by the omitted variables problem. There is no question that augmenting small empirical models with factors keeps them small, the relevant issue is whether the use of factors makes the misspecification problem less severe.

Forward-looking Taylor rules in which monetary policy is determined by the output gap and future expected inflation have become a common tool for tracking the behaviour of central banks. A first natural issue is whether and by how much the inclusion of the components in the instrument set used for future inflation in estimation helps the performance of the first-stage regression and hence reduces uncertainty on parameter estimates.

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 *et al*., 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 emblematic: VAR models lead to events such as an increase in prices after an interest rate hike, identified as an exogenous monetary policy shock. 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 into 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 and Faust, 1999). This approach clearly has some merits but limits the potential role of misspecification in the explanation of the puzzle. Obviously, in a counterfactual scenario where monetary policy shocks are always exclusively identified by imposing sign restrictions on the response of prices to monetary policy shocks, the price puzzle would never have been observed.

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The second reaction to the puzzle has been the enlargement of the information set, by including in 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 paper is organized as follows. Section 2 briefly reviews the dynamic factor model and the alternative estimation methods. Section 3 describes the data sets for the USA and the Euro area. Section 4 evaluates the role of the static and dynamic principal components in Taylor rule estimation. Section 5 studies the consequences of the inclusion of the components in monetary VARs. Section 6 concludes.

2. THE DYNAMIC FACTOR MODEL AND THE ALTERNATIVE ESTIMATORS

The rationale underlying dynamic factor models is that the behaviour 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 data sets, 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). AQ2

A general formulation of a dynamic factor model is

$$x_t = B(L)u_t + \xi_t \tag{1}$$

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 $B(L) = I + B_1 L + B_2 L^2 + \cdots + B_p L^p$ (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

$$x_t = \Lambda f_t + \xi_t \tag{2}$$

where $f_t = (u_{1t}, \ldots, u_{1t-p}, \ldots, u_{qt}, \ldots, u_{qt-p})$, so that now $r = p \times q$ factors drive the variables, but the factors have only a contemporaneous effect on x_t, with loadings grouped in the $N \times r$ 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) can be rewritten as

$$x_t = \Lambda G G^{-1} f_t + \xi_t = \Psi p_t + \xi_t \tag{3}$$

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 *et al.* (2000), 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 (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 vice versa), they assume that the first (largest) idiosyncratic dynamic eigenvalue, λ_{n1}^{ξ}, is uniformly bounded, and that the first (largest) q common dynamic eigenvalues, $\lambda_{n1}^{\chi}, \ldots, \lambda_{nq}^{\chi}$, diverge, where dynamic eigenvalues are the eigenvalues of the spectral density matrix, see e.g. Brillinger (1981, chap. 9). In words, the AQ3 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), focusing on the specification in (2), while the static version of this model was analysed, 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. AQ4

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 stepwise procedure. (i) Estimate the spectral density matrix of x_t as

$$\Sigma^T(\theta_h) = \sum_{k=-M}^{M} \Gamma_k^T \omega_k e^{-ik\theta_h}, \quad \theta_h = 2\pi h/(2M+1), \quad h = 0, \ldots, 2M \tag{4}$$

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 $\Sigma^T(\theta_h)$, $p_j^T(\theta_h)$, $j = 1, \ldots, q$, for $h = 0, \ldots, 2M$. (iii) Define $p_j^T(L)$ as

$$p_j^T(L) = \sum_{k=-M}^{M} p_{j,k}^T L^k, \quad p_{j,k}^T = \frac{1}{2M+1} \sum_{h=0}^{2M} p_j^T(\theta_h) e^{ik\theta_h}, \quad k = -M, \ldots, M \tag{5}$$

$p_j^T(L)x_t$, $j = 1, \ldots, q$, 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.

In fact, the dynamic principal components underlying the FHLR approach are a linear combination of past, present and *future* economic variables, while the static principal component underlying the SW approach is a 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 developed a one-sided version of their methodology which we shall use in the empirical part of our paper to extract one-sided FHLR factors.

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

$$V_{N,T}(f, \Lambda) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \Lambda_i f_t)^2 \tag{6}$$

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 $\underline{x}_i = (x_{i1}, \ldots, x_{iT})$. 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 $\widehat{f}_t$, $i = 1, \ldots, N$. 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, apart 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 analysing 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 analyse data sets 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 choose 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. DATA FOR THE USA AND FOR THE EURO AREA

We apply the dynamic factor model to two large monthly macroeconomic data sets, for the USA and for the four largest countries in the Euro area, i.e., Germany, France, Italy and Spain. The series for the USA come from Stock and Watson (1998), those for the European countries from Marcellino *et al*. (2000a,b), to whom we refer for additional information and details on data transformations.

The data sets 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 labour 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 miscellaneous variables. The level of disaggregation of some of these variables, such as industrial production and price indices, is much finer for the USA.

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 data set to be balanced and without outlying observations. Hence, we have only retained series that satisfy their requirements. We end up with 146 series over the period 1959 : 1–1998 : 12 for the USA, 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 complete list of the variables is reported in the Data Appendix.[1]

To evaluate whether the additional series in the non-balanced panel (69 for the USA and 65 for the Euro area) contain useful information, we have also computed and compared results for the SW methodology in this case. This is also relevant to evaluate the role of real variables in the Euro area, since several of them are excluded from the balanced panel. Our results using the balanced and the non-balanced panel have been uniformly similar, so we report only the results from the balanced panel.

Figure 1 graphs the average over frequencies of the first dynamic eigenvalues, when the number of variables increases, for the USA and for the Euro area. From the graphs, in both cases $q = 3$ could already be a good choice for the number of FHLR factors, since the first three eigenvalues diverge at a faster rate than the others. For safety, we also report results for $q = 6$. As far as the choice of the number of factors in the SW approach is concerned, we have seen in Section 2 that typically $r = p \times q$, where q is the number of FHLR factors, r is the number of SW factors, and p is the number of lags of the FHLR factors possibly affecting the variables of interest. Yet, 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 three factors. Therefore, we consider 3, 6 and 12 factors in the SW approach. Where setting $r = 3$ is in line with the available evidence discussed above, $r = 6$ is coherent with $q = 3$ and $p = 2$ and $r = 12$ is coherent with $q = 3$ and $p = 4$ or $q = 6$ and $p = 2$.

The performance of common components in explaining macroeconomic variables is in line with the results available in the empirical literature.[2] Moreover, in the case of SW, we have considered both the balanced (bp) and the non-balanced (nbp) panels. The additional information in the non-balanced panel turned out to be not very useful, or at least the EM algorithm developed by SW does not manage to capture it efficiently in these data sets. 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. Our choice of the width of the macroeconomic information set from which

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

[2] The average adjusted R^2 obtained from the regression of each variable in the information set on factors fluctuates around 0.5.

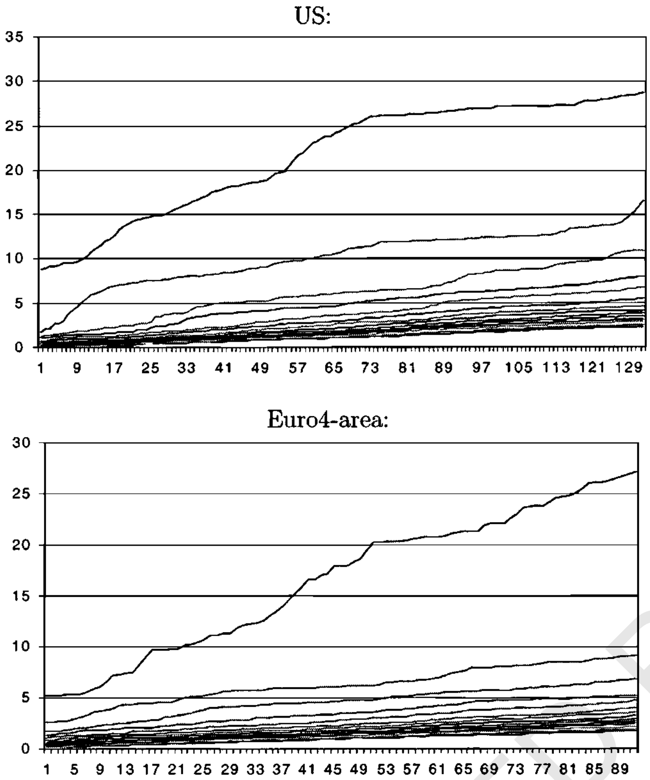

Figure 1. Choice of the number of factors. *Notes*: The number of factors to use is chosen according to a heuristic procedure suggested by FHLR (see Forni *et al*., 2000 for details). The figures graph the average over frequencies of the dynamic eigenvalues as the number of series used to calculate them increases

to extract factors is standard in the literature. It could be argued that the common co-movement in a much smaller information set of variables and some measures about the movement in the individual series could be of more help in the process of economic policy. In fact, we share the view that central bankers do monitor a very wide set of variables and that extracting factors from a large number of variables increases the signal-to-noise ratio, as averaging over a large number of factors reduces the impact of the idiosyncratic component of each series. Moreover, the focus of our study is not the explanatory power of factors for predicting all macroeconomic variables but rather their significance in predicting the (small) subset of variables which are relevant to study the effect of monetary policy. This is what we study in detail in the next two sections.

4. 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. The rationale behind our exercise is that central bankers rely on a large set of indicators in the conduct of monetary policy, and 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

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to the US case, which was analysed in a related context by Bernanke and Boivin (2000)• within the SW framework.

In the specification of the Taylor rules, we follow Clarida *et al*. [1998 (CGG), 2000 (CGG2)]. The starting point is the equation

$$r_t^* = \bar{r} + \beta(\pi_{t+12}^e - \pi_t^*) + \gamma(y_t - y_t^*) \tag{7}$$

where r_t^* is the target nominal interest rate, $\bar{r}$ is the equilibrium rate, π_{t+12}^e is the forecast of the 1-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,

$$r_t = (1 - \rho)r_t^* + \rho_1 r_{t-1} + v_t \tag{8}$$

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

Combining equations (7) and (8), and substituting the forecasts with their realized values, we obtain

$$r_t = \alpha + (1 - \rho)\beta(\pi_{t+12}^e - \pi_t^*) + (1 - \rho)\gamma(y_t - y_t^*) + \rho_1 r_{t-1} + \varepsilon_t \tag{9}$$

where $\alpha = (1 - \rho)\bar{r}$ and $\varepsilon_t = (1 - \rho)\beta(\pi_{t+12}^e - \pi_{t+12}) + v_t$. All equations are estimated by GMM, appropriately corrected for the presence of an MA component in the error ε_t, over the period 1979 : 1–1998 : 12. Our objective is to compare a baseline estimation where no factors are used as instruments for future expected variables with alternative scenarios in which factors constructed using alternative methods are added to the instrument set. If these factors contain useful information, more precise estimates of the parameters should be obtained, as measured by the corresponding t-tests.

4.1. USA

For the US case 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, and includes lags of the output gap, inflation and commodity price index. Then we also include as instruments either the FHLR or the SW estimated factors.

The results are reported in Table I. For the base case, the estimated values for β and γ are, respectively, 1.96 and 1.24. The uncertainty around the point estimates, though, is rather large. Actually, the 95% confidence interval on the coefficient on output gap ranges from 0.2 to 2.2. The inclusion of three factors estimated either by the SW method or the FHLR method generates a clear improvement in forecasting inflation, as witnessed by the results from the first-stage regressions reported in Table I, reflected in a higher and, especially in the case of SW factors, more precisely estimated coefficient on the expected inflation in the forward-looking Taylor rule. Including more

Table I. Forward-looking Taylor rules for the USA

USA	ρ	Υ	β	R^2-adj	SE of reg.	J-stat	First-stage regression		
							R^2-adj	SE of reg.	F-test
no factors	0.94 (0.030)	1.24 (0.512)	1.96 (0.785)	0.984	0.272	8.56 (0.03)	0.278	0.977	
fhlr_os (3)	0.95 (0.015)	1.39 (0.613)	2.57 (1.250)	0.978	0.505	8.64 (0.05)	0.416	0.879	14.690 (0.000)
fhir_os (6)	0.99 (0.021)	2.34 (6.319)	−6.11 (26.068)	0.976	0.524	11.53 (0.10)	0.372	0.911	5.349 (0.000)
sw (3, bp)	0.92 (0.025)	1.31 (0.362)	2.30 (0.587)	0.980	0.300	9.81 (0.13)	0.401	0.89	12.860 (0.000)
sw (6, bp)	0.92 (0.024)	1.38 (0.356)	2.52 (0.653)	0.979	0.305	10.34 (0.32)	0.392	0.897	6.409 (0.000)
sw (12, bp)	0.97 (0.017)	2.26 (1.302)	4.10 (1.789)	0.982	0.287	16.39 (0.35)	0.434	0.865	4.991 (0.000)

Notes: The estimated equation for the USA is $r_t = \alpha + (1-\rho)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho)\gamma(y_t - y_t^*) + \rho r_{t-1} + \varepsilon_t$ (see text for details). The parameters are estimated by GMM over 1983.01–1997.12. In the base case (scenario with no factors) the set of instruments used includes lags of the output gap, inflation and commodity price index. In the other models, different amounts of FHLR and SW factors are added to the instruments. In the SW case, both factors are calculated from balanced (bp) panels. The table entries are coefficient estimates (standard errors in brackets), adjusted R^2, standard error of the regressions, the J-test, (associated p-values in brackets) for the validity of the instruments. The last three columns contain statistics related to the first-stage regression of the 1-year-ahead expected inflation on the set of instruments used. In particular, we report the adjusted R^2, the standard error of the regression and the F-test for the joint significance of the coefficients on factors, when factors are added to the baseline model.

factors drives the autoregressive parameters in the rule very close to unity and generates a less precise estimate of the coefficients of interest.

Note, importantly, that the fact that the standard errors of regression of the model without factors are smaller does not convey any message on the importance of factors as instruments for future inflation. In fact, when GMM is applied to the estimation of Taylor rules, π^e_{t+12} is instrumented by $\hat{\pi}_{t+12}$, the projection of 12 month-ahead expected inflation on the chosen instrument sets. Hence, the residuals in the Taylor rule can be written as $\varepsilon_t + (1-\rho)\beta(\pi^e_{t+12} - \hat{\pi}_{t+12})$. As witnessed by the results on the first-stage regression reported in Table I, the inclusion of factors reduces the variance of $(\pi_{t+12} - \hat{\pi}_{t+12})$ and therefore also likely reduces the variance of $(\pi^e_{t+12} - \hat{\pi}_{t+12})$. However, the inclusion of factors as instruments typically delivers a lower estimate of ρ and a higher estimate of β, which more than compensate the effect of the reduction of the standard errors in expectations errors on the standard errors of residuals from forward-looking Taylor rules.

The evidence discussed so far establishes rather clearly that including factors in the instrument sets reduces the uncertainty by increasing the first-stage fit. However, it is important to remember that this increase in efficiency will happen even if the additional instruments are not valid, as they are endogenous variables. To evaluate the validity of instruments we implement J-tests for the validity of the instruments. The null of validity of over-identifying restrictions is never rejected when factors are added to the model and observed values for the tests change very little across different applications, even when the enlargement of the information set generated by the inclusion of factors is sizeable.

4.2. Euro Area

In the specification of the Taylor rules for European countries, we follow Clarida *et al.* (1998). For Germany, we consider a specification similar to the USA, namely,

$$\tau_t^* = \overline{r} + \beta(\pi^e_{t+12} - \pi_t^*) + \gamma(y_t - y_t^*) \tag{10}$$

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

$$r_{it}^* = r_t + \beta(\pi_{it+12}^e - \pi_t^*) + \gamma(y_{it} - y_{it}^*) \tag{11}$$

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

We then maintain a partial adjustment mechanism of the actual rate to the target rate r^*, so that

$$r_t = (1-\rho)r_t^* + \rho r_{t-1} + v_t \tag{12}$$

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

Combining equations (10) and (12), and substituting the forecasts with their realized values, for Germany we obtain

$$r_t = \alpha + (1-\rho)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho)\gamma(y_t - y_t^*) + \rho r_{t-1} + \varepsilon_t \tag{13}$$

where $\alpha = (1-\rho)\bar{r}$ and $\varepsilon_t = (1-\rho)\beta(\pi_{t+12}^e - \pi_{t+12}) + v_t$. For the other countries

$$r_{it} = (1-\rho)r_t + (1-\rho)\beta(\pi_{it+12} - \pi_t^*) + (1-\rho)\gamma(y_{it} - y_{it}^*) + \rho r_{it-1} + \varepsilon_{it} \tag{14}$$

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 USA, the parameters α, β, γ and ρ in equations (13) and (14) 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 includes lagged values of the regressors, of the dependent variable, of the commodity price index and of US inflation for Germany, while for all other European countries the instrument set is augmented by the German policy rate and by the German inflation target. We then add the SW or FHLR estimated factors to this set.[3]

Table II summarizes the results for the four European countries. We report the most significant results selected for the FHLR and the SW factors, by selecting from a range of factors going from 3 to 12 for SW and from 3 to 6 for FHLR, we also select from factors extracted from the single country database and from the Euro-area database. Overall, the inclusion of the FHLR and SW factors in the instrument set improves the precision of estimates and also delivers some sharp modification in the point estimates. Consider, for example, the case of Spain. The inclusion of the SW factors moves the point estimate on the weight on 1 year-ahead expected inflation from 0.25 to 1.43, with a crucial sharpening of the precision of the estimate. 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. As in the case of the USA, the reported statistics from the first-stage regression confirm the importance of factors in predicting 1 year-ahead expected inflation. Overall the SW factors deliver the best-fitting first-stage regression. In fact, in the case of Germany and

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

Table II. Forward-looking Taylor rules for Germany, France, Italy and Spain

		ρ	γ	β	Wald-stat	B^2-adj	SE of reg.	J-stat	Reduced-form equations		
									R^2-adj	SE of reg.	F-stat
Ger	no factors	0.92	0.47	1.49		0.984	0.257	2.86	0.588	0.967	
		(0.039)	(0.243)	(0.226)				(0.23)			
	fhlr (3) sc	0.94	0.69	1.32		0.985	0.248	5.76	0.586	0.968	0.839
		(0.035)	(0.384)	(0.268)				(0.32)			(0.475)
	sw (3) sc	0.88	0.40	1.54		0.980	0.286	3.78	0.612	0.938	4.610
		(0.034)	(0.150)	(0.182)				(0.58)			(0.004)
Fra	no factors	0.98	1.48	0.77	0.26	0.972	0.426	3.90	0.891	0.582	
		(0.011)	(1.542)	(0.702)	(0.117)			(0.42)			
	fhlr (6) eu	0.97	1.04	1.00	−0.05	0.972	0.424	11.03	0.899	0.560	3.279
		(0.009)	(0.975)	(0.450)	(0.233)			(0.35)			(0.005)
	sw (6) eu	0.97	0.03	1.35	0.10	0.972	0.424	14.17	0.903	0.549	4.573
		(0.010)	(0.645)	(0.285)	(0.114)			(0.16)			(0.000)
Ita	no factors	0.98	2.47	1.76	0.31	0.965	0.586	3.24	0.752	1.127	
		(0.014)	(2.231)	(0.347)	(0.363)			(0.51)			
	fhlr (3) eu	0.98	2.63	1.72	0.14	0.965	0.586	3.51	0.753	1.126	1.140
		(0.012)	(1.815)	(0.363)	(0.415)			(0.83)			(0.335)
	sw (3) sc	0.97	2.02	1.82	0.01	0.965	0.585	5.24	0.818	0.965	21.500
		(0.013)	(1.444)	(0.266)	(0.394)			(0.63)			(0.000)
Spa	no factors	0.99	4.70	0.25	0.11	0.965	0.694	2.77	0.767	1.193	
		(0.025)	(9.867)	(3.153)	(1.114)			(0.59)			
	fhlr (6) eu	0.97	3.42	0.11	0.31	0.964	0.706	8.42	0.806	1.089	6.612
		(0.019)	(2.846)	(1.348)	(0.364)			(0.58)			(0.000)
	sw (6) eu	0.95	0.79	1.43	0.29	0.964	0.702	10.09	0.824	1.037	10.10262
		(0.017)	(0.550)	(0.325)	(0.171)			(0.43)			(0.000)

Notes: The estimated equations are $r_t = \alpha + (1-\rho)\beta(\pi_{t+12} - \pi_t^*) + (1-\rho)\gamma(y_t - y_t^*) + \rho r_{t-1} + \varepsilon_t$ for Germany and $r_{it} = (1-\rho)r_t^{Ger} + (1-\rho)\beta(\pi_{it+12} - \pi_t^*) + (1-\rho)\gamma(y_{it} - y_{it}^*) + \rho r_{it-1} + \varepsilon_{it}$ for the other countries (see text for details). The parameters are estimated by GMM over 1983.01–1997.08. The basic set of instruments includes lagged values of the regressors, of the dependent variable, of the commodity price index and of US inflation for Germany, while for all other European countries the instrument set is augmented by the German policy rate and by the German inflation target. We then add the SW or FHLR estimated factors to this set. In the SW case, both factors are calculated from balanced (bp) panels. The table entries are coefficient estimates (standard errors in brackets), adjusted R^2, standard error of the regressions, the J-test (associated p-values in brackets) for the validity of the instruments. The last three columns contain statistics related to the first-stage regression of the 1-year-ahead expected inflation on the set of instruments used. In particular, we report the adjusted R^2, the standard error of the regression and the F-test for the joint significance of the coefficients on factors, when factors are added to the baseline model. For each country we report only the best results for each method adopted to extract factors. Full results for different combinations of factors are available upon request from the authors.

Italy, the contribution of SW factors in forecasting inflation is clearly more significant than that of FHLR factors. The analysis of first-stage regression reveals that FHLR factors do not generate a significant improvement with respect to the baseline models for these two countries. Importantly, the role of inflation as a determinant of monetary policy is rather homogeneously estimated when SW factors are adopted, while otherwise significant heterogeneity emerges.

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 similar for the USA and for the Euro area, although the effect of change in the point estimate of the response of policy rates to expected inflation generated by the inclusion of factors is more sizeable in the European case. On both data sets the SW approach seems to deliver a consistently slightly better performance.

5. 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. To provide evidence in this direction we follow Bernanke and Boivin (2000)•, and augment the standard VAR with FHLR and SW factors. Importantly, as stated in Section 2, we consider a one-sided version for all factors so that no future information is explicitly included in the variables used in the VAR. AQ6

The baseline VAR model can be written as:

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

where the vector $\mathbf{X}_t$ contains domestic output, domestic inflation, commodities price inflation, in the case of the USA. In the case of Germany, the same set of domestic variables is augmented by US inflation, which turned out to be an important leading indicator for German inflation. Finally, in the case of non-German European countries, the set of domestic variables is augmented by US inflation and the German monetary policy rate. 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. The point that we want to stress here is the importance of factors in capturing additional information used by monetary policy makers but not generally included in monetary VARs, and to assess the impact of the inclusion of this additional information on the description of the monetary transmission mechanism derived by the VAR. Identification is not our main focus here. If this were the case, then the natural way to estimate shocks and propagation, consistent with the empirics of factor models, would have been to derive shocks and impulses directly from the factor model (see, for example, Giannone *et al*., 2002).

In Figure 2 we report the responses of the US output, inflation and the policy rate to a domestic monetary policy shock, together with 95% analytical standard errors. In the baseline case the standard results available in the literature are replicated: we observe a u-shaped response of output and inflation shows a mild positive and non-significant response to a restrictive monetary policy shock. In fact, as is very well known in the literature (see, for example, Christiano *et al*., 1998), a much more significant 'perverse' response would be obtained when the commodity price index, monitored by the policy maker as a leading indicator for inflation, is excluded from the VAR (the so-called 'price puzzle'). Interestingly, if the price puzzle is a consequence of a misrepresentation of the information set effectively used by the monetary policy maker in the adopted econometric specification, then one could expect that further improvement in tracking the response of macroeconomic variables to monetary policy shocks could be obtained by including factors in the information set. In fact, the inclusion of factors

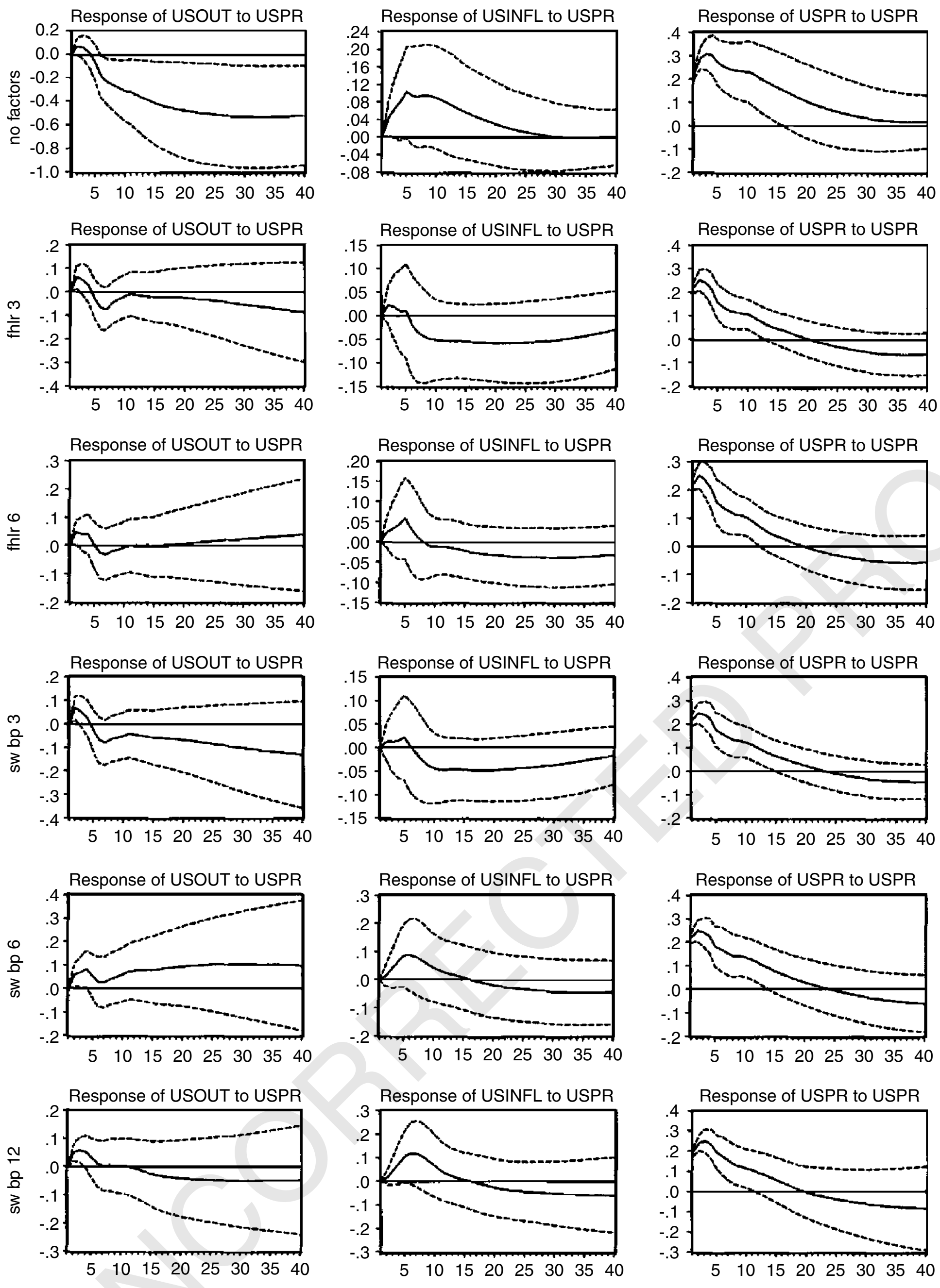

Figure 2. Responses to 1 SD shock to domestic policy rate for the USA. *Notes*: Each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analytically. The log-differences of commodity prices and of the exchange rate US$/DM are added to the endogenous regressors. In the augmented scenarios, different amounts of SW and FHLR factors (indicated in brackets) are used as additional regressors in the VARs

changes the shape and significance of the responses of inflation to monetary policy shocks. Interestingly, the inclusion of the same factors which delivered the best performance in the estimation of forward-looking Taylor rules (three FHLR and three SW factors) makes the price puzzle disappear completely.

The extension of the analysis to European countries strengthens the results obtained in the US case.

In the case of Germany (Figure 3) we have very strong evidence for the price puzzle, which totally disappears when the best performing factors (SW) in the estimation of forward-looking Taylor rules are included. Similar evidence emerges in the cases of France and Italy (Figures 4 and 5), while results are less strong in the case of Spain (Figure 6).

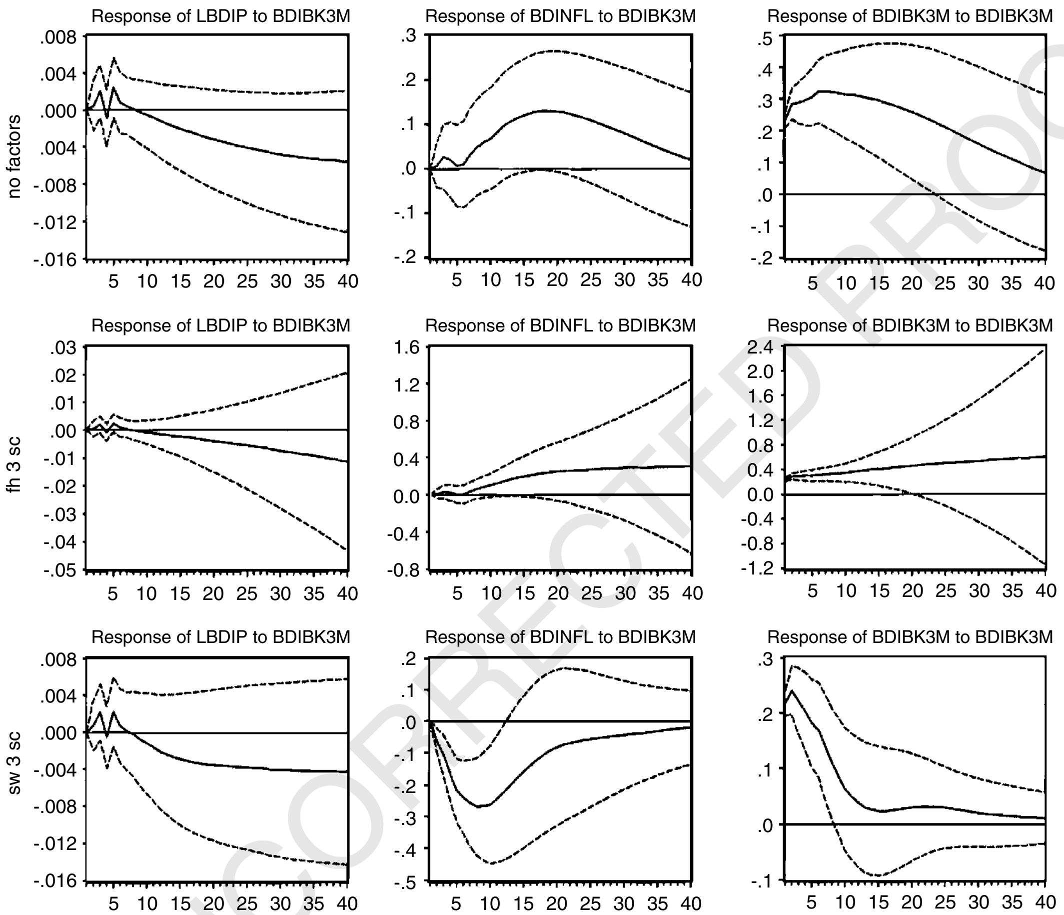

Figure 3. Responses to 1 SD shock to domestic policy rate for Germany. *Notes*: Each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analytically. In the baseline scenario domestic output, domestic inflation, commodities price inflation, the monetary policy rate are included in the VAR and US inflation is considered as an exogenous variable. We then consider an alternative scenario based on the inclusion of the same FHLR or SW factors included in the forward-looking Taylor rules

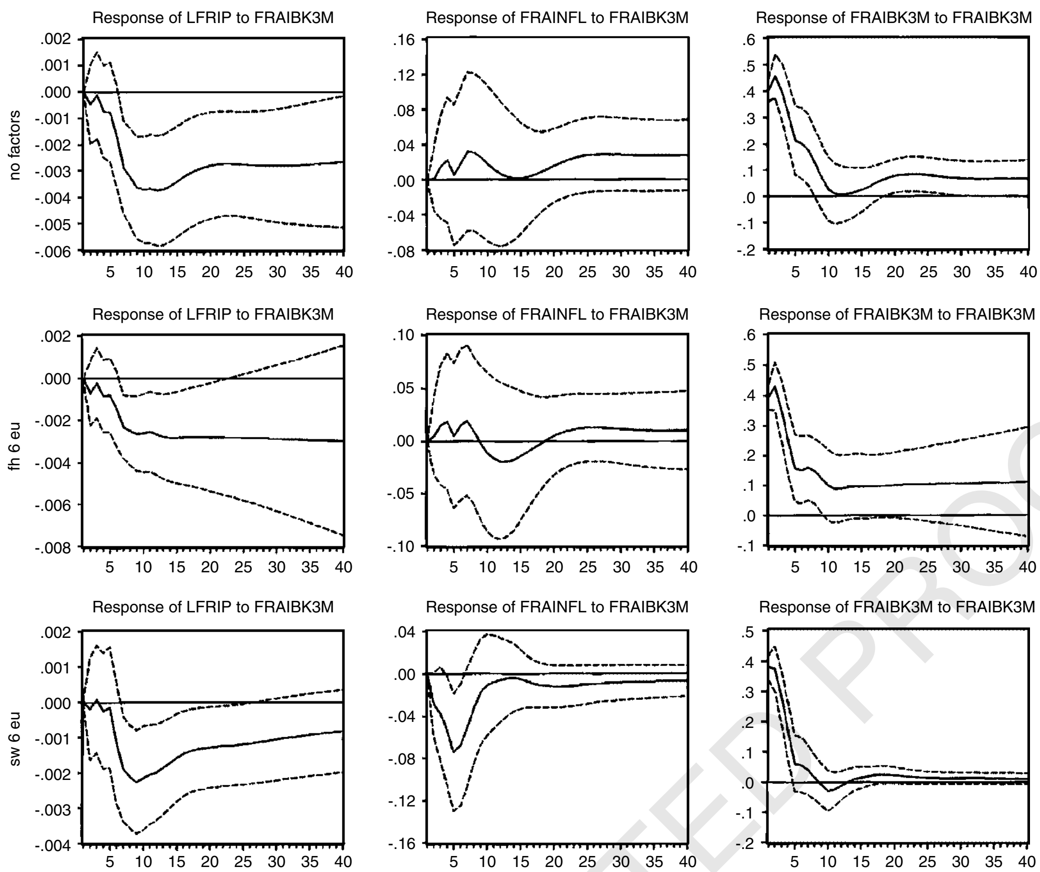

Figure 4. Responses to 1 SD shock to domestic policy rate for France. *Notes*: Each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analytically. In the baseline scenario domestic output, domestic inflation, commodities price inflation, the monetary policy rate are included in the VAR and US inflation and the German monetary policy rate are considered as exogenous variables. We then consider an alternative scenario based on the inclusion of the same FHLR or SW factors included in the forward-looking Taylor rules

In summary, the results we have obtained support the inclusion of the factors in monetary VARs. 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 is more easily interpretable from the economic point of view.

6. CONCLUSIONS

In this paper we have used two large data sets of macroeconomic variables for the USA 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

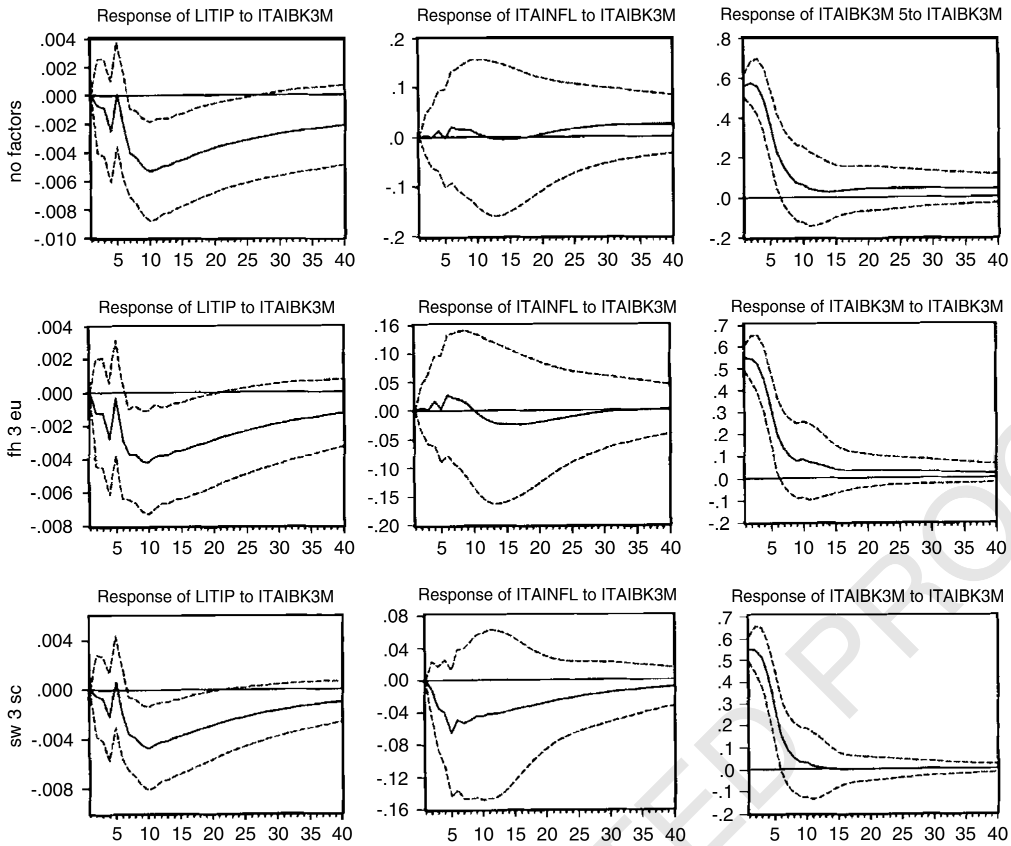

Figure 5. Responses to 1 SD shock to domestic policy rate for Italy. *Notes*: Each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analytically. In the baseline scenario domestic output, domestic inflation, commodities price inflation, the monetary policy rate are included in the VAR and US inflation and the German monetary policy rate are considered as exogenous variables. We then consider an alternative scenario based on the inclusion of the same FHLR or SW factors included in the forward-looking Taylor rules

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 data sets 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 is capable of eliminating the main puzzle in the transmission mechanism of monetary policy.

Overall, our results suggest that factor models naturally produce very useful instruments for the estimation of forward-looking economic models involving future expected variables.

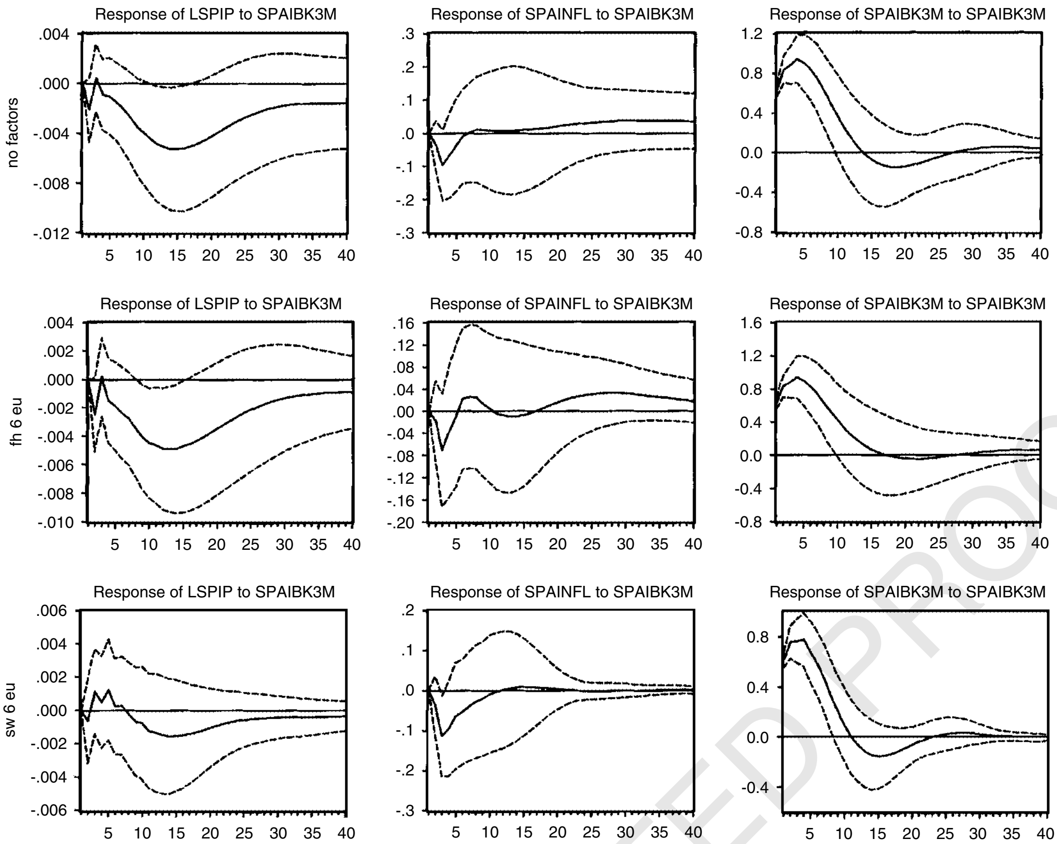

Figure 6. Responses to 1 SD shock to domestic policy rate for Spain. *Notes*: Each graph reports point estimates of the impulse responses in the different scenarios, along with their 95% confidence intervals computed analytically. In the baseline scenario domestic output, domestic inflation, commodities price inflation, the monetary policy rate are included in the VAR and US inflation and the German monetary policy rate are considered as exogenous variables. We then consider an alternative scenario based on the inclusion of the same FHLR or SW factors included in the forward-looking Taylor rules

ACKNOWLEDGEMENTS

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

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