Structural Factor-Augmented VAR (SFAVAR).*

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Abstract

Recent research has combined monetary VAR models with factor analysis, to exploit information from large data sets. Although extremely interesting, factor-augmented VARs have an important shortcoming: so far, it has not been possible to assign an economic interpretation to the factors.

This paper tries to identify them, aiming at deriving 'structural' factors, marked with a more immediate economic meaning, i.e. real activity factor, inflation factor, financial market factor, and so on. This leads us to propose a novel Structural Factor-Augmented VAR (SFAVAR).

We estimate our structural dynamic factors by Bayesian methods, using Gibbs sampling. This also permits to provide an indication of uncertainty surrounding factor extraction. In this setting, we evaluate the effects of monetary policy.

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1 Introduction.

The analysis of monetary policy in the context of VAR models has been the center of a large bulk of literature. With a few exceptions, as Leeper, Sims, and Zha (1996), the models employed were fairly small. Standard VARs typically include three variables: Industrial Production, Consumer Price Index and Federal Funds rate.

It is apparent that the analysis of monetary policy under these frameworks do not take into account the fact that central banks, in reality, monitor a huge amount of economic data and indicators.

Therefore, recently, great attention has been given to the attempt to incorporate a larger information set. This is obtained by augmenting the standard VAR model with one or more factors. The pioneering works in this area are Bernanke and Boivin (2001), and Bernanke, Boivin and Eliasz (2002). Their contribution is the use of Factor-Augmented VARs (FAVARs), in which they add common factors to a standard VAR specification.

The aim of this paper is trying to go a step further, seeking to provide a structural interpretation to the factors. The main drawback of their approach was, in fact, the impossibility to assign any sort of economic interpretation to the factors. To our knowledge, this is the first attempt in this direction.

We analyze monetary policy and the dynamics of the economy using more information than a standard VAR analysis. We start from the FAVAR approach, proposed by Bernanke and Boivin (2001) and Bernanke, Boivin and Eliasz (2002), and we try to individuate plausible restrictions that allow us to give a structural interpretation to the factors. That is, we seek to identify each factor as a basic force that governs the economy as 'real activity', 'foreign sector', 'credit sector' and so on.

Therefore, we propose a vector autoregression augmented with 'structural' factors: we name this novel approach Structural Factor-Augmented VAR (SFAVAR).

The VAR estimated using these identified factors describes the dynamics of the economy. We believe that this description is indeed more accurate than a standard VAR because we consider a data-rich environment. That is, our Structural FAVAR (SFAVAR) is able to extract information from many variables. This is useful in evaluating the impact of monetary policy on the economy.

Moreover, the history of the factors may be used in looking for the causes of the business cycle, pointing at which are the main forces and interactions that lead to the observed evolution of the economy.

Furthermore, the proposed Structural FAVAR can be a useful tool for the policy maker. Indeed, Sims (2002) poses the problem that other econometric approaches can fail in treating the huge amount of data central banks consider when deciding their actions. Sims emphasizes the role of sectoral experts, disaggregated variables, local economical dynamics in deciding policy. Our approach would allow to use all these data to infer the state of the economy, understanding the main forces determining the movements of the variables, and so to better choose the appropriate policy.

To derive the factors, we use Bayesian methods, estimating the system jointly by Maximum Likelihood, using Gibbs sampling. In the factors literature, standard approaches have been the estimation through principal components, as in Stock and Watson (2002), and with spectral analysis, as in Forni, Hallin, Lippi and Reichlin (2000). They both move in the context of 'approximate' factor models, obtaining static factors and dynamic factors, respectively. A particular advantage of a Bayesian approach is that it becomes possible to introduce restrictions on the loadings, facilitating their economic interpretability. With this procedure, we are also able to accompany the factors with an indication of uncertainty surrounding their estimation, as shown by the relative error bands.

We include in the analysis several structural factors: a real activity factor, which we deem more suitable to better capture the theoretical and unobservable macroeconomic concept of 'output gap', an inflation factor, interest rates factor, financial market factor, foreign, money and credit factor. In this way, we assign them an economic meaning. Another original characteristics of the framework we propose is the insertion of an expectation factor in the VAR. This leads to useful insights in the study of the interactions between the real economy and expectations, also permitting to assess if the latter move in accordance with the rationality hypothesis.

In the context of our Structural Factor-Augmented VAR setting, we seek to evaluate the effects of monetary policy. It is interesting to analyze the impulse responses of structural factors to a monetary policy shock. These should be more reliable than those derived under traditional VARs, as we are now exploiting a larger information set. Also the interactions between factors themselves are a subject of potentially great interest.

The rest of the paper is organized as follows. Section 2 describes the model and the restrictions we use to identify the factors. Sections 3 and 4 discuss the principal components and Bayesian approaches to estimation, respectively. The empirical framework is illustrated in section 5, where we introduce our structural factors and SFAVAR estimation. Section 6 reports and discusses our results, and an evaluation of factor model's fit is performed in Section 7. Section 8 compares the forecasting performance under our setting and a traditional VAR. Policy reaction functions under the traditional framework and a large information environment are described in Section 9. Section 10 concludes.

2 The Model.

Let Y_t and X_t be two vectors of economic variables we want to study, with dimension $M \times 1$ and $N \times 1$ respectively and where $t = 1, 2, ..., T$ is a time index. We will interpret Y_t as a set of truly exogenous instruments controlled by the policy maker, such as the Federal Funds rate, and X_t as a large data set of economic variables. We may think that there exist some unobservable fundamental forces that affect the dynamics of X_t, that can be summarized by a $K \times 1$ vector of factors F_t, so that

$$X_t = \Lambda F_t + e_t \tag{1}$$

where e_t are errors with mean zero and, for now, possibly weakly correlated. Take a partition of X_t, say $X_t^1, X_t^2, ..., X_t^I$, where X_t^i is a $N_i \times 1$ vector and $\sum_i N_i = N$. Assume that each of the vectors X_t^i is now explained by only some of the elements of the vector F_t. That is, there is a partition of F_t given by $F_t^1, F_t^2, ...F_t^I$ where F_t^i is a $K_i \times 1$ vector, $\sum_i K_i = K$ and $K_i < N_i$. Also, assume that X_t^i is explained by only F_t^i. Hence we have

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \end{bmatrix} + \begin{bmatrix} e_t^1 \\ e_t^2 \\ ... \\ e_t^I \end{bmatrix} \tag{2}$$

where $\mathbb{E}\left[e_t^i e_t^j\right] = 0$ for all i, $j = 1, ..., I$ and $i \neq j$. That is, the restriction we impose on our model is that each of the variables in the X_t vector is influenced by the state of the economy only through the corresponding factors. For the rest of the paper we assume that each segment of X_t is explained by exactly one factor, that is $K_i = 1$ for all i.

Also assume that the dynamics of $\left(Y_t, F_t^1, F_t^2, ...F_t^I\right)$ is given by a factor-augmented autoregression (FAVAR):

$$\begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \\ Y_t \end{bmatrix} = \Phi\left(L\right) \begin{bmatrix} F_{t-1}^1 \\ F_{t-1}^2 \\ ... \\ F_{t-1}^I \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{3}$$

where $\Phi\left(L\right)$ is a conformable lag polynomial of finite order d and ν_t is an error term. Clearly, the difference between this model and a standard VAR is the presence of unobservable factors.

Our main contribution is given by the set of restriction illustrated in equation (2). Indeed, assume that the vector of economic variables X_t is divided in subsets of similar variables. For example a subset of variables related to the real activity, a subset of variables related to inflation and so on. We assume that the common force that moves these variables is now economically interpretable. For instance they represent wide concepts such as economic activity or basic movements in prices and so forth.

Our aim is to show that using structural factors in a VAR is 'better' than estimating a VAR with the observed data, that is that our approach is more suitable in explaining the dynamics of the economy and in forecasting. First, using factors may reduce measurement problems.[1] Indeed some factors are extracted by similar variables, such as disaggregate or regional versions of the principal variable. For instance, Real Activity is extracted, among others, from 'New Orders in durable good industries' as well as 'New Orders in non-defense capital goods'. But what is the nature of the structural factors? We think that factors are more than simple re-aggregation of variables. Indeed in our model the loadings also are unknown and to be estimated. Hence,

[1] Correcting measurement problems with factors is a widely used technique.

what criteria should the model use when fixing the loadings?

The Bayesian joint estimation of equations (2) and (3) helps answering this question.

Factors are the unobserved variables that determine at the same time the value of all the other variables in the economy and the dynamics of the whole economy. Indeed each factor, through equation (2), is the sole responsible for today's value of the variables related to it, with the exception of an idiosyncratic error. This error is given by measurement errors as well as true idiosyncratic (i.e. relative to a single sector or region) shocks to the single variable.

And also factors, with the exogenous policy instrument, enter alone in the VAR equation (3). That is, given the state of the economy today, the future depends only on the level of current and past values of factors and policy instruments. All the idiosyncratic shocks will be 'reabsorbed'. That is we expect that an idiosyncratic shock to a single variable will not affect the path of the economy.

Continuing the example of the Real Activity factor, it may be for a few months New Orders in durable good industries may be well above average. But this does not necessarily mean that the whole economy will be affected by such limited shocks. But in our framework this is equivalent to say that we don't expect the general level of production, of inflation and of the other fundamental forces of the economy to be affected. Hence, with our estimation we try to 'clean' the dynamics of the observed variable in order to find the main interactions between the different parts of the economy.

Thanks to this structural interpretation, our model is maybe more robust to the modifications of the economic reality also for forecasting purposes.

The fact that our factors not only have an economic interpretation but are a better description of the state of the economy leads us to call this approach Structural FAVAR (SFAVAR).

We now describe two procedures that allow for the estimation of factors and of the parameters of the model: Principal Components and Bayesian joint estimation.

3 Principal Components Estimation.

The first method we use to estimate the model is Principal Components. As will become clear later, we perform Principal Components (PC) estimation in order to obtain a reasonable guess of the model's parameter to be used in the joint estimation. We will not present the results we obtain with PC.

The reason we prefer the joint estimation to PC, is that PC constructs the estimated factors using only (2) and thus ignoring the restrictions on the dynamics of the factors given by (3): as discussed by Eliasz (2002), factors estimated by PC have unknown dynamic properties. Loosely speaking, the factors estimated by PC are an unknown moving average of some more fundamental factors, where the fundamental factors are identified through the VAR dynamics. As we already discussed, considering the dynamics of factors is important for their estimation and interpretation. Moreover, the apparently higher complexity of the Bayesian joint estimation is repaid with an easier and theoretically clearer assessment of the level of uncertainty: the error bands are simple to construct and to interpret.

Also note that the number of variables in each subsegment X_t^i can be rather small. Hence, if we were using PC, asymptotic results would not be true anymore (we know, in fact, that PC gives consistent estimates when T and $N \to \infty$). This complication does not arise in the Bayesian approach.

However, note that the PC's results are similar to the Bayesian joint estimation ones.

To estimate the factors with PC we follow Bernanke, Boivin and Eliasz (2002) two-step procedure. The identification of the factors is obtained imposing $F^{i\prime}F^{i}/T = I$.

The procedure is reported in Appendix A.

4 Bayesian Approach: Joint Estimation.

The model can be written as:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda & 0 \\ 0 & I_M \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix} \tag{4}$$

where Λ has all the restrictions we imposed. Also:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t. \tag{5}$$

Assume that $e_t \sim$i.i.d.$N(0, R)$ where R is diagonal. Also assume that $\nu_t \sim$ i.i.d.$N(0, Q)$ and v_t and e_t are independent. Following Eliasz (2002) and Bernanke, Boivin and Eliasz (2002) we can apply a Bayesian likelihood approach. In order to identify the factors, we impose that the first element of Λ_i^f is one for all i.

The estimation procedure is discussed in Appendix B.

5 Empirical Framework.

In the previous sections, we have presented the theoretical framework, which enables a structural interpretation of the factors and leads to the definition of Structural Factor-Augmented VARs (SFAVAR). In the rest of the paper, we apply this novel SFAVAR approach in order to study the effects of monetary policy.

5.1 Structural factors.

We segment the vector of economic variables X_t so that each variable is explained by one of the following structural factors:

- REAL ACTIVITY factor. This factor can be reconducted to the abstract macroeconomic concept of 'output gap', providing a summary of the real activity situation. It determines variables such as industrial production, capacity utilization rates, employment/unemployment indicators, inventories stocks, new and unfilled orders, consumer expenditures and so on.

- INFLATION factor, which indicates a more general concept of inflation, incorporating data from the evolution of consumer prices, producer prices, wages, oil price, and so forth.

- INTEREST RATES factor, that explains a number of public and private bonds interest rates, at different maturities.

- FINANCIAL MARKET factor. The introduction of this variable in the SFAVAR is important, as there exist recent examples in the literature seeking to evaluate if monetary policy responds to movements in asset prices (among others Bernanke and Gertler (2001)); moreover, this permits us to verify the existence and the relevance of a financial market channel of monetary policy transmission.

- FOREIGN factor. With this factor we want the capture the influence of a number of foreign variables, like foreign GDPs, foreign prices and interest rates, on the US economy.

- MONEY factor, which explains a number of money stock variables, together with data on deposits, bank reserves and other similar variables.

- CREDIT factor, which explains many private credit and loans variable. With this factor, we are able to verify the empirical dimension of the credit channel of monetary transmission. This represents a potentially very interesting experiment and it is usually disregarded in standard VAR analysis.

- EXPECTATIONS factor. The introduction of expectations is another original feature of the proposed framework. Expectations regarding production, employment, inventories, new orders (derived from NAPM surveys), future inflation and future short-term rates (via surveys and interest rate spreads), are all considered. The dynamics of expectations with respect to the other variables of the system is an interesting issue to examine.

The complete list of which factor explains each variable is in Appendix C.

Moreover we assume that Y_t, our policy variable, is exogenously set by the central bank. The policy measure, in our case, is the Federal Funds rate (FF).

5.2 SFAVAR Estimation.

The data set builds upon the balanced panel, employed by Stock and Watson (2002) . This consists of 120 monthly economic time series, for a sample starting in January 1959 to December 1998. To this panel of data we add a consistent number of other variables, mainly for money and credit sectors. Finally, we include several series characterizing the foreign sector, as GDP, inflation and interest rates for Europe, Canada and Japan. All these additional data are taken from FRED, the database of the Federal Reserve Bank of Saint Louis, or from Datastream.

Therefore, we end up for estimation with a balanced data set, consisting of 204 variables, spanning the period 1959:01-1998:12. All the series have been transformed to reach stationarity and seasonally adjusted, if necessary. Moreover, the series are demeaned and standardized . Our data set, with the complete list of variables divided into segments, the source, and the relevant transformation applied is reported in Appendix C.

In the VAR, we consider 13 lags for all the variables to allow sufficient dynamics.

We estimate jointly the system (14)-(15) by Gibbs sampling as illustrated in section 4. The total number of parameters and factors to be estimated is 5,073, so that we have approximately 19 data points for each parameter. The estimates are based on 5,000 draws, with the first 2,000 omitted to reduce the influence of the initial guess on final results.

To evaluate the convergence of the Gibbs sampler, we plot factors calculated from the first half of the kept draws, together with those derived from the second half. We also plot selected impulse response functions (whose specifications will be discussed later) calculated from the first half of the kept draws, together with those derived from the second half.

Insert Figure 1-2 about here.

We calculated the autocorrelations of parameters within each parameter chain: the autocorrelations are small. We perform, then, the Raftery-Lewis test[2]. This suggests a thinning parameter of 1, an initial burn-in of 3 draws and a total number of draws to achieve the desired accuracy of 1,035 draws. Our choice to perform 5,000 draws omitting the first 2,000 seems, therefore, safe.

[2]See Raftery and Lewis (1992).

6 Results.

Since our factors have a structural interpretation, a first interesting thing to do is to analyze their dynamics. The estimated factors are reported in Figure 3. The factors we obtain with Gibbs sampling are not far from those we have derived under principal components estimation. However, there are significant differences: the correlations between the two estimates range from 0.81, for Money, to 0.99 for the Interest Rates factor.

Insert Figure 3 about here.

Together with the factors, in the graph, we show the 95% probability bands. This is another new feature of the proposed approach. In our case, the error bands are almost indistinguishable from the estimated series, signalling that factors are sharply derived; a certain degree of uncertainty characterizes only the estimates of Expectations (and to a lesser extent Money and Inflation).

We plot the estimated loadings for each factor. We can infer that the factors do not follow closely a single variable, but, instead, the weights are spread across many series.

Insert Figure 4 about here.

Now that we have our economically interpretable factors, it is interesting to examine their reaction to a monetary policy shock, the reaction of monetary policy to different shocks, and, also, the interactions between the factors themselves. We identify the system by means of a Cholesky decomposition. We need, therefore, to recursively order the variables. One problem, arising from our system, is the presence of an Interest Rates factor, which includes data on several long-term rates. If we allowed our policy rate to respond to several market rates, we would have indeterminacy. Therefore, allowing the Federal Funds rate to respond to our long-term interest rates factor, we would face an identification problem: we run the risk of confusing an arbitrage condition with the policy rule. This issue is discussed in greater detail in Leeper, Sims and Zha (1996). In a context like ours, it is assumed that the policy maker can observe and react to the state of the economy. Thus, variables containing expectations on the economy, like long-term rates, do not contain additional relevant information besides what is directly observed. For this reason, we assume that the monetary authority does not react to the Interest Rates factor.

Following the same line of reasoning, since it is possible to observe the current state of the economy, we exclude a contemporaneous response of the policy rate to Expectations. For the Cholesky ordering, therefore, the Interest Rates factor and Expectations are ordered after the Federal Funds rate.

A contemporaneous response of Y_t is, instead, permitted to the other factors (while these factors can react to policy only with a lag). We consider the following ordering of factors: Foreign, Inflation, Real Activity, Credit, Money, Financial Market, Federal Funds rate, Interest Rates and Expectations. Note that even if monetary and financial variables could surely react faster than one or two months to policy innovations, however Federal Funds rate changes happen after FOMC meetings, that take place, for the Fed, approximately every six weeks; as the variables are monthly averages, the response within the same month, therefore, can be incorrect if the meeting is not held in the first days of the month. However, different orderings have been tried and the results are, substantially, unchanged.

We show the derived impulse responses for all the variables and to all the shocks in the system in Figures 5-13. The impulse responses display the dynamics of the economy after a one standard deviation shock to each variable. Note that the scale has been normalized to one standard deviation for each. Error bands represent 68% probability bands, point by point (i.e. approximately one-standard-error bands). These are derived as the 16^{th} and 84^{th} percentile of the obtained responses from Gibbs sampling. This procedure gives us a more accurate indication of the uncertainty, as it includes also uncertainty about factors' estimates.

Insert Figures 5-13 about here.

A particular advantage of the factor-augmented framework is that we can derive impulse responses not only for the fundamental factors, but also for all the variables explained by factors. We provide impulse responses to a monetary policy shock for some of the most interesting variables in Figures 14-15.

Insert Figures 14-15 about here.

The estimated impulse responses generally show intuitive dynamics.

- Monetary policy shock.

Starting from Figure 11, we can look at the reaction of the structural factors to a one standard deviation monetary policy shock. Inflation has a small increase right after the shock and then declines significantly. Hence, there is little evidence of the 'price puzzle'. Real Activity drops, with the maximal decline one year later the shock, and then returns back to the previous level only after two years, showing the usual U-shape behavior. Credit follows the Real Activity factor, but lagged of about six months and with a more prolonged response. Money has a persistent and quick drop. Moreover the Federal Funds rate slowly goes back to its previous value: there is evidence of a strong liquidity effect. The Financial Market factor quickly drops for half-one year. The Interest Rates factor follows the Federal Funds rate, but with a smaller variation.

Moreover, after a monetary contraction, we notice an immediate downward adjustment of expectations, that after half-one year come back to the previous level. Their response clearly leads the response of the Real Activity factor. Moreover the quick reaction to the (supposedly) informative policy shock seems to be an important evidence in favor of the rational expectations hypothesis. As we will show later, the central bank reacts to current Inflation and Real Activity. Hence, the private sector, after observing the policy decisions, rationally and quickly update its expectations about future dynamics of the economy.

In Figure 14-15 we see that a shock to the Federal Funds Rate raise unemployment, reduces Industrial Production, Average Weekly hours, Capacity Utilization Rate. Moreover it reduces Inventories to a lesser extent and leave unaffected US Imposts and exports. Note also the big drop of M1 and the smaller one of M2.

- Financial Market shock.

An interesting result that emerges from Figure 13 is that the central bank reacts to a positive shock to Financial Markets, typically an increase in asset prices. Indeed, the Federal Funds rate increases significantly and returns to its previous value only after about two-three years. That is, our results support the view that the central bank reacts actively to the financial situation and in particular try to avoid 'booms'. Indeed our framework appears to perfectly fit the idea of a financial boom: we have a shock to Financial Markets not supported by a similar increase in the fundamentals. Note moreover that after several months the Real Activity is depressed following such a shock. We find reasonable to say that this is the cost of the central bank's reaction.

As a supplemental evidence of the willingness of the central bank to control the path of financial markets, see Section 9, where we estimate the central bank's policy reaction function.

- Expectations shock.

From Figure 13, we see that a shock to Expectations is not persistent, as would be predicted by the rational expectation theory. However the central bank reacts to the shock increasing the Federal Funds rate.

7 Does Using Factors Improve Fit?

Adding factors to standard VARs, in order to account for a large information set, has proven useful in many respects. Bernanke and Boivin (2001) and Bernanke, Boivin and Eliasz (2002) show that a factor-augmented VAR can help explaining the price puzzle. Stock and Watson (2002) and many related papers, demonstrates that using information from large data sets, summarized by few common factors, results in better forecasting performances. Since then, the use of factor models have become increasingly popular.

But does using factors improve fit? In the following, we try to give an answer to this question. We are not aware of any study that calculates posterior odds between models, with and without factors, to evaluate which one is more favored by the data.

The posterior model probabilities are given by:

$$pr\left(\mathcal{M}_k|D\right)=\frac{pr\left(D|\mathcal{M}_k\right)pr\left(\mathcal{M}_k\right)}{\sum_{j=1}^{K}pr\left(D|\mathcal{M}_j\right)pr\left(\mathcal{M}_j\right)}, \tag{6}$$

where $pr\left(\mathcal{M}_k|D\right)$ is the probability of model $\mathcal{M}_k$, given the data D, and it is obtained from the product of the likelihood $pr\left(D|\mathcal{M}_k\right)$ and the prior probability of the model.

We consider the simplest case. We compare the standard VAR, estimated with Industrial Production, Consumer Price Index inflation and the Federal Funds rate with the closer alternative: a VAR with our estimated Real Activity factor and Inflation factor always together with the Federal Funds rate.

For the standard VAR, we obtain a log-likelihood of 1564; using factors, instead of individual variables, the likelihood increase to 1729. The posterior probabilities for the two models are:

	Standard VAR	Factor-Augmented VAR
Posterior Model Probability	0.47	0.53

Although, the victory is far from being overwhelming, there is, however, a certain improvement, which has been obtained just by replacing the usual variables with the corresponding factors. We can conclude that using factors, somehow, improves fit. We are considering better tests that can take account of our whole estimated model.

8 Forecasting.

Stock and Watson (2002) have shown that the use of factors can lead to improved forecasting performances. We will compare the predictive ability of the following alternative models:

- a benchmark univariate autoregression, AR(p), where the lag length p is selected according to the BIC (Bayesian Schwarz Information Criterion);

- a standard vector autoregression, with IP, CPI inflation and Federal Funds rate as regressors, and p selected as before;

- a FAVAR specification, where the previous VAR is augmented with factors à la Bernanke and Boivin (2001);

- our SFAVAR model, where the factors are jointly estimated by Gibbs sampling, and have an economic meaning.

We first estimate the models on the sample 1959:01-1997:12, then we mimic the real-time central bank's problem, by re-estimating the parameters, re-calculating the factors and generating one-step ahead forecasts for each of the following period. Due to computational and time constraints (required by a recursive Gibbs sampling procedure), we limit the forecasts to the last 12 period of the sample. We are continuously increasing the sample in which we derive our forecasts for future versions of the paper.

The forecasts under our model consist of the median forecast from the Gibbs sampling. An appealing characteristics of our approach is that we are also able to provide a 95% probability band for our forecasts. Looking at the thickness of the line of predicted values, we can immediately evaluate the amount of uncertainty as well as its dynamics over time (we could also look at the skewness, to assess whether very high or very low realizations are more likely). The forecasts' error bands take into account the uncertainty due to the estimation of parameters and factors. They can also possibly represent uncertainty about the future developments of the economy.

We provide out-of-sample forecasts for Industrial Production, CPI Inflation and FF. As measures of predictive accuracy of the different specifications, we use the Root Mean Squared Error (RMSE) and the Theil U statistic. The relative performance is evaluated by observing the RMSE ratio between each model and the benchmark AR case. There seems to be the potential for improvement in predictive performance, through the use of structural factors. We postpone our conclusions until we have results, derived under a longer forecast sample.

[...This Section will be expanded and completed...Tables with results to be inserted...]

9 Policy Reaction Function.

Federal Reserve behavior is usually expressed by a policy reaction function (PRF), under which the instrument is adjusted according to the state of the economy. A standard specification, which has proved quite successful in tracking US monetary policy, is the well-known forward-looking Taylor rule with partial-adjustment:

$$i_t = \rho i_{t-1} + (1-\rho)(\phi^{\pi}\pi_{t+12|t} + \phi^{y} y_t) + \varepsilon_t, \tag{7}$$

where the federal funds rate i_t is set in response to deviations of forecasted inflation and output from their respective targets. The rule include a partial-adjustment mechanism to match the interest-rate smoothing, observed in the data.

Here, we want to consider an alternative in which we allow the central bank to exploit a large amount of information. The policy rate is set based on the state of the economy. The state of the economy is summarized by our structural factors. The policy reaction function can be expressed as:

$$i_t = \rho i_{t-1} + (1-\rho)(\phi^{F}\mathbf{F}_t) + \varepsilon_t, \tag{8}$$

where $\mathbf{F}_t$ includes the factors to which we assume monetary policy responds, i.e. Real Activity factor, Inflation factor, Financial Market factor, Foreign factor, Money factor and Credit factor.

Estimates for the standard Taylor rule and the policy rule with factors are reported in Table 1 and 2, respectively.

Insert Tables 1-2 about here.

We notice the usual sluggish adjustment of the policy instrument to the target rate, suggested by the coefficient ρ very close to 1. We obtain Taylor rule coefficient values of 1.435 for expected inflation and 1.035 for the real activity measure.

It is interesting to evaluate the response of policy to a larger information set. In Table 2, we can see that the estimated response to our inflation factor is 2.504, consistently higher than the Taylor rule result. This indicates that the reaction to price pressures is considerably stronger, if we employ a broader measure of inflation. The response to real activity is substantially unchanged. From the estimated rule, we can observe a quite large and significant reaction of monetary policy to the Financial Market factor developments (coeff. 0.841). Therefore, the Fed seem indeed to respond to asset prices: this is usually an omitted term in monetary policy rules. No significant reaction to foreign, money and credit factors is, instead, detected.

Bernanke and Boivin (2001) tries to determine the existence of an excess policy response, inserting the fitted value $\widehat{i}_t$ derived from the rule with factors, in the common Taylor rule. Being this additional term is significant, they conclude that there is indeed an excess response. This signals that there is omitted information in the traditional Taylor rule. Here, we also aim to test if the Fed actually makes use of more information about the state of the economy, when setting policy. In order to compare the two rules, we employ a test of encompassing. We compute the fitted values from (7) and (8), and we call them $\widehat{i}_t^{Taylor}$ and $\widehat{i}_t^{Factors}$, respectively. The test of encompassing, to choose between competing non-nested specifications, consists in a regression of the actual i_t on the fitted values coming from the two formulations:

$$i_t = \alpha \widehat{i}_t^{Taylor} + (1-\alpha)\widehat{i}_t^{Factors} + \nu_t. \tag{9}$$

We obtain:

$$i_t = \underset{(0.235)}{0.12}\, \widehat{i}_t^{Taylor} + \underset{(0.235)}{0.88}\, \widehat{i}_t^{Factors} + \nu_t, \tag{10}$$

where we can easily accept the hypothesis $\alpha = 0$ at all usual confidence levels. This outcome proves that the Fed responds to a larger information set in taking policy decisions. The omitted information in the standard Taylor rule appears to be, mainly, a broader measure of inflation, caught by our inflation factor, and financial market variables.

10 Conclusions.

Some recent advances in the measurement of monetary policy effects were obtained by combining VAR models with factor analysis. This has permitted to exploit a larger information set. So far, the main shortcoming of this young literature has been the inability to identify the factors, which were lacking in economic interpretation.

We have suggested a solution to this drawback, considering a factor-augmented VAR, where we have provided a structural interpretation to the factors. We managed to assign to each factor a more immediate economic interpretation, since the factors explain different sub-categories of the data.

With these structural factors at hand, we have proposed SFAVAR estimation and we have compared it to standard small-information VAR results in monetary policy analysis. Under this new approach we have examined the impulse responses, now obtained taking into account a larger amount of information, to shocks in monetary policy and in the factors. This framework also allowed us to obtain several interesting findings about the dynamics of the various factors, as well as their interactions.

We have shown that a policy reaction function that responds to the state of the economy, through the proposed structural factors, seems empirically more plausible in explaining the evolution of US monetary policy than a traditional Taylor rule with partial adjustment.

As an evaluation of the worthiness of factor models, we have offered an assessment of the improvement in fit and forecast accuracy they consent.

We believe that this approach could be useful to better model the central banks' decision environment, giving a more accurate characterization of the large information set they can exploit.

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A Estimation with Principal Components.

The estimation goes as follows.

1. Using principal components, we find the factors $\left(F_t^1, F_t^2, ...F_t^I\right)$ from the model

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} F_t^1 \\ F_t^2 \\ ... \\ F_t^I \end{bmatrix} + e_t. \tag{11}$$

   We obtain $\left(\hat{F}_t^1, \hat{F}_t^2, ...\hat{F}_t^I\right)$.

2. We run a standard VAR

$$\begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ ... \\ \hat{F}_t^I \\ Y_t \end{bmatrix} = \Phi\left(L\right) \begin{bmatrix} \hat{F}_{t-1}^1 \\ \hat{F}_{t-1}^2 \\ ... \\ \hat{F}_{t-1}^I \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{12}$$

We obtain $\hat{\Phi}\left(L\right)$.

3. To find the loadings, we do OLS of the equation

$$\begin{bmatrix} X_t^1 \\ X_t^2 \\ ... \\ X_t^I \end{bmatrix} = \begin{bmatrix} \Lambda_1^f & 0 & ... & 0 \\ 0 & \Lambda_2^f & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \Lambda_I^f \end{bmatrix} \cdot \begin{bmatrix} \hat{F}_t^1 \\ \hat{F}_t^2 \\ ... \\ \hat{F}_t^I \end{bmatrix} + e_t. \tag{13}$$

   We obtain $\left(\hat{\Lambda}_1^f, \hat{\Lambda}_2^f, ..., \hat{\Lambda}_I^f\right)$.

B Likelihood-Based Gibbs Sampling.

We want to estimate the parameters $\theta = (\Lambda, R, vec(\Phi), Q)$ and the factors $\{F_t\}_{t=1}^{T}$. We start from the state-space model in (4) and (5), where Λ is restricted as described in the text, e_t ∼i.i.d. $N(0, R)$, ν_t ∼i.i.d. $N(0, Q)$, v_t and e_t are independent and R is diagonal. We can use Gibbs sampling to estimate the model. We closely follow Eliasz (2002), to whom we refer for more details.

We can rewrite the model defining $\mathbf{X}_t = (X_t', Y_t')'$, $\mathbf{F}_t = (F_t', Y_t')'$ and $\mathbf{e}_t = (e_t', 0, ..., 0)'$:

$$\mathbf{X}_t = \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{14}$$

$$\mathbf{F}_t = \Phi(L)\mathbf{F}_t + \nu_t \tag{15}$$

where $\mathbf{e}_t$ ∼i.i.d.$N(0, \mathbf{R})$, $\mathbf{\Lambda} = \begin{bmatrix} \Lambda & 0 \\ 0 & I_M \end{bmatrix}$, $\mathbf{R} = \begin{bmatrix} R & 0 \\ 0 & 0_M \end{bmatrix}$.

Recall that $\Phi(L)$ is of finite order d. We want to rewrite the VAR as a first-order Markov process. Let $\Phi(L) = \Phi_1 L + \Phi_2 L^2 + ... + \Phi_d L^d$. Define $\bar{\mathbf{F}}_t = \left(\mathbf{F}_t', \mathbf{F}_{t-1}', ..., \mathbf{F}_{t-d+1}'\right)'$, $\bar{v}_t = (\nu_t, 0, ..., 0)'$,

$$\bar{\Phi} = \begin{bmatrix} \Phi_1 & \Phi_2 & ... & \Phi_{d-1} & \Phi_d \\ I_{(K+M)} & 0 & ... & 0 & 0 \\ 0 & I_{(K+M)} & ... & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & ... & I_{(K+M)} & 0 \end{bmatrix} \tag{16}$$

and so we get

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_t + \bar{\nu}_t, \tag{17}$$

where $\bar{v}_t = (v_t', 0, ..., 0)$, $\bar{Q} = \begin{bmatrix} Q & 0 & ... & 0 \\ 0 & 0_{(K+M)} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & 0_{(K+M)} \end{bmatrix}$. We can also write

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \tag{18}$$

where $\bar{\mathbf{\Lambda}} = \begin{bmatrix} \mathbf{\Lambda} & 0 & \ldots & 0 \end{bmatrix}$. Hence, the system to be estimated is

$$\mathbf{X}_t = \bar{\mathbf{\Lambda}}\bar{\mathbf{F}}_t + \mathbf{e}_t \quad (19)$$

$$\bar{\mathbf{F}}_t = \bar{\Phi}\bar{\mathbf{F}}_{t-1} + \bar{\nu}_t \quad (20)$$

According to the Bayesian approach, we treat the model's parameters $\theta = (\Lambda, R, vec(\Phi'), Q)$ and the factors $\{F_t\}_{t=1}^T$ as random variables. Let $\widetilde{X}_T = (X_{1,\ldots,}X_T)$ and $\widetilde{F}_T = (F_{1,\ldots,}F_T)$ be the histories of X and F, respectively. We need to derive the posterior densities of F and θ: $p(\widetilde{F}_T) = \int_\Omega p(\widetilde{F}_T, \theta)d\theta$ and $p(\theta) = \int_F p(\widetilde{F}_T, \theta)d\widetilde{F}_T$, where $p(\widetilde{F}_T, \theta)$ is the joint posterior distribution and Ω and F are the supports of θ and F.

We apply multi-move Gibbs sampling, to obtain an empirical approximation of the joint distribution. We start with an initial set of values, θ^0. Then, conditional on θ^0 and $\widetilde{X}_T$, we draw $\widetilde{F}_T^1$ from the conditional density $p(\widetilde{F}_T \mid \widetilde{X}_T, \theta^0)$ and θ^1 from the conditional distribution $p(\theta \mid \widetilde{X}_T, \widetilde{F}_T^1)$. These steps are repeated for s iterations, until the empirical distributions of $\widetilde{F}_T^s$ and θ^s have converged. It can be proven that, as $s \to \infty$, under regularity conditions, the marginal and joint distributions of sampled parameters $\left(\widetilde{F}_T^s, \theta^s\right)$ converge to the true distributions (F_T, θ), at an exponential rate (see Geman and Geman (1994)).

The procedure is as follow.

1. Choice of starting value θ^0. It is advisable to start with a dispersed set of parameter values, verifying that they lead to similar empirical distributions. Unless otherwise specified, we use the principal components estimates, transformed to satify our normalization.

2. How to draw from $p(\widetilde{F}_T \mid \widetilde{X}_T, \theta)$. This conditional distribution can be expressed as the product of conditional distributions:

$$p(\widetilde{F}_T \mid \widetilde{X}_T, \theta) = p(F_T \mid \widetilde{X}_T, \theta) \prod_{t=1}^{T-1} p(F_t \mid F_{t+1}, \widetilde{X}_T, \theta)$$

which is derived, by exploiting the Markov property of the state-space model. The model is linear and Gaussian, therefore we have

$$\begin{gathered} F_T \mid \widetilde{X}_T, \theta \sim N(F_{T|T}, P_{T|T}), \\ F_t \mid F_{t+1}, \widetilde{X}_t, \theta \sim N(F_{t|t+1,F_{t+1}}, P_{t|t,F_{t+1}}), \quad t = T-1, ..., 1, \end{gathered}$$

where

$$\begin{gathered} F_{T|T} = E(F_T \mid \widetilde{X}_T, \theta), \\ P_{T|T} = Cov(F_T \mid \widetilde{X}_T, \theta), \\ F_{t|t+1,F_{t+1}} = E(F_t \mid \widetilde{X}_t, F_{t+1}, \theta) = E(F_t \mid F_{t+1}, F_{t|t}, \theta), \\ P_{t|t,F_{t+1}} = Cov(F_t \mid F_{t+1}, \widetilde{X}_t, \theta) = Cov(F_t \mid F_{t+1}, F_{t|t}, \theta). \end{gathered}$$

Here $F_{t|t}$ refers to the expectation of F_t conditional on information dated t or earlier. We can, then, obtain $F_{t|t}$ and $P_{t|t}$, $t = 1, ..., T$ by Kalman Filter, conditional on θ and the data $\widetilde{X}_t$, by applying the formulas in Hamilton (1994), for example. From the last iteration, we obtain $F_{T|T}$ and $P_{T|T}$ and using those and (**??**), we can draw F_t. Then, we can go backwards through the sample, deriving $F_{T-1|T-1,F_t}$ and $P_{T-1|T-1,F_t}$ by Kalman Filter, drawing F_{T-1} from (**??**), and so on for F_t, $t = T-2, T-3, ..., 1$. A modification of the Kalman filter procedure, as described in Kim and Nelson (1999), is necessary when the number of lags d in (15) is greater than 1.

3. How to draw from $p(\theta \mid \widetilde{X}_T, \widetilde{F}_T)$. Conditional on the data and on the factors generated by the previous step, we can draw values for θ. As the factors are taken as known, (14) and (15) can be treated as two separate sets of equations, the former specifying the distribution of Λ and R, the latter that of $vec(\Phi')$ and Q. Let's start from (14): we can apply equation-by-equation OLS, to obtain $\widehat{\Lambda}$ and $\widehat{e}$. We have $\widehat{R}_{ii} = \widehat{e}'\widehat{e}/(T - K_i)$, where K_i is the number of regressors in equation i, and we set $R_{ij} = 0$, for $i \neq j$. With an uninformative prior, we have

$$R_{ii} \mid \widetilde{X}_T, \widetilde{F}_T = (T - K_i)\, \frac{\widehat{R}_{ii}}{x} \text{ where } x \sim \chi^2(T - K_i).$$

After drawing R_{ii}, we can draw $\Lambda_i \sim N(\widehat{\Lambda}_i, R_{ii}[\widetilde{F}_T^{(i)\prime}\ \widetilde{F}_T^{(i)}]^{-1})$.

Let's focus now on (15). Here we have a standard VAR system, which can, thus, be estimated equation by equation to get $vec(\widehat{\Phi})$ and $\widehat{Q}$. Then, with a flat prior on $\log|Q|$, we can draw Q from

$$InvWishart\left(\left[(T-d)\widehat{Q}\right]^{-1}, T - (K+M)d\right)$$

and, conditional on the generated Q, we draw $vec(\Phi') \sim N(vec(\widehat{\Phi}'), Q \otimes (\widetilde{F}_T'\widetilde{F}_T)^{-1})$, where $vec(\Phi')$ contains the rows of Φ' in stacked form, forming a vector of length $d(K+M)^2$ and "$\otimes$" refers to the Kronecker product.

Steps 2 and 3 are repeated for each iteration s. Then, inference is based on the distribution of $\left(\widetilde{F}_T^s, \theta^s\right)$, after convergence (that is, discarding a big enough number B of initial draws). We calculate medians and percentiles of $\left(\widetilde{F}_T^s, \theta^s\right)$ for $s = B+1, ..., S$ to form estimates of the factors and model parameters and of the associated uncertainty. Also, we evaluate the impulse response functions for each draw and calculate their medians and percentiles.

C The Data Set.

The data are taken from Stock and Watson (2002), FRED or Datastream.

1. Real Activity Factor.

	Mnemonic	Description	Source	T
1	IP	Industrial Production: total index (1992=100,sa)	SW	5
2	IPP	Industrial Production: products, total (1992=100,sa)	SW	5
3	IPF	Industrial Production: final products (1992=100,sa)	SW	5
4	IPC	Industrial Production: consumer goods (1992=100,sa)	SW	5
5	IPCD	Industrial Production: durable consumer goods (1992=100,sa)	SW	5
6	IPCN	Industrial Production: nondurable consumer goods (1992=100,sa)	SW	5
7	IPE	Industrial Production: business equipment (1992=100,sa)	SW	5
8	IPI	Industrial Production: intermediate products (1992=100,sa)	SW	5
9	IPM	Industrial Production: materials (1992=100,sa)	SW	5
10	IPMND	Industrial Production: nondurable goods materials (1992=100,sa)	SW	5
11	IPMFG	Industrial Production: manufacturing (1992=100,sa)	SW	5
12	IPD	Industrial Production: durable manufacturing (1992=100,sa)	SW	5
13	IPN	Industrial Production: nondurable manufacturing (1992=100,sa)	SW	5
14	IPMIN	Industrial Production: mining (1992=100,sa)	SW	5
15	IPUT	Industrial Production: utilities (1992=100,sa)	SW	5
16	IPXMCA	Capacity Util rate: manufacturing, total (% of capacity,sa)(frb)	SW	1
17	GMYXPQ	Personal Income less transfer payments (chained)(#51)(bil92$,saar)	SW	5
18	LHEL	Index of help-wanted advertising in newspapers (1967=100,sa)	SW	5
19	LHELX	Employment: ratio; help-wanted ads: no. unemployed clf	SW	4
20	LHEM	Civilian Labor Force: employed, total (thous.,sa)	SW	5
21	LHNAG	Civilian Labor Force: employed, nonagric. industries (thous.,sa)	SW	5
22	LHUR	Unemployment rate: all workers, 16 years & over (%,sa)	SW	1
23	LHU680	Unemploy. by duration: average(mean) duration in weeks (sa)	SW	1
24	LHU5	Unemploy. by duration: persons unempl. less than 5 wks (thous.,sa)	SW	1
25	LHU14	Unemploy. by duration: persons unempl. 5 to 14 wks (thous.,sa)	SW	1
26	LHU15	Unemploy. by duration: persons unempl. 15 wks + (thous.,sa)	SW	1
27	LHU26	Unemploy. by duration: persons unempl. 15 to 26 wks (thous.,sa)	SW	1
28	LPNAG	Employees on nonag. payrolls: total (thous.,sa)	SW	5
29	LP	Employees on nonag. payrolls: total, private (thous.,sa)	SW	5
30	LPGD	Employees on nonag. payrolls: goods-producing (thous.,sa)	SW	5

31	LPCC	Employees on nonag. payrolls: contract construction (thous.,sa)	SW	5
32	LPEM	Employees on nonag. payrolls: manufacturing (thous.,sa)	SW	5
33	LPED	Employees on nonag. payrolls: durable goods (thous.,sa)	SW	5
34	LPEN	Employees on nonag. payrolls: nondurable goods (thous.,sa)	SW	5
35	LPSP	Employees on nonag. payrolls: service-producing (thous.,sa)	SW	5
36	LPTc	Employees on nonag. payrolls: wholesale & retail trade (thous.,sa)	SW	5
37	LPFR	Employees on nonag. payrolls: finance, insurance & real estate (thous.,sa)	SW	5
38	LPS	Employees on nonag. payrolls: services (thous.,sa)	SW	5
39	LPGOV	Employees on nonag. payrolls: government (thous.,sa)	SW	5
40	LPHRM	Avg. weekly hrs. of prod. wkrs.: manufacturing (sa)	SW	1
41	LPMOSA	Avg. weekly hrs. of prod. wkrs.: mfg, overtime hrs. (sa)	SW	1
42	MSMTQ	Manufacturing & trade: total (mil of chained 1992 dollars)(sa)	SW	5
43	MSMQ	Manufacturing & trade: manufacturing; total (mil of chained 1992 dollars)(sa)	SW	5
44	MSDQ	Manufacturing & trade: mfg; durable goods (mil of chained 1992 dollars)(sa)	SW	5
45	MSNQ	Manufacturing & trade: mfg; nondurable goods (mil of chained 1992 dollars)(sa)	SW	5
46	WTQ	Merchant wholesalers: total (mil of chained 1992 dollars)(sa)	SW	5
47	WTDQ	Merchant wholesalers: durable goods total (mil of chained 1992 dollars)(sa)	SW	5
48	WTNQ	Merchant wholesalers: nondurable goods total (mil of chained 1992 dollars)(sa)	SW	5
49	RTQ	Retail trade: total (mil of chained 1992 dollars)(sa)	SW	5
50	RTNQ	Retail trade: nondurable goods (mil of chained 1992 dollars)(sa)	SW	5
51	GMCQ	Personal consumption expend (chained)-total (bil 92$,saar)	SW	5
52	GMCDQ	Personal consumption expend (chained)-total durables (bil 92$,saar)	SW	5
53	GMCNQ	Personal consumption expend (chained)-total nondurables (bil 92$,saar)	SW	5
54	GMCSQ	Personal consumption expend (chained)-services (bil 92$,saar)	SW	5
55	GMCANQ	Personal consumption expend (chained)-new cars (bil 92$,saar)	SW	5
56	HSFR	Housing starts: nonfarm (1947-58); total farm&nonfarm (1959-)(thous.,sa)	SW	4
57	HSNE	Housing starts: northeast (thous.u.) s.a.	SW	4
58	HSMW	Housing starts: midwest (thous.u.) s.a.	SW	4
59	HSSOU	Housing starts: south (thous.u.) s.a.	SW	4
60	HSWST	Housing starts: west (thous.u.) s.a.	SW	4
61	HSBR	Housing authorized: total new priv housing units (thous.,saar)	SW	4
62	HMOB	Mobile homes: manufacturers'shipments (thous. of u., saar)	SW	4
63	IVMTQ	Manufacturing & trade inventories: total (mil of chained 1992)(sa)	SW	5
64	IVMFGQ	Inventories, business, mfg (mil of chained 1992 dollars,sa)	SW	5
65	IVMFDQ	Inventories, business durables (mil of chained 1992 dollars,sa)	SW	5
66	IVMFNQ	Inventories, business, nondurables (mil of chained 1992 dollars,sa)	SW	5
67	IVWRQ	Manufacturing & trade inventories: merchant wholesalers (mil of chained 1992)(sa)	SW	5
68	IVRRQ	Manufacturing & trade inventories: retail trade (mil of chained 1992)(sa)	SW	5

69	IVSRQ	Ratio for mfg & trade: inventory/sales (chained 1992 dollars,sa)	SW	2
70	IVSRMQ	Ratio for mfg & trade: mfg; inventory/sales (87$)(sa)	SW	2
71	IVSRWQ	Ratio for mfg & trade: wholesaler; inventory/sales (87$)(sa)	SW	2
72	IVSRRQ	Ratio for mfg & trade: retail trade; inventory/sales (87$)(sa)	SW	2
73	MOCMQ	New orders (net)-consumer goods & materials, 1992 dollars (bci)	SW	5
74	MDOQ	New orders, durable goods industries, 1992 dollars (bci)	SW	5
75	MSONDQ	New orders, nondefense capital goods, 1992 dollars (bci)	SW	5
76	MO	mfg new orders: all manufacturing industries, total (mil$,sa)	SW	5
77	MOWU	mfg new orders: mfg industries with unfilled orders, total (mil$,sa)	SW	5
78	MDO	mfg new orders: durable goods industries, total (mil$,sa)	SW	5
79	MDUWU	mfg new orders: durable goods indust with unfilled orders, total (mil$,sa)	SW	5
80	MNO	mfg new orders: nondurable goods industries, total (mil$,sa)	SW	5
81	MNOU	mfg new orders: nondurable goods ind with unfilled orders, total (mil$,sa)	SW	5
82	MU	mfg unfilled orders: all manufacturing industries, total (mil$,sa)	SW	5
83	MDU	mfg unfilled orders: durable goods industries, total (mil$,sa)	SW	5
84	MNU	mfg unfilled orders: nondurable goods industries, total (mil$,sa)	SW	5
85	MPCON	contracts & orders for plant & equipment (bil$,sa)	SW	5
86	MPCONQ	contracts & orders for plant & equipment in 1992 dollars (bci)	SW	5
87	DSPIC96	Real Disposable Personal Income	FRED	5
88	EMRATIO	Civilian Employment-Population Ratio	FRED	5
89	CIVPART	Civilian Participation Rate	FRED	5
90	USSHIM..A	US Shipments - All Manufacturing Industries (disc.) CURN	Datastream	5

2. Inflation Factor.

91	PWFSA	Producer price index: finished goods (82=100,sa)	SW	5
92	PWFCSA	Producer price index: finished consumer goods (82=100,sa)	SW	5
93	PSM99Q	Index of sensitive materials prices (1990=100)(bci-99a)	SW	5
94	PUNEW	CPI-U: all items (82-84=100,sa)	SW	5
95	PU83	CPI-U: apparel & upkeep (82-84=100,sa)	SW	5
96	PU84	CPI-U: transportation (82-84=100,sa)	SW	5
97	PU85	CPI-U: medical care (82-84=100,sa)	SW	5
98	PUC	CPI-U: commodities (82-84=100,sa)	SW	5
99	PUCD	CPI-U: durables (82-84=100,sa)	SW	5
100	PUS	CPI-U: services (82-84=100,sa)	SW	5
101	PUXF	CPI-U: all items less food (82-84=100,sa)	SW	5
102	PUXHS	CPI-U: all items less shelter (82-84=100,sa)	SW	5
103	PUXM	CPI-U: all items less medical care (82-84=100,sa)	SW	5

104	GMDC	PCE, impl. price defl.: pce (1987=100)	SW	5
105	GMDCD	PCE, impl. price defl.: pce; durables (1987=100)	SW	5
106	GMDCN	PCE, impl. price defl.: pce; nondurables (1987=100)	SW	5
107	GMDCS	PCE, impl. price defl.: pce; services (1987=100)	SW	5
108	LEHCC	Avg. hr earnings of constr wkrs: construction ($,sa)	SW	5
109	LEHM	Avg. hr earnings of prod wkrs: manufacturing ($,sa)	SW	5
110	PFCGEF	Producer Price Index: Finished Consumer Goods Excluding Foods	FRED	5
111	PPICPE	Producer Price Index Finished Goods: Capital Equipment	FRED	5
112	PPICRM	Producer Price Index: Crude Materials for Further Processing	FRED	5
113	PPIFCF	Producer Price Index: Finished Consumer Foods	FRED	5
114	PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components	FRED	5
115	OILPRICE	Spot Oil Price: West Texas Intermediate	FRED	5
116	USLABCOSE	US Unit Labor Costs in Manufacturing, Index (BCI 62) sadj	Datastream	5

3. Interest Rates Factor.

117	FYGT5	Interest rate: US Treasury const maturities 5-yr (% per ann,nsa)	SW	1
118	FYGT10	Interest rate: US Treasury const maturities 10-yr (% per ann,nsa)	SW	1
119	FYAAAC	Bond yield: moody's aaa corporate (% per annum)	SW	1
120	FYBAAC	Bond yield: moody's baa corporate (% per annum)	SW	1
121	FYFHA	Secondary market yields on fha mortgages (% per annum)	SW	1
122	GS1	1-Year Treasury Constant Maturity Rate	FRED	1
123	GS3	3-Year Treasury Constant Maturity Rate	FRED	1
124	LTGOVTBD	Long-Term U.S. Government Securities	FRED	1
125	TB3MS	3-Month Treasury Bill: Secondary Market Rate	FRED	1
126	TB6MS	6-Month Treasury Bill: Secondary Market Rate	FRED	1

4. Financial Market Factor.

127	FSNCOM	NYSE common stock price index: composite (12/31/65=50)	SW	5
128	FSPCOM	S&P's common stock price index: composite (1941-43=10)	SW	5
129	FSPIN	S&P's common stock price index: industrials (1941-43=10)	SW	5
130	FSPCAP	S&P's common stock price index: capital goods (1941-43=10)	SW	5
131	FSPUT	S&P's common stock price index: utilities (1941-43=10)	SW	5
132	FSDXP	S&P's composite common stock: dividend yield (% per annum)	SW	1
133	FSPXE	S&P's composite common stock: price-earnings ratio (%,nsa)	SW	1
134	USSHRPRCF	US Dow Jones Industrials Share Price Index (EP)	Datastream	5

5. Foreign Factor.

135	USIMPORTB	US Imports f.a.s. cura	Datastream	5
136	USEXPRTSB	US Exports f.a.s. cura	Datastream	5
137	CNCONPRCF	CN Consumer Price Index sadj	Datastream	5
138	CNLEADIN	CN Composite Index of Leading Indicators(disc,see CN100053)	Datastream	5
139	CNI61...	CN Govt Bond yield - Longterm	Datastream	1
140	CNI66..CE	CN Industrial Production sadj	Datastream	5
141	CNB14007	CN Interest Rates:3 month Treasury Bill Tender (end month)	Datastream	1
142	CNI62...F	CN Share Price Index nadj	Datastream	5
143	UKGBOND.	UK Gross Redemption Yield on 20 year Gilts (period average)	Datastream	1
144	UKCONPRCF	UK Retail Price Index sadj	Datastream	5
145	UKI61...	UK Govt Bond Yield - longterm	Datastream	1
146	JPSHRPRCF	JP Tokio Stock Exchange - topix (EP) nadj	Datastream	5
147	JPUN%TOTQ	JP Unemployment rate sadj	Datastream	1
148	JPCONPRCF	JP CPI: national measure sadj	Datastream	5
149	BDGBOND.	BD Long Term Government Bond Yield (9-10 years maturity)	Datastream	1
150	BDUN%TOTR	BD Unemployment Rate - Dependent Labour (PAN BD M0191) sadj	Datastream	1
151	BDCONPRCF	BD CPI sadj	Datastream	5
152	BDPROPRCF	BD PPI - Industrial Products sadj	Datastream	5
153	ITCONPRCF	IT CPI including Tobacco (NIC) sadj	Datastream	5

6. Money Factor.

154	FM1	Money stock: m1 (curr,trav.cks,dem dep,other ck'able dep)(bil$,sa)	SW	5
155	FM2	Money stock: m2 (m1+o'nite rps,euro$,g/p&b/d mmmfs&sav&sm time dep)(bil$,sa)	SW	5
156	FM3	Money stock: m3 (m2+lg time dep,term rp's&inst only mmmfs)(bil$,sa)	SW	5
157	FM2DQ	Money-supply-m2 in 1992 dollars (bci)	SW	5
158	FMFBA	Monetary base, adj for reserve requirement changes (mil$,sa)	SW	5
159	FMRRA	Depository inst reserves: total,adj for reserve req chgs (mil$,sa)	SW	5
160	FMRNBC	Depository inst reserves: nonborrow+ext cr,adj for res req chgs (mil$,sa)	SW	5
161	BOGNONBR	Non-Borrowed Reserves of Depository Institutions	FRED	5
162	CURRDD	Currency Component of M1 Plus Demand Deposits	FRED	5
163	CURRSL	Currency Component of M1	FRED	5
164	DEMDEPSL	Demand Deposits at Commercial Banks	FRED	5
165	EXCRESNS	Excess Reserves of Depository Institutions	FRED	2
166	LGTDCBSL	Large Time Deposits at Commercial Banks	FRED	5

167	LTDSL	Large Time Deposits - Total	FRED	5
168	NFORBRES	Net Free or Borrowed Reserves of Depository Institutions	FRED	2
169	REQRESNS	Required Reserves, Not Adjusted for Changes in Reserve Requirements	FRED	5
170	RESBALNS	Reserve Balances with Federal Reserve Banks, Not Adj for Changes in Res Reqs	FRED	5
171	SAVINGSL	Savings Deposits - Total	FRED	5
172	STDCBSL	Small Time Deposits at Commercial Banks	FRED	5
173	STDSL	Small Time Deposits - Total	FRED	5
174	SVGCBSL	Savings Deposits at Commercial Banks	FRED	5
175	SVSTCBSL	Savings and Small Time Deposits at Commercial Banks	FRED	5
176	SVSTSL	Savings and Small Time Deposits - Total	FRED	5
177	TCDSL	Total Checkable Deposits	FRED	5
178	TOTTDP	Total Time and Savings Deposits at All Depository Institutions	FRED	5

7. Credit Factor.

179	AUTOSL	Total Automobile Credit Outstanding	FRED	5
180	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	FRED	5
181	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	FRED	5
182	INVEST	Total Investments at All Commercial Banks	FRED	5
183	LOANINV	Total Loans and Investments at All Commercial Banks	FRED	5
184	LOANS	Total Loans and Leases at Commercial Banks	FRED	5
185	NONREVSL	Total Nonrevolving Credit Outstanding	FRED	5
186	OTHERSL	Total Other Credit Outstanding	FRED	5
187	OTHSEC	Other Securities at All Commercial Banks	FRED	5
188	REALLN	Real Estate Loans at All Commercial Banks	FRED	5
189	TOTALSL	Total Consumer Credit Outstanding	FRED	5

8. Expectations.

190	PMI	Purchasing managers'index (sa)	SW	1
191	PMP	NAPM production index (percent)	SW	1
192	PMEMP	NAPM employment index (percent)	SW	1
193	PMNV	NAPM inventories index (percent)	SW	1
194	PMNO	NAPM new orders index (percent)	SW	1
195	PMDEL	NAPM vendor deliveries index (percent)	SW	1
196	PMCP	NAPM commodity prices index (percent)	SW	1

197	HHSNTN	U.of Mich. index of consumer expectations (bcd-83)	SW	1
198	sFYCP90	Spread sFYCP90-Fedfund	SW	1
199	sFYGM3	Spread sFYGM3-Fedfund	SW	1
200	sFYGM6	Spread sFYGM6-Fedfund	SW	1
201	sFYGT1	Spread sFYGT1-Fedfund	SW	1
202	sFYGT5	Spread sFYGT5-Fedfund	SW	1
203	sFYGT10	Spread sFYGT10-Fedfund	SW	1

9. Federal Funds Rate.

204	FEDFUNDS	Effective Federal Funds Rate	FRED	1

Note: T is the transformation code: 1=no transformation, 2=first difference, 4=logarithm, 5=first difference of logarithms.

Sample	Partial-Adjustment ρ	Response to inflation ϕ^{π}	Response to real activity ϕ^{y}
1960:01-1998:12	0.966 (0.011)	1.435 (0.384)	1.035 (0.480)

Table 1 - Estimated Policy Reaction Function (Taylor Rule).

		Response to Structural Factors					
Sample	ρ	Real Activity	Inflation	Financial Market	Foreign	Money	Credit
1960:01-1998:12	0.956* (0.013)	1.079* (0.415)	2.504* (0.736)	0.841* (0.326)	−0.592 (0.413)	0.251 (0.149)	0.181 (0.305)

Table 2 - Estimated Policy Reaction Function with Structural Factors.

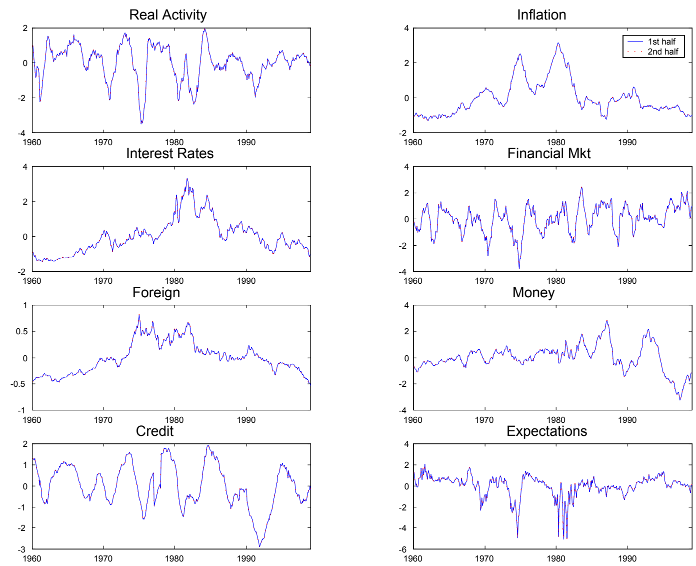

Figure 1 - Convergence: estimated factors first half vs. second half of the sampling.

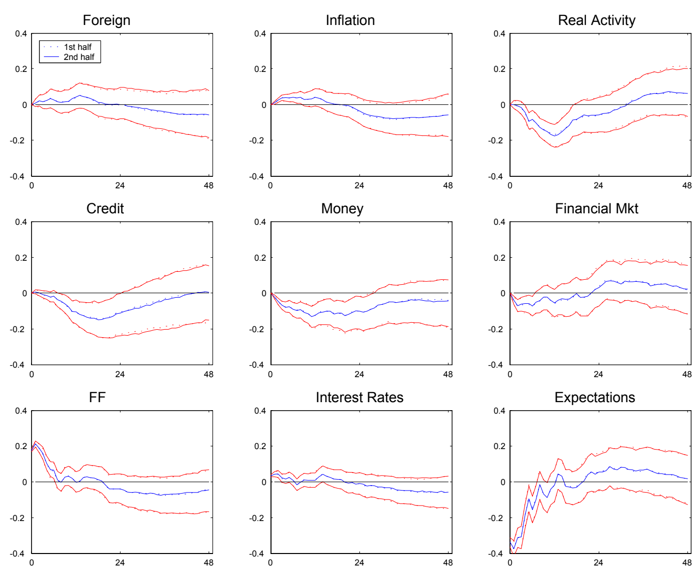

Figure 2 - Convergence: impulse response functions, first and second half.

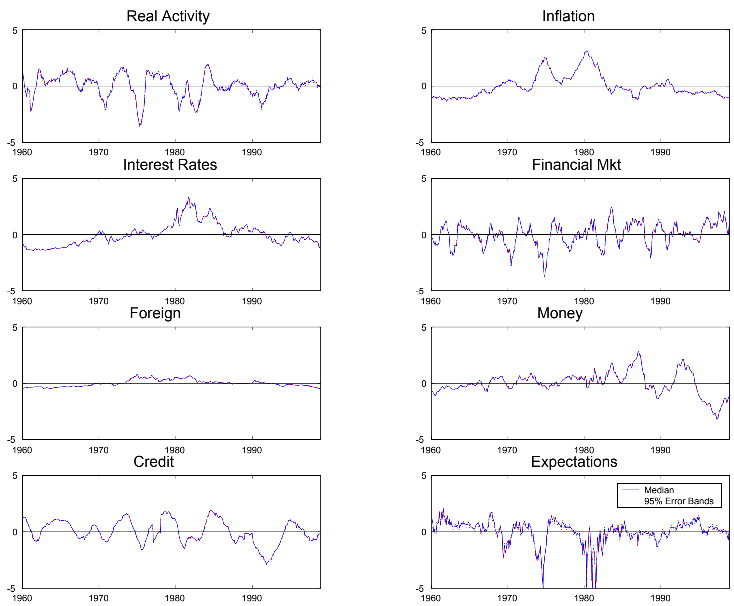

Figure 3 - Estimated structural factors with error bands.

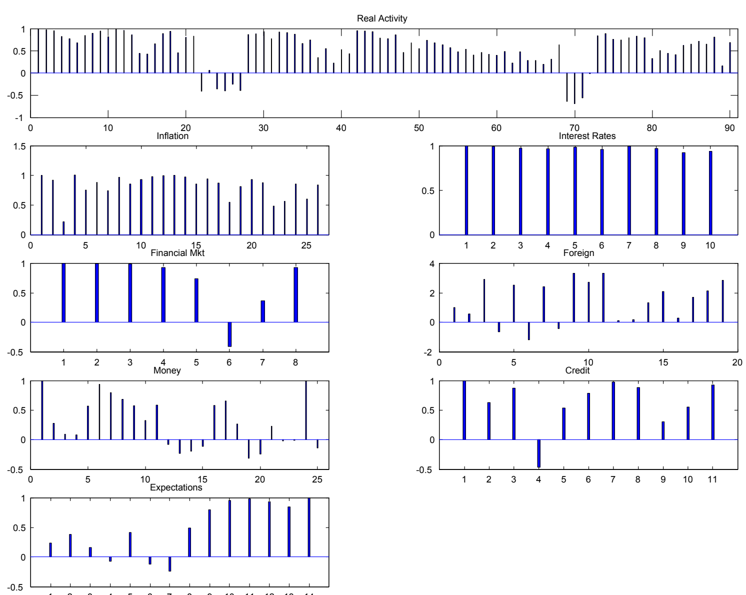

Figure 4 - Estimated loadings.

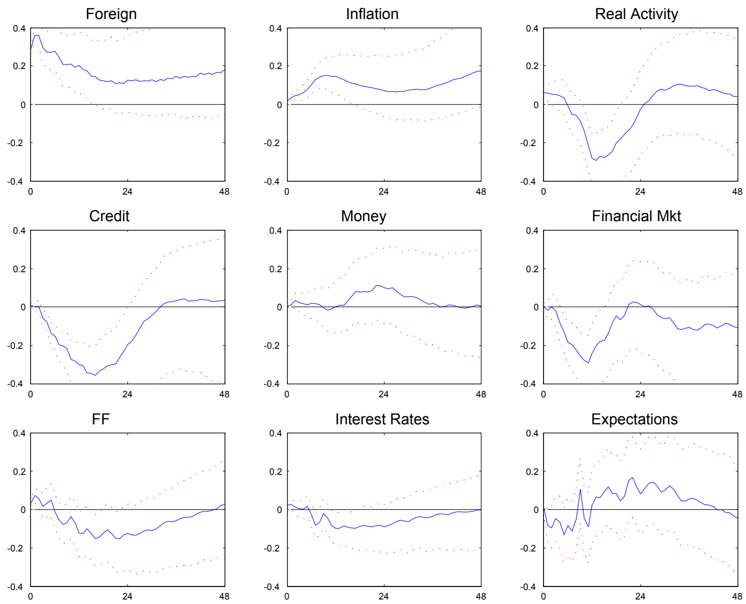

Figure 5 - Impulse responses to one std. shock to Foreign factor.

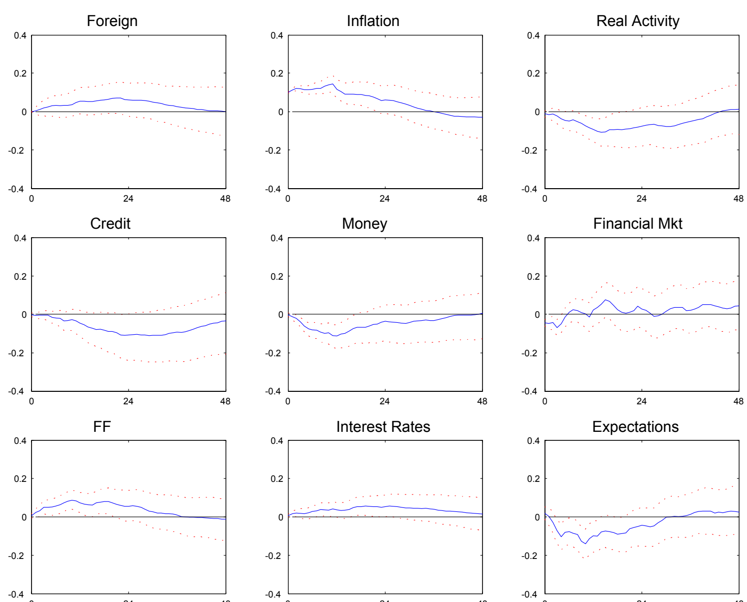

Figure 6 - Impulse responses to one std. shock to Inflation factor.

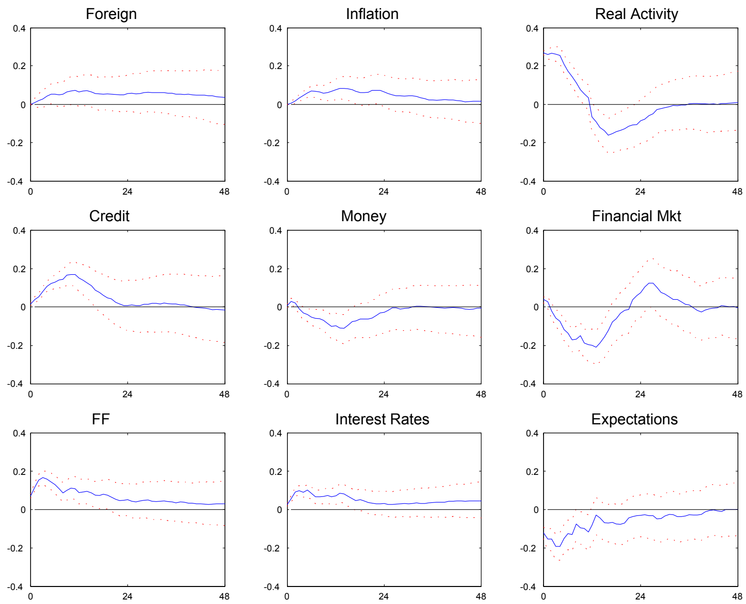

Figure 7 - Impulse responses to one std. shock to Real Activity factor.

Figure 8 - Impulse responses to one std. shock to Credit factor.

Figure 9 - Impulse responses to one std. shock to Money factor.

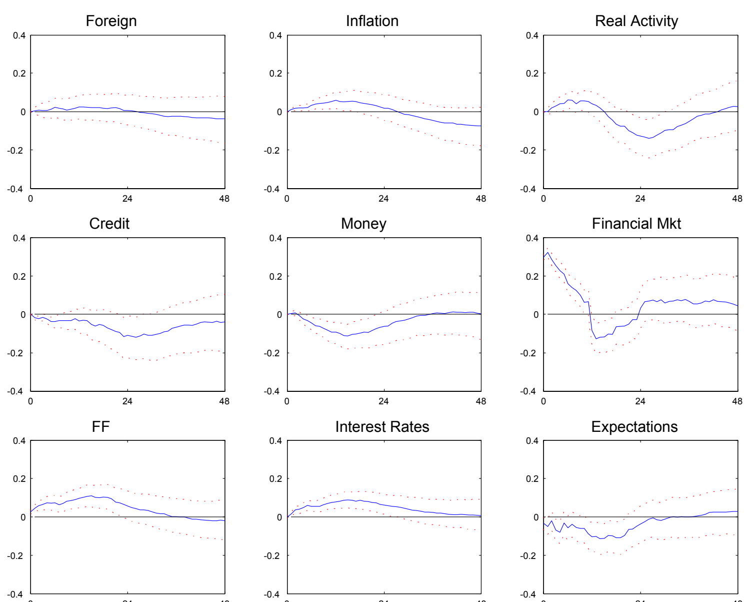

Figure 10 - Impulse responses to one std. shock to Financial Market factor.

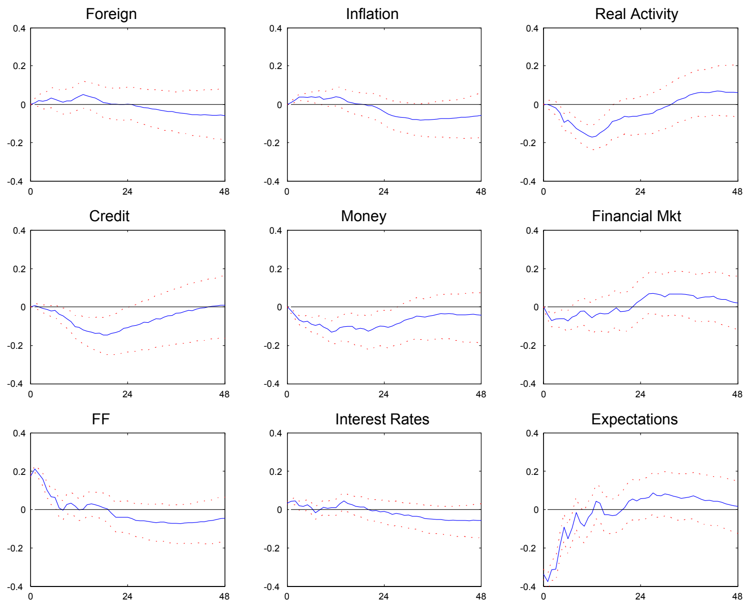

Figure 11 - Impulse responses to one std. shock to Federal Funds Rate.

Figure 12 - Impulse responses to one std. shock to Interest Rate factor.

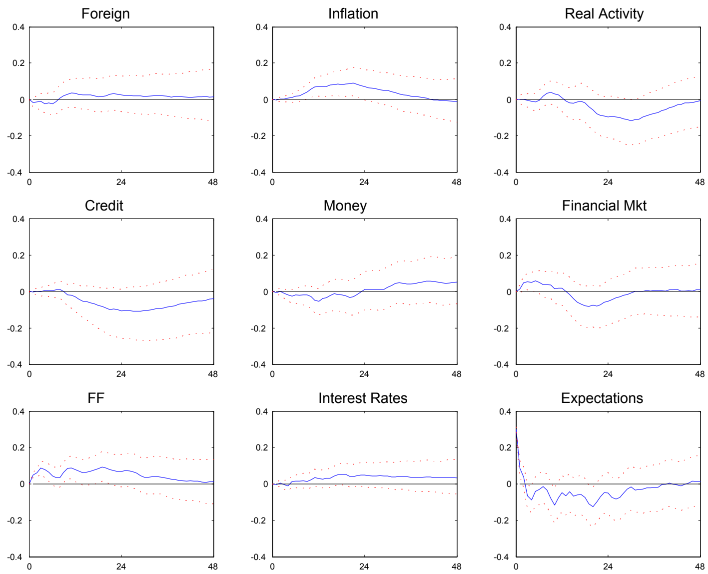

Figure 13 - Impulse responses to one std. shock to Expectations.

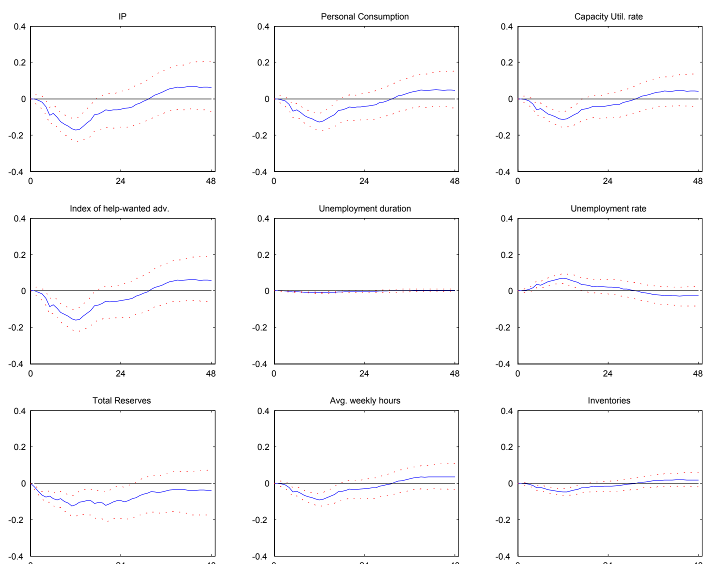

Figure 14 - Impulse responses to a monetary policy shock of various variables.

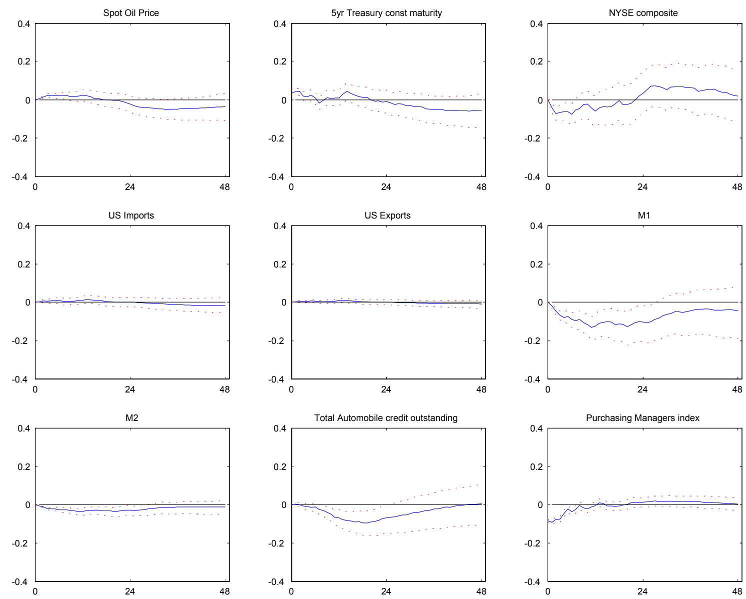

Figure 15 - Impulse responses to a monetary policy shock of various variables.