The dynamic effects of monetary policy: A structural factor model approach

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Abstract

A structural factor model for 112 US monthly macroeconomic series is used to study the effects of monetary policy. Monetary policy shocks are identified using a standard recursive scheme, in which the impact effects on both industrial production and prices are zero. The main findings are the following. First, the maximal effect on bilateral real exchange rates is observed on impact, so that the "delayed overshooting" puzzle disappears. Second, after a contractionary shock prices fall at all horizons, so that the price puzzle is not there. Finally, monetary policy has a sizable effect on both real and nominal variables.

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1 Introduction

Mainstream theory predicts that a monetary policy tightening reduces prices and produces an immediate appreciation of the domestic currency followed by a depreciation. Empirical studies based on structural VAR analysis fail to find evidence supporting such theoretical predictions. Sims (1992) finds that, after a monetary contraction, prices increase, a result known as the *price puzzle*. Eichenbaum and Evans (1995) and Grilli and Roubini (1995) find that exchange rates react with a long delay, being barely affected on impact, a result known as the *delayed overshooting puzzle*.

In recent years there have been many attempts to reconcile empirical results with the theory. On the one hand, some authors call into question the standard recursiveness assumption and propose alternative identification schemes. A notable example is Kim and Roubini (2000), where a substantial mitigation of the delayed overshooting puzzle is obtained. However their identifying restrictions have been questioned by other authors (see e.g. Faust and Rogers, 2003); moreover, it has been shown that, under very mild sign restrictions, the overshooting puzzle is restored (Scholl and Uhlig, 2005).

On the other hand, influential papers argue convincingly that the puzzles could be due to a deficient information set: if the VAR includes less information than that used by Central Banks and private economic agents, empirical results can be completely wrong. As a matter of fact, the price puzzle can be solved by adding to the VAR data set either commodity prices or suitable linear combinations of variables (Sims, 1992, Bernanke, Boivin and Eliasz, 2005, BBE from now on).

Nevertheless, even including commodity prices, the estimated reaction of prices to monetary policy is negligible in size and disproportionately small as compared to the large response of output (see e.g. Christiano, Eichenbaum, Evans, 1999, CEE from now on). This finding, somewhat understated in the literature, can hardly be reconciled with mainstream theories. Moreover, the delayed overshooting puzzle seems to be robust to different VAR specifications within the recursive approach.

Adding further variables to the data set could in principle enlarge the estimated response of prices and/or solve the delayed overshooting puzzle. Unfortunately, there are no obvious criteria to determine *a priori* how many and which variables should be added. Furthermore, adding too many variables would lead to inaccurate estimates. In short, insufficient information is a problem which cannot be easily solved within the VAR framework (see however Banbura *et al.*, 2007, where it is shown that large Bayesian VARs can be successfully used for both forecasting and structural analysis, provided that suitable priors are set).

In the last decade, a relevant stream of research has focused on models specifically designed to handle a large amount of information, i.e. the generalized (or approximate) dynamic factor models (early works are Forni, *et al.*, 2000, 2005, Forni and Lippi, 2001, Stock and Watson, 2002a, 2002b, Bai and Ng, 2002, Bai, 2003). Such models, successfully used for forecasting and the construction of coincident indicators[1], have recently been proposed for structural macroeconomic analysis, (Forni, Giannone, Lippi and Reichlin, (2009, FGLR from now on). Macroeconomic variables are represented as the sum of a common component and an idiosyncratic component. The idiosyncratic components represent measurement errors or sectoral variations and are not of direct interest for the analysis. The common components are driven by a few macroeconomic shocks which are loaded with different impulse response functions. Identification can be obtained in just the same way as in VAR models. Factor models like FGLR are compatible with neoclassic or neo-Keynesian DSGE models augmented with measurement errors (see Sargent, 1989; Altug, 1989; Ireland, 2004 and the literature mentioned therein).

In this paper the FGLR model and the related estimation procedure are used to analyze the effects of exogenous monetary policy shocks. The data set is made up of 112 US monthly macroeconomic series covering the flexible exchange rate period March 1973 — November 2007. The monetary policy shock is identified by imposing a standard recursive scheme on industrial production, the consumer price index, the federal funds rate, and a real exchange rate. Within a VAR model, such identification produces both the price and the delayed overshooting puzzles. The main finding is that in the factor model both puzzles disappear. Moreover, the response of prices in the medium run is relatively large and similar in size to that of industrial production. Finally, reasonable responses for many economic variables are found.

This paper is closely related to BBE. The general line of research is the same. The difference is that here a pure structural factor model is employed, whereas BBE use a mixture of a factor model and a VAR model (the FAVAR model). From this point of view, this paper is closer to Stock and Watson (2005) and Giannone *et al.* (2004). Mumtaz and Surico (2008), using a FAVAR model, find that the delayed overshooting puzzle is somewhat reduced for the UK. Yet, it is argued in Section 3.6. that the puzzle cannot be solved within a FAVAR approach with US data.

The paper is structured as follows. Section 2 presents the factor model and the estimation procedure and discusses the relation with VAR and FAVAR. Section 3 is devoted to the empirical analysis and shows the results. Section 4 concludes.

2 Theory

This section provides a presentation of the FGLR model and the related estimator. FGLR is a special case of the generalized dynamic factor model proposed by Forni *et al.* (2000) and Forni and Lippi (2001). Such models differ from the traditional dynamic factor model of Sargent and Sims (1977) and Geweke (1977) in that the number of cross-sectional variables is infinite and the idiosyncratic components are allowed to be mutually correlated to some extent, along the lines of Chamberlain (1983), Chamberlain and Rothschild (1983) and Connor

[1]See Altissimo *et al.* (2006)

and Korajczyk (1988). Closely related models have been studied by Stock and Watson (2002a, 2002b, 2005), Bai and Ng (2002, 2007) and Bai (2003).

2.1 The factor model

Each variable x_{it} is the sum of two mutually orthogonal unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it}:

$$x_{it} = \chi_{it} + \xi_{it}. \tag{2.1}$$

The idiosyncratic components are poorly correlated in the cross-sectional dimension (see FGLR, Assumption 5 for a precise statement). They arise from shocks or sources of variation which considerably affect only a single variable or a small group of variables; in this sense, they are not "macroeconomic" shocks. For variables related to particular sectors, the idiosyncratic component may reflect sector specific variations (let us say "microeconomic" fluctuations); for exchange rates, the idiosyncratic component might reflect non-US shocks, specific to foreign countries (see below); for strictly macroeconomic variables like GDP, investment or consumption, the idiosyncratic component must be interpreted essentially as a measurement error.

The common components are responsible for the main bulk of the co-movements between the macroeconomic variables, being linear combinations of a relatively small number r of factors $f_{1t}, f_{2t}, \cdots, f_{rt}$, not depending on i:

$$\chi_{it} = a_{1i} f_{1t} + a_{2i} f_{2t} + \cdots + a_{ri} f_{rt} = a_i \boldsymbol{f}_t. \tag{2.2}$$

The dynamic relations between the macroeconomic variables arise from the fact that the vector $\boldsymbol{f}_t$ of the common factors follows the VAR relation

$$\begin{array}{rcl} \boldsymbol{f}_t & = & D_1 \boldsymbol{f}_{t-1} + \cdots + D_p \boldsymbol{f}_{t-p} + \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t & = & R \boldsymbol{u}_t, \end{array} \tag{2.3}$$

where R is a $r \times q$ matrix and $\boldsymbol{u}_t = (u_{1t} \ u_{2t} \ \cdots \ u_{qt})'$ is a q-dimensional vector of orthonormal white noises, with $q \leq r$. Such white noises are the "common" or "primitive" shocks or "dynamic factors" (whereas the entries of $\boldsymbol{f}_t$ are the "static factors"). Observe that, if $q < r$, the residuals of the above VAR relation have a singular variance covariance matrix.[2]

From equations (2.1) to (2.3) it is seen that the variables themselves can be written in the dynamic form

$$x_{it} = b_i(L) \boldsymbol{u}_t + \xi_{it}, \tag{2.4}$$

where

$$b_i(L) = a_i (I - D_1 L - \cdots - D_p L^p)^{-1} R. \tag{2.5}$$

The dynamic factors $\boldsymbol{u}_t$ and $b_i(L)$ are assumed to be structural macroeconomic shocks and impulse response functions respectively.

[2]Equations (2.1) to (2.3) need further qualification to ensure that all of the factors are loaded, so to speak, by enough variables with large enough loadings (see FGLR, Assumption 4); this "pervasiveness" condition is necessary to have uniqueness of the common and the idiosyncratic components, as well as the number of static factors r and dynamic factors q.

2.2 Interpretation of the static factors and the parameter r

Unlike the dynamic factors, the static factors do not have a structural economic interpretation; rather, they are a statistical tool which is useful to model the dynamics of the system. They enable us to represent such dynamics in a flexible but parsimonious way, by means of the vector autoregression in (2.3).

A proper choice of the number of static factors r is crucial to reach a good compromise between parsimony and flexibility. Loosely speaking, given q, the larger is the number of static factors r, the more cross-sectional heterogeneity is allowed for in the impulse response functions.

Consider for instance the simple case with just one shock ($q = 1$). If there is one static factor as well, i.e. $r = 1$, all the impulse response functions $b_i(L)$ become proportional to that of the factor itself. Different variables can load the shock with different "intensity" and different sign (so that both pro-cyclical and counter-cyclical behaviors are allowed); but the "shape" of the impulse response function is the same for all variables. In order to allow for a more heterogeneous dynamics, e.g. leading, coincident and lagging, a larger r is needed.

With a large r, the dynamics of the system may be quite general. For instance, sticking to the case $q = 1$, a factor model with non restricted MA(s) impulse response functions, i.e.

$$\chi_{it} = b_{i0}u_t + b_{i1}u_{t-1} + \cdots + b_{is}u_{t-s}$$

can be written in the form (2.2)-(2.3) with $r = s+1$ static factors and $p = 1$ by setting $\boldsymbol{f}_t = (u_t \ u_{t-1} \ \cdots \ u_{t-s})'$, $a_i = (b_{i0} \ b_{i1} \ \cdots \ b_{is})$,

$$D_1 = \begin{pmatrix} 0 & 0 & \cdots & 0 & 0 \\ 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{pmatrix}$$

and $R = (1 \ 0 \ \cdots \ 0)'$.[3] With $q > 1$, $r = q(s+1)$ is required to encompass the MA(s) case.

2.3 Identification

As observed above, common components are identified; however, representation (2.4) is not unique, since the impulse response functions are not identified. In particular, if H is any orthogonal $q \times q$ matrix, then $R\boldsymbol{u}_t$ in (2.3) is equal to $S\boldsymbol{v}_t$, where $S = RH'$ and $\boldsymbol{v}_t = H\boldsymbol{u}_t$, so that $\boldsymbol{\chi}_{it} = c_i(L)\boldsymbol{v}_t$, with $c_i(L) = b_i(L)H' = a_i(I - D_1L - \cdots - D_pL^p)^{-1}S$. Post-multiplication by H' is the only admissible transformation, i.e. the impulse response functions are unique up to orthogonal rotations, just like in structural VAR models (see FGLR, Proposition 2). As a

[3] Observe that in this case the static factors are simply the lags of the dynamic factor.

consequence, structural analysis in factor models can be carried on along lines very similar to those of standard SVAR analysis.

To be precise, let us assume that economic theory implies a set of restrictions on the impulse response functions of some variables, the first m with no loss of generality. Let us write such functions in matrix notation as $B_m(L) = (b_1(L)'b_2(L)' \cdots b_m(L)')'$. Given any non-structural representation

$$\boldsymbol{\chi}_{mt} = C_m(L)\boldsymbol{v}_t, \tag{2.6}$$

along with the relation

$$B_m(L) = C_m(L)H, \tag{2.7}$$

it is assumed that theory-based restrictions are sufficient to obtain H and therefore $b_i(L)$ for any i (just identification).

Consider first the case $m = q$: in such a case, any set of restrictions, like for instance zero impact or long-run restrictions, which identifies a structural VAR with q variables, identifies the factor model as well. The triangular identification scheme is a typical example. While the case of just identification is described above, restrictions producing partial identification or inequality restrictions (Uhlig, 2005) can be used as well.

The number of variables contributing to identification, however, can be larger than the number of structural shocks (and even equal to n). For instance a demand shock could be identified by minimizing some function of its long-run effects on several monetary variables (which are not necessarily of direct interest for the analysis); or the monetary policy shock could be identified by minimizing the sum of the squared impact effects on many slow-moving variables, like prices and industrial production indexes.

In this paper the traditional scheme with $m = q$ is adopted to help comparison with VAR results. Nonetheless, the possibility of identifying using restrictions involving a large number of variables is an interesting feature of structural factor models. In particular, inequality restrictions, when imposed on a large number of series, would likely be much more effective in reducing the set of admissible impulse response functions.

2.4 Estimation

The estimation is performed as follows. First, starting with an estimate $\hat{r}$ of the number of static factors, the static factors themselves are estimated by means of the first $\hat{r}$ ordinary principal components of the variables in the data set, and the factor loadings by means of the associated eigenvectors. Precisely, let $\hat{\Gamma}^x$ be the sample variance-covariance matrix of the data: the estimated loading matrix $\hat{A}_n = (\hat{a}_1'\hat{a}_2' \cdots \hat{a}_n')'$ is the $n \times r$ matrix having on the columns the normalized eigenvectors corresponding to the first largest $\hat{r}$ eigenvalues of $\hat{\Gamma}^x$, and the estimated factors are $\boldsymbol{f}_t = \hat{A}_n'(x_{1t}x_{2t} \cdots x_{nt})'$.

Second, a VAR(p) is run with $\boldsymbol{f}_t$ to get estimates of $D(L)$ and the residuals $\boldsymbol{\epsilon}_t$, say $\hat{D}(L)$ and $\hat{\boldsymbol{\epsilon}}_t$.

Now, let $\hat{\Gamma}^\epsilon$ be the sample variance-covariance matrix of $\hat{\boldsymbol{\epsilon}}_t$. As the third step, having an estimate $\hat{q}$ of the number of dynamic factors, an estimate of a non-structural representation of the common components is obtained by using the spectral decomposition of $\hat{\Gamma}^\epsilon$. Precisely, let $\hat{\mu}_j^\epsilon$, $j = 1, \ldots, \hat{q}$, be the j-th eigenvalue of $\hat{\Gamma}^\epsilon$, in decreasing order, $\hat{\mathcal{M}}$ the $q \times q$ diagonal matrix with $\sqrt{\hat{\mu}_j^\epsilon}$ as its (j, j) entry, $\hat{K}$ the $r \times q$ matrix with the corresponding normalized eigenvectors on the columns. Setting $\hat{S} = \hat{K}\hat{\mathcal{M}}$, the estimated matrix of non-structural impulse response functions is

$$\hat{C}_n(L) = \hat{A}_n \hat{D}(L)^{-1} \hat{S}. \tag{2.8}$$

Finally, $\hat{H}$ and $\hat{b}_i(L) = \hat{c}_i(L)\hat{H}$ $i = 1, \ldots, n$ are obtained by imposing the identification restrictions on

$$\hat{B}_m(L) = \hat{C}_m(L)\hat{H}. \tag{2.9}$$

Proposition 3 of FGLR states that $\hat{b}_i(L)$, for a fixed i, is a consistent estimator of $b_i(L)$. To be more precise, as $\min(n, T) \to \infty$, T being the number of observation over time, $\hat{b}_i(L)$ tends to $b_i(L)$ in probability with rate $\max\left(\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{T}}\right)$.

Confidence bands are obtained by a standard non-overlapping block bootstrap technique. Let $X = [x_{it}]$ be the $T \times n$ matrix of data. Such matrix is partitioned into S sub-matrices X_s (blocks), $s = 1, \ldots, S$, of dimension $\tau \times n$, τ being the integer part of T/S.[4] An integer h_s between 1 and S is drawn randomly with reintroduction S times to obtain the sequence $h_1, \ldots, h_S$. A new artificial sample of dimension $\tau S \times n$ is then generated as $X^* = \left[X'_{h_1} X'_{h_2} \cdots X'_{h_S}\right]'$ and the corresponding impulse response functions are estimated. A distribution of impulse response functions is obtained by repeating drawing and estimation.

2.5 Discussion

Factor models impose a considerable amount of structure on the data, implying restricted VAR relations among variables (see Stock and Watson, 2005 for a comprehensive analysis). In this sense, factor models are less general than VAR models. On the other hand, factor models, being more parsimonious, can model a larger amount of information. Within VAR models, the number of variables cannot be enlarged very much, because of both estimation and identification problems. Estimation would become rather inaccurate given the number of observations usually available in the time dimension. Identification can be even more problematic, since the number of restrictions needed to reach a complete identification grows with n^2, n being the number of series in the data set. Since theory-based restrictions are often questionable, keeping their number small is essential for credibility and ease of interpretation. By contrast, in the factor model described here, the number of primitive shocks q and the associated number of identifying restrictions do not change at all as n increases. The

[4]Note that τ has to be large enough to retain relevant lagged auto- and cross-covariances.

ability to model a large number of variables without requiring a huge number of theory-based identifying restrictions is a remarkable feature of structural factor models.

The relevance of the information issue is stressed in several influential papers, including Quah (1990), Sims (1992), Bernanke and Boivin (2003), BBE. If, as is reasonable, economic agents base their decisions on all of the available macroeconomic information, structural shocks should be innovations with respect to a large information set, which can hardly be included in a VAR model.

A problem which is strictly related to the information set used by economic agents is the possibility of non-fundamental representations. Assume that the number of structural shocks is q and measurement errors are not there. Let us consider a q-dimensional vector of macroeconomic variables of interest. There is simply no reason why its structural representation should be invertible (indeed, if economic agents observe at least one additional variable Granger-causing such a vector, the representation cannot be invertible). Obviously, a non-invertible structural representation cannot be found by inverting a VAR (Lippi and Reichlin, 1994). The fundamentalness problem is considerably mitigated in the context of factor models. For a comprehensive discussion of this point see FGLR. The intuition is that factor models use a large information set, virtually including all available macroeconomic data, so that superior information of economic agents is much less likely.

The FAVAR model recently proposed by BBE is very close to a structural factor model. Indeed, the name FAVAR is somewhat misleading, since it is essentially a structural factor model including observable factors. Though, there is an important difference with the model described above: BBE does not distinguish between r, the number of static factors, and q, the number of structural shocks. As a consequence, an important advantage of the factor model is lost: a relatively large r, needed to retain relevant information, cannot be set without having to impose a large number of economic restrictions in order to reach identification. Moreover, existing tests applied to US data do not support the restriction $r = q$ (see e.g. Bai and Ng, 2007, Amengual and Watson, 2007, and Section 3.2 below).

In addition, a noticeable difference between the present paper and BBE concerns identification. In BBE identification is reached by imposing restrictions on the impulse response functions of the static factors, rather than the impulse response functions of the variables. The static factors are identified only up to orthogonal rotations and do not have any economic interpretation, so that it is hard to say which restrictions should be satisfied by the factors according to economic theory. This is the reason why BBE departs from standard principal components estimators and considers factors which are linear combinations of "slow-moving" variables, like prices and production indexes, so that imposing zero impact effects of the monetary shock is reasonable. But excluding "fast-moving" variables implies an efficiency loss.

3 Empirical analysis

This section describes the data used in the empirical analysis, discusses the choice of the number of dynamic and static factors, presents the results and checks their robustness to different parameter specifications.

3.1 Data and data treatment

The data set is made up of 112 US monthly series, covering the period from March 1973 to November 2007. Most series are those of the Stock-Watson data set used in BBE. A few real exchange rates and short-term interest rate spreads between US and some foreign countries are added, and some discontinued series are eliminated. The starting date has been chosen in such a way as to discard the fixed exchange rate regime.

As in BBE, transformations are kept to a minimum. For instance, interest rates and real exchange rates are taken in levels (rather than first differences) and prices are taken in differences of logs (rather than second differences). For a few series (particularly interest rates) stationarity is problematic according to standard tests. Nonetheless, these transformations are the most widely used and help comparison with both VAR and FAVAR results.

The full list of variables along with the corresponding transformations is reported in the supplementary materials.

3.2 The number of static and dynamic factors

To determine the number of static factors, the criterion used here is the popular IC_{p2} proposed by Bai and Ng (2002), which gives $\hat{r} = 16$. Most of the results below are obtained conditioning on such $\hat{r}$. Obviously, there is uncertainty about the number of factors, but how to deal with it is far from trivial within the present frequentist framework. The strategy adopted here is to repeat the analysis with different specifications of r. Section 3.6 below shows results for $\hat{r} = 10$ and $\hat{r} = 4$.[5]

To determine the number of dynamic factors three criteria are used: Bai and Ng (2007), Amengual and Watson (2007) and Hallin and Liska (2007). The Bai and Ng (2007) criterion is computed using the residuals of a VAR(2) with the first 16 estimated factors. Using the covariance matrix of such residuals (parameters $\delta = .1$, $m = 1$) it is found $\hat{q}_3 = 7$ and $\hat{q}_4 = 10$. Using the correlation matrix (parameters $\delta = .1$, $m = 1.25, 2.25$) it is found $\hat{q}_3 = 7$, $\hat{q}_4 = 7$. Using the Amengual and Watson criterion $\hat{BN}^{ICP}(\hat{y}^A)$, with $\hat{r} = 16$ and $p = 2$,

[5]In the present paper confidence bands are computed as usual by assuming a fixed r for all repetitions of the bootstrap procedure described in Section 2.4. An alternative would be to choose a criterion (such as IC_{p2}) and let r vary across bootstrap repetitions according to such criterion. The latter strategy would only partially take into account model specification uncertainty since, of course, it would not document uncertainty related to the choice of the criterion. A second alternative would be to use an estimation method not requiring the specification r. Preliminary work along this line of research can be found in Forni and Lippi (2008).

gives 7 primitive factors with IC_{p1} and 4 primitive factors with IC_{p2}. Finally, the "non-log" criterion proposed by Hallin and Liska produces 4 to 6 factors depending on the penalty function and the initial random permutation. We conclude that the number of dynamic factors is in the interval 4-7. In the benchmark specification 4 dynamic factors are used; Section 3.6 shows results for a seven-shock specification.

The number of lags p of $\hat{D(L)}$ appearing in equation (2.8) is set equal to 2, i.e. the average of AIC (3 lags) and BIC (1 lags).

To conclude this subsection, let us have a look at the common-idiosyncratic variance decomposition of a few key variables (the ones appearing in the benchmark VAR below) with $\hat{r} = 16$. The common variance of industrial production, the consumer price index and the federal funds rate are respectively 94, 92 and 96% of total variance. These numbers seem compatible with the measurement error interpretation of the idiosyncratic components. Note in particular the very low noise-to-signal variance ratio of the federal funds rate, which should be essentially free of measurement errors. On the other hand, the common variance of the Swiss/US real exchange rate is relatively low (71%). The Japan/US, UK/US and Canada/US exchange rates have similar common-to-total variance ratios (82, 72 and 79% respectively). A reasonable interpretation is that such relevant idiosyncratic fluctuations are due to non-US, country specific sources of variation.

3.3 The benchmark VAR

Before showing the results for the structural factor model, let us present for comparison the impulse response functions to a contractionary monetary policy shock of a simple VAR including industrial production, a consumer price index (CPI), the federal funds rate and the Swiss/US real exchange rate (i.e. the series nos. 5, 96, 75 and 106 in the Appendix). The VAR is estimated using 9 lags. Similar results are obtained by replacing the Swiss/US rate with either the Japan/US rate, or the UK/US rate, or the Canada/US rate, and using different lag specifications. Similar results are also obtained by adding monetary aggregates such as M2, total reserves or borrowed reserves, and/or the spread between US and Swiss short-term interest rates (like in Eichenbaum and Evans, 1995). We prefer the four-variable specification to help comparison with the four-shock factor model.

Following Eichenbaum and Evans (1995), identification is achieved by assuming that both industrial production and prices do not respond contemporaneously to the monetary policy shock, neither directly, nor indirectly, through its impact on the exchange rate, and the exchange rate does not affect contemporaneously the federal funds rate. In other words, a standard recursive scheme (see CEE) is employed, where the monetary policy shock is the third one with the above order of variables.[6]

[6]Zero impact effects on prices and output are also assumed in the benchmark VAR of BBE, where exchange rates are not included.

The impulse response functions are reported in Figure 1, left column, along with 80% confidence band computed with standard bootstrap. Two well known results emerge. First, prices significantly increase. Second, the response of the real exchange rate is hump-shaped with a maximal value reached after five years. The first finding, known as the price puzzle, is in contrast with predictions from standard theoretical models of monetary policy since a contractionary action should reduce prices. The second finding, known as the delayed overshooting puzzle, is in contrast with simple overshooting models like Dornbusch (1976) in which the largest response of the real exchange rate should occur contemporaneously. Observe also that industrial production is negatively affected even in the long run.

To our knowledge, the delayed overshooting puzzle has never been solved within a recursive identification approach. On the other hand the price puzzle can be solved, as far as the sign of the long-run response is concerned, either by including in the VAR a commodity price index (not shown here) or within the FAVAR approach. However, in both cases the reaction of prices is nearly zero or still positive during the first year.[7] Moreover, in both cases the percentage of the forecast error variance of prices explained by the policy shock is very low (less than 5%) even in the long run (see CEE and BBE). This finding, somewhat understated in the literature, is particularly puzzling in view of the large reactions commonly estimated for real variables when the federal funds rate is taken as the policy instrument.[8] In the reference VAR above the monetary policy shock accounts for about 30% of the forecast error variance of industrial production at a four year horizon (Table 1); similar results are obtained with more sophisticated VAR specifications, including commodity prices (see CEE).

3.4 Main results

Let us now come to the factor model. For the sake of comparison, identification is obtained just in the same way as the VAR model above. More precisely, with reference to equation (2.9), letting $\hat{B}_m(L)$ be the matrix of impulse response functions of industrial production, CPI, federal funds rate and Swiss/US real exchange rate (in this order), $\hat{B}_m(0)$ is restricted to be lower triangular. Letting G_m be the (lower triangular) Cholesky factor of $\hat{C}_m(0)\hat{C}_m(0)'$, the above restriction is obtained by setting $\hat{H} = \hat{C}_m(0)^{-1}G_m$. The monetary policy shock is the third one[9].

Figure 1, right column, displays the responses of the four series included in the VAR to a monetary policy shock raising the federal funds rate by 50 basis points. The dotted lines are the 80% confidence bands obtained with the block bootstrap procedure described in Section 2.4 (the block length is 52 months).

[7] In the FAVAR model prices still react positively to a contractionary monetary policy shock for about one year both in the 3 and the 5 factor specifications.

[8] This is not the case for the FAVAR, where the reaction of industrial production is also relatively small.

[9] As for the VAR, global identification is just a standard device to obtain the monetary policy shock (see CEE).

The most striking result is that both puzzles disappear.

The Swiss/US real exchange rate reacts immediately, with an appreciation of about 7%, and from the first month the effect starts to converge quickly to zero, vanishing after about one year. Confidence bands are rather large, so that the effect is not significant. Nevertheless, the point estimate is perfectly consistent with Dornbusch (1976)'s overshooting theory, where the maximal effect is predicted to occur contemporaneously. Also, to the best of our knowledge, such a clear-cut result has never been obtained before. Observe also that the magnitude of the impact effect is about six time larger than the maximal VAR response (around 1.2%).

As for prices, the CPI falls from the second month, reducing by about 0.2% after six months and 0.4% after one year. These numbers are compatible with a monetary policy aimed at controlling short run price fluctuations and differ from those obtained by both CEE with commodity prices (see CEE, Figures 2) and BBE with the FAVAR. There, after one year the effects are still slightly positive.

Observe also that industrial production significantly falls for about 20 months, the response displaying the typical inverted hump-shape. The maximal reduction, of about 1%, is reached after about one year. Moreover, the federal funds rate displays negative, albeit not significant, responses after 4-5 months. This is consistent with the existence of a counter cyclical feedback rule of the central bank to prices and output. Overall, impulse response functions are consistent, from both a qualitative and quantitative point of view, with predictions about the transmission mechanisms of monetary policy arising in standard theoretical models. Specifically, after a contractionary policy shock, prices and industrial production sensibly fall, the former permanently while the latter only temporarily, and the real exchange rate substantially appreciates in the month the shock occurs.

Let us come now to the variance decomposition (Table 2). At a six months horizon the shock has small effects on both industrial production and prices. Only 6.5% and 0.5% of the variance of the two series respectively is accounted for by the shock. The effects however increase at longer horizons; after four years the shock explains 13% and 16% of the volatility of industrial production and prices respectively. Overall, results confirm a sizable role of the monetary policy in affecting the dynamics of both real and nominal variables.

Figure 2 depicts the impulse response functions of the three real exchange rates Canada/US, UK/US and Japan/US (left column) and the relative conditional UIP (right column), computed as in Scholl and Uhlig (2005). Impulse response functions are similar to that of the Swiss/US exchange rate: the maximal effect is observed on impact or, in the case of the Japan/US exchange rate, in the second month, and quickly reduces to zero afterward. Such effects are relatively large ranging from 3 to 4%. The point estimates of the conditional UIP (right column, annualized percentage returns) are not negligible although the confidence bands are very large making the responses not significant.

The last four rows of Table 2 display the variance decomposition of real exchange rates. A few results are worth noting. First, on impact the percentage of variance explained by the shock is quite heterogeneous, ranging from 19% for the Japan/US up to 75% for the Canada/US exchange rates. Second, with the exception of the Japan/US rate, at longer horizons the importance of the shock reduces. For instance at a four years horizon the percentage of variance explained by the shock ranges from 12% to 38%.[10] This finding is in sharp contrast with that obtained with SVARs where, given the very tiny effects on exchange rates on impact, the portion of variance explained by the shock in the short run is much smaller.

3.5 Additional results

Figure 3 depicts the impulse response functions of a number of relevant macroeconomic variables.

The response of both nominal earnings and the producer price index (PPI) is very similar to that of consumer prices. The two variables react very little on impact, suggesting a certain degree of price and wage stickiness, and reduce at longer horizons (although the effects are never significant). Notice that, given the present identification scheme, also the (log of) real wage responds with a delay to the shock. M2 reduces, although not significantly, from the second month after a nearly zero impact effect. Consistently with findings in Bernanke and Blinder (1992), loans reduce on impact by a relatively modest amount. After the first year the effect becomes significant and persistent, suggesting long lasting effects of monetary policy on credit variables.

The figure also depicts a consistent picture of the reaction of firms and consumers to monetary policy shocks. Real personal consumption immediately falls, reaching the minimum after about one quarter, and reverts back to the pre-shock level after two years. The fall in consumption triggers a delayed and significant reduction in consumer credit. The response of orders is very similar in terms of shape to that of consumer credit, the effects being particularly long lasting and persistent. Given that production is unaffected and sales decline immediately, inventories initially increase, while after the second month they start reducing significantly. This behavior is consistent with the goal of keeping the amount of inventories to a target level. Housing starts is the real variable that most rapidly reacts to the monetary policy shock with a large negative impact effect (around -5%).

Finally let us look at the impulse response of selected labor market variables. Hours, employment and vacancies immediately and significantly fall with the largest effect observed after one year. Such an effect is particularly pronounced for vacancies (-4%). On the other hand, consistently with CEE, unemployment, both number of persons and the rate, reacts to the shock with one month of delay. After one year the unemployment rate increases by about 0.2%.

[10] Such numbers are in line with Scholl and Uhlig (2005) and Kim and Roubini (2000), and smaller than those of Clarida and Gali (1994) and Rogers (1999).

3.6 Robustness

This subsection studies the robustness of the results to changes in the number of both dynamic and static factors.

First let us compare the results of our benchmark specification ($r = 16$, $q = 4$) with two alternative specifications: $r = 10$, $q = 4$ and $r = 16$, $q = 7$.[11] Figure 4 displays the impulse response functions of the main macro aggregates. In the seven dynamic factor case the magnitude of the responses are generally smaller. Still, the shapes are qualitatively the same for the three specifications. In particular, the responses of real exchange rates are noticeably similar: a sizable immediate appreciation is followed by nearly zero responses.

In the second exercise let us stick to the 4 dynamic shock specification and study what happens to exchange rates and prices when varying the number of static factors from 4 to 16. The response of prices do not change that much. On the other hand, the response of exchange rates changes substantially. Figure 5 displays the responses of the four real exchange rates with 4, 10 and 16 static factors. Results for the 10 and the 16 factor cases are similar. On the contrary, in the 4 factor case the response functions become very similar to those of the SVAR model. The delayed overshooting is apparent, the maximal level being reached several months after the shock. The 4 static factor case is particularly interesting in that, when the number of static and dynamic factors is the same, the factor model is very much like to a FAVAR. This suggests that a FAVAR including 4 factors would not be able to solve the delayed overshooting puzzle. This result empirically highlights the importance of allowing for a number of static factors substantially larger than that of dynamic factors.[12]

Overall results seem to be robust to changes in model specification.

4 Conclusions

This paper studies the effects of monetary policy shocks within a structural factor model approach. The factor model enables the researcher to handle a large amount of information and therefore to avoid an important limitation of structural VAR models. The monetary policy shock is identified by imposing on the factor model a standard recursive scheme that, when imposed on a VAR model, produces both the price puzzle and the delayed overshooting puzzle. The results obtained with the factor model are in sharp contrast with those obtained with the VAR model. First, bilateral real exchange rates react contemporaneously with sizable appreciations to a contractionary monetary policy shock. After the initial increase, the effects of the shock are negligible. Second, prices fall

[11] For the seven dynamic factor specification Identification is implemented in just the same way, the only difference being that now the other three real exchange rates are added after the federal funds rate in the recursive identification scheme.

[12] As suggested by an anonymous referee, economic arguments concerning the plausibility of impulse response functions might also be used to determine the number of static factors r in situations where existing criteria provide conflicting results. Here, for instance, at least 10 factors should be retained.

at all horizons after a zero impact effect. Furthermore, the monetary policy shocks have a sizable role in affecting the dynamics of both real and nominal variables. These results highlight the importance of using extended information sets and show that the structural factor model is a promising tool for applied macroeconomics.

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Tables

Table 1: Variance decomposition SVAR (*)

	k=0	k=6	k=12	k=48
Ind. production	0 (0)	0.0361 (0.0634)	0.1129 (0.1388)	0.3062 (0.1737)
CPI	0 (0)	0.0483 (0.0300)	0.0461 (0.0364)	0.0170 (0.0358)
Federal funds rate	0.9209 (0.0205)	0.5435 (0.0182)	0.3996 (0.0208)	0.1854 (0.0322)
Swi/US real ER	0.0275 0.0313	0.0685 (0.0420)	0.0923 (0.0497)	0.1434 (0.0607)

(*) Months after the shocks on the columns.

Table 2: Variance decomposition SDFM (*)

	k=0	k=6	k=12	k=48
Ind. production	0 (0)	0.0657 (0.0465)	0.1299 (0.0674)	0.1346 (0.0710)
CPI	0 (0)	0.0057 (0.0243)	0.0333 (0.0608)	0.1634 (0.1679)
Federal funds rate	0.5345 (0.2335)	0.1463 (0.2036)	0.1986 (0.1676)	0.2989 (0.1575)
Swi/US real ER	0.5227 (0.2704)	0.4330 (0.2123)	0.4041 (0.2028)	0.3836 (0.1666)
Can/US real ER	0.7541 (0.2605)	0.3474 (0.1825)	0.2523 (0.1794)	0.1643 (0.1580)
Jap/US real ER	0.1885 (0.2897)	0.2371 (0.2101)	0.2092 (0.2013)	0.1746 (0.1765)
UK/US real ER	0.2313 (0.2165)	0.1463 (0.1841)	0.1227 (0.1795)	0.1200 (0.1543)

(*) Months after the shocks on the columns.

Figures

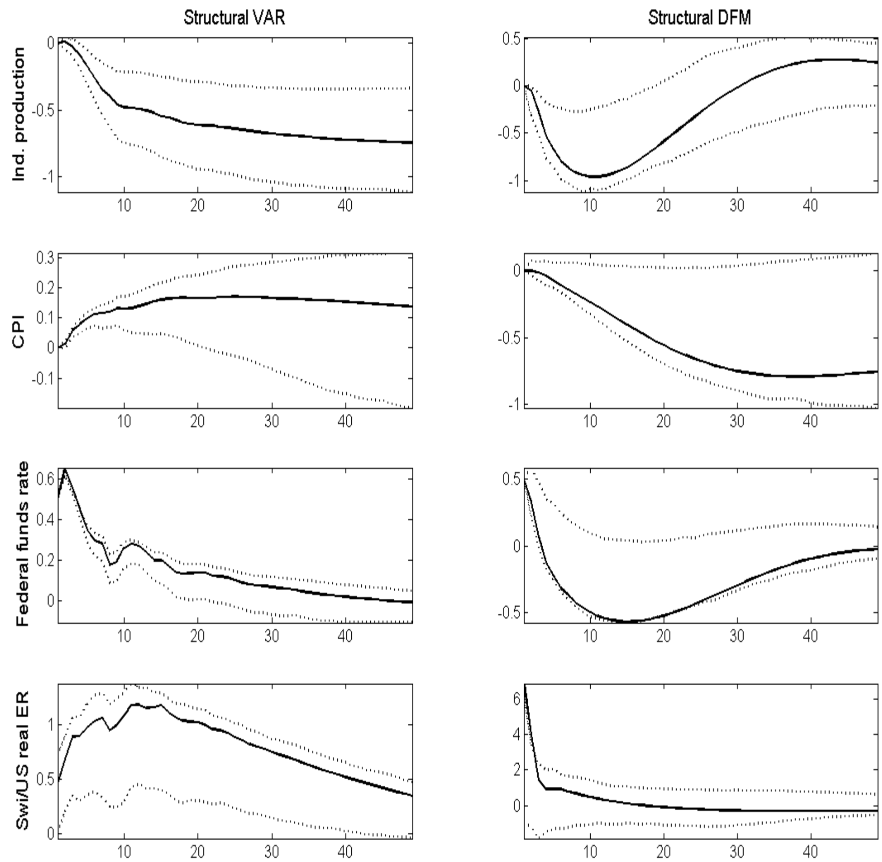

Figure 1: Impulse response functions to a contractionary monetary policy shock increasing the federal funds rate by 50 basis points. VAR: left column. Dynamic Factor Model (16 static factors, 4 dynamic factors): right column. Solid line: point estimates. Dotted line: 80% confidence bands. Vertical axis: percentages.

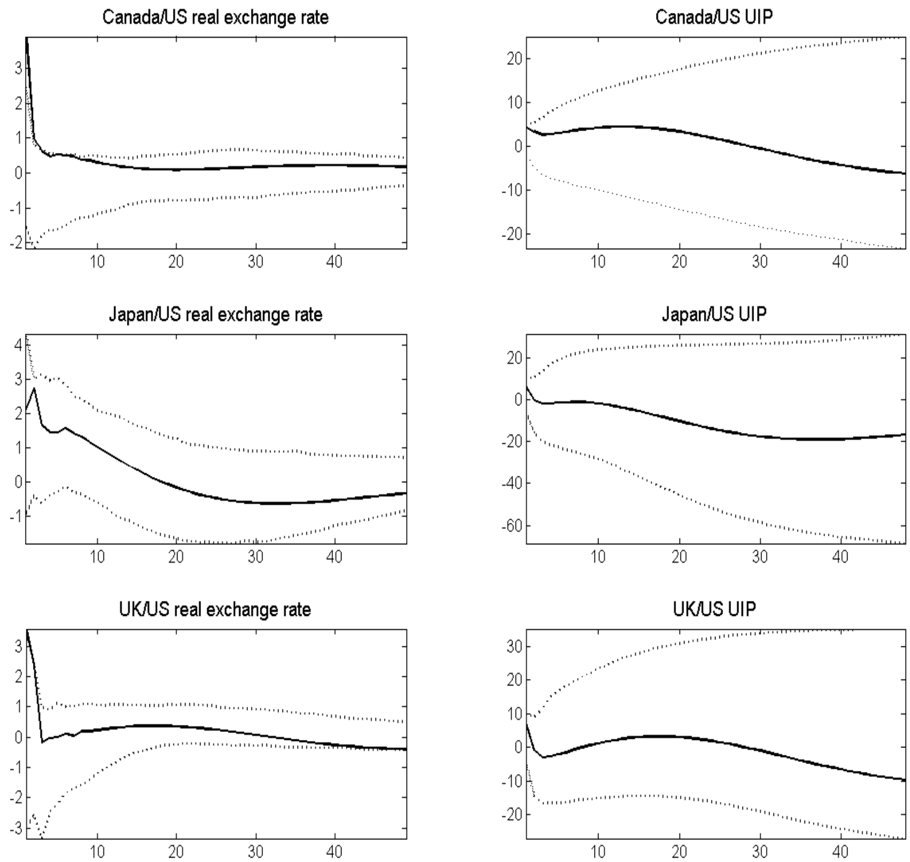

Figure 2: Dynamic Factor Model (16 static factors, 4 dynamic factors) impulse response functions to a contractionary monetary policy shock increasing the federal funds rate by 50 basis points. Solid line: point estimates. Vertical axis: percentages (annualized for UIP). Dotted line: 80% confidence bands.

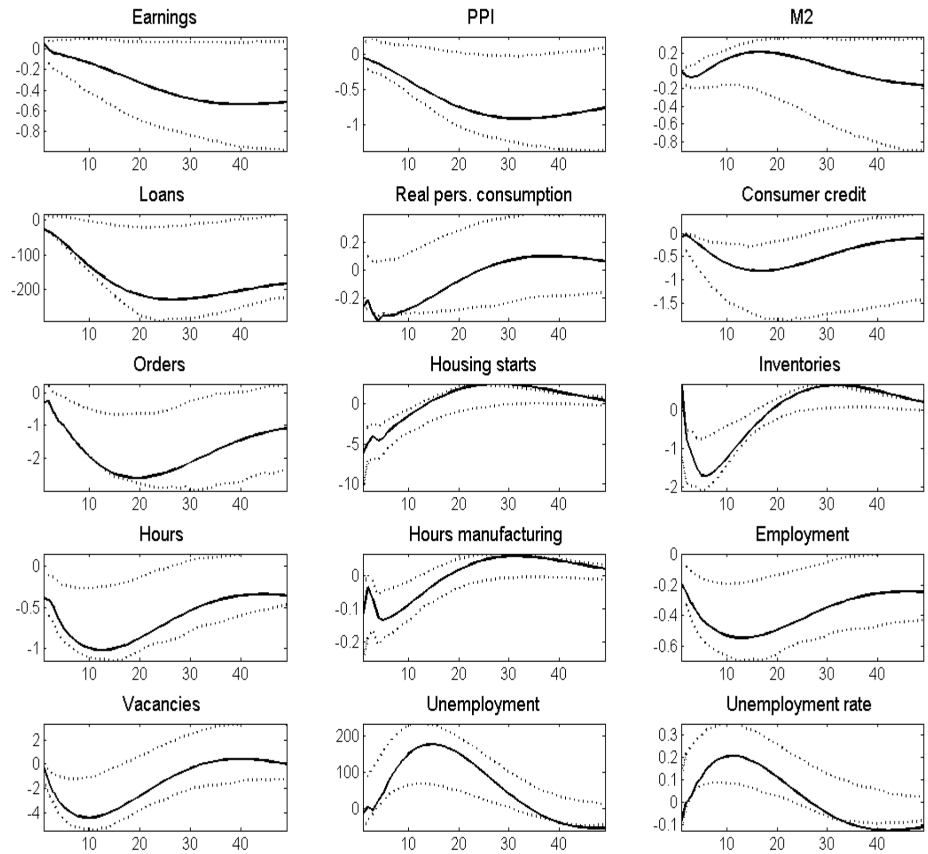

Figure 3: Dynamic Factor Model (16 static factors, 4 dynamic factors) impulse response functions to a contractionary monetary policy shock increasing the federal funds rate by 50 basis points. Solid line: point estimates. Dotted line: 80% confidence bands. Vertical axis: percentages except for Loans (billion dollars), Inventories (index), Hours Manufacturing (weekly hours), Unemployment (thousand people).

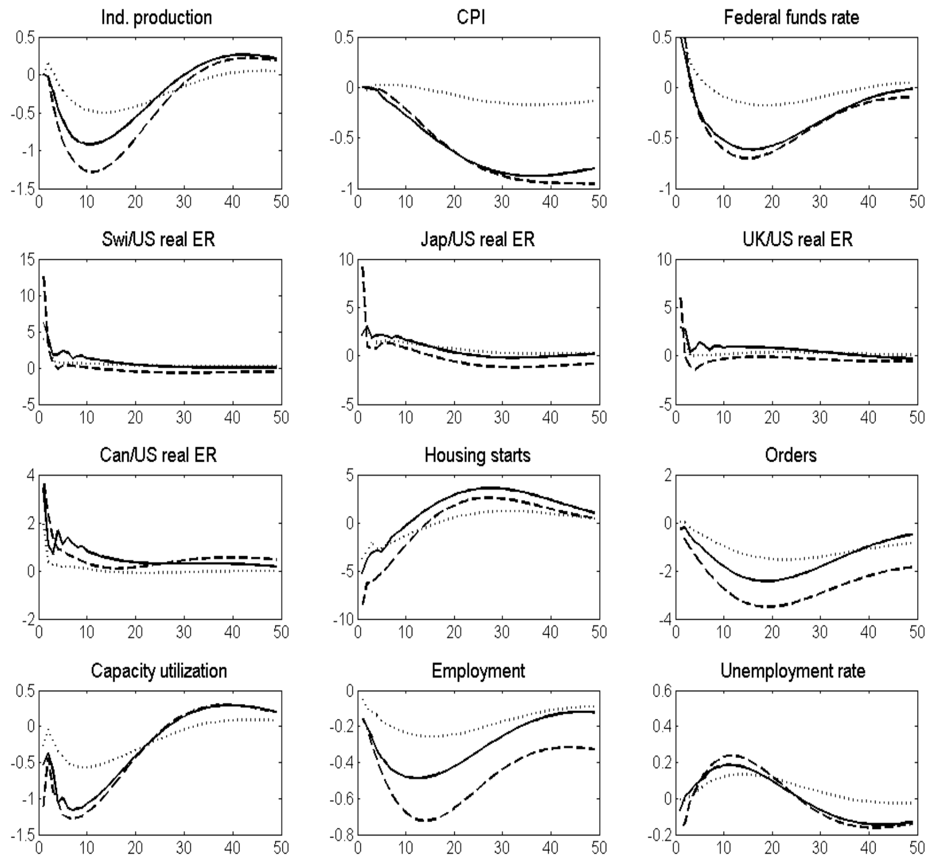

Figure 4: Dynamic Factor Model impulse response functions to a contractionary monetary policy shock increasing the federal funds rate by 50 basis points, for different specifications of the number of static (r) and dynamic (q) factors. Solid line: $r = 16$, $q = 4$. Dotted line: $r = 16$, $q = 7$. Dashed line: $r = 10$, $q = 4$. Vertical axis: percentages.

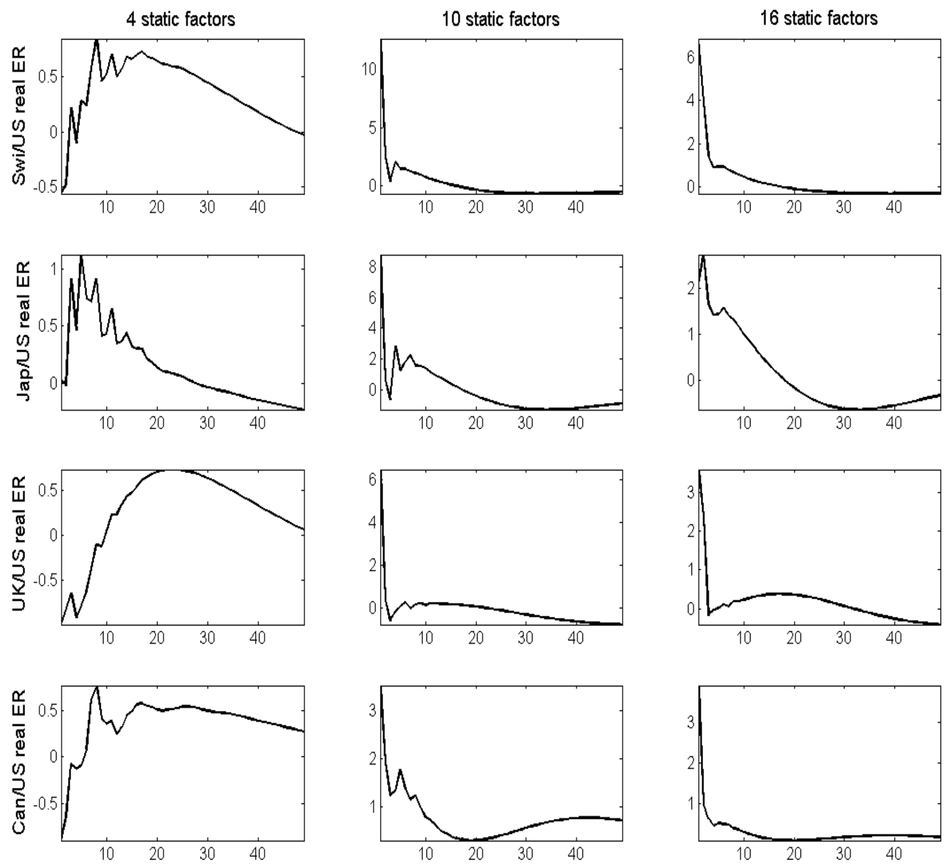

Figure 5: Dynamic Factor Model impulse response functions to a contractionary monetary policy shock increasing the federal funds rate by 50 basis points, for different specifications of the number of static factors ($r = 4, 10, 16$). Vertical axis: percentages.