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

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Abstract

We use the structural factor model proposed by Forni, Giannone, Lippi and Reichlin (2007) to study the effects of monetary policy. The advantage with respect to the traditional vector autoregression model is that we can exploit information from a large data set, made up of 112 US monthly macroeconomic series. Monetary policy shocks are identified using a standard recursive scheme, in which the impact effects on both industrial production and prices are zero. Such a scheme, when applied to a VAR including a suitable selection of our variables, produces puzzling results. Our main findings are the following. (i) The maximal effect on bilateral real exchange rates is observed on impact, so that the "delayed overshooting" or "forward discount" puzzle disappears. (ii) After a contractionary shock prices fall at all horizons, so that the price puzzle is not there. (iii) Monetary policy has a sizable effect on both real and nominal variables. Such results suggest that the structural factor model is a promising tool for applied macroeconomics.

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1 Introduction

Since Sims' (1980) seminal paper, structural vector autoregression models have been a major tool for empirical macroeconomics. Much work has been devoted to the effects of exogenous monetary policy shocks. In this context, a few puzzles have emerged. Here we focus on two of them, i.e. the price puzzle (prices react positively to a contractionary policy; Sims, 1992) and the "delayed overshooting" or "forward discount" puzzle (exchange rates react to monetary policy with a large delay; Eichenbaum and Evans, 1995; Grilli and Roubini, 1995). Influential papers argue convincingly that such puzzles could be due to a deficient information set (Sims, 1992; Bernanke, Boivin and Eliasz, 2005, BBE from now on). 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, BBE).

On the other hand, the delayed overshooting puzzle appears to be robust to different VAR specifications and identification schemes (Scholl and Uhlig, 2005). Moreover, 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.

Adding further variables to the data set could in principle enlarge the estimated response of prices and/or solve the delayed overshooting puzzle. However, we do not have criteria to determine *a priori* how many and which variables should be added. Furthermore, we cannot add too many variables, since estimates would become inaccurate. In short, insufficient information is a problem which cannot be easily solved within the VAR framework (see however Banbura, Giannone and Reichlin, 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, Hallin, Lippi and Reichlin, 2000; Forni and Lippi, 2001, Stock and Watson, 2002a, 2002b; Bai and Ng, 2002; Bai, 2003). Such models have been successfully used for forecasting (Stock and Watson 2002a, 2002b, Forni, Hallin, Lippi and Reichlin, 2005) and the construction of coincident indicators (Altissimo, Cristadoro, Forni, Lippi and Veronese, 2006).

Recently, Forni, Giannone, Lippi and Reichlin (2007, FGLR from now on) proposed a factor model for structural macroeconomic analysis. Macroeconomic variables are represented as the sum of a common component and an idiosyncratic component. The idiosyncratic components are not necessarily orthogonal to each other (i.e. the factor model is "approximate") and, resulting from measurement errors or sectoral sources of variation, 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 and the impulse response functions can be consistently estimated by means of a relatively simple procedure. 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 we use the FGLR model and the related estimation procedure to analyze the effects of exogenous monetary policy shocks. We use 112 US monthly macroeconomic series covering the flexible exchange rate period March 1973 — November 2007. We identify the monetary policy shock 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. We find 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 we find reasonable responses for many economic variables.

Our paper is closely related to BBE. The general line of research is the same. However, there are a few noticeable differences. First, we use a pure structural factor model, whereas BBE use a mixture of a factor model and a VAR model (the FAVAR model). From this point of view, our paper is closer to Stock and Watson (2005) and Giannone, Reichlin and Sala (2004). Second, we focus on both the price puzzle and the delayed overshooting puzzle, and argue that the delayed overshooting puzzle could not be solved within a FAVAR. Third, concerning the price puzzle, we get a more clear-cut result, i.e. prices react negatively to a contractionary policy even in the short run, and the size of the response is considerably larger.

The paper is structured as follows. Section 2 presents the factor model and the estimation procedure and discusses the relation between our model, VAR and FAVAR. Section 3 is devoted to the empirical analysis. Sections 3.1 to 3.3 are preliminary; Sections 3.4 and 3.5 show the results; Section 3.6 is devoted to a robustness analysis. Section 4 concludes.

2 Theory

In this section we provide a presentation of the FGLR model and the related estimator. FGLR is a special case of the generalized dynamic factor model proposed by Forni, Hallin, Lippi and Reichlin (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 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

We assume that each variable x_{it} of our macroeconomic data set 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, we could say that they are not "macroeconomic" shocks. For variables related to particular sectors, the idiosyncratic component may reflect sector specific variations (with a slight abuse of language we could 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

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

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.[1]

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.

2.2 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.

[1] 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.

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 we have just 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 we may have pro-cyclical as well as counter-cyclical behaviors); 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, we need a larger r.

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 $R = (1 \ 0 \ \cdots \ 0)'$.[2] With $q > 1$, $r = q(s + 1)$ is required to encompass the MA(s) case.

2.3 Identification

As observed above, our assumptions ensure identification of the common components; 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 $c_i(L) = b_i(L)H' =$

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

$a_i(I - D_1 L - \cdots - D_p L^p)^{-1} S$. However, 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 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 $B_m(L) = C_m(L)H$, we assume 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. Whereas we describe above the case of just identification, restriction 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 we could identify a demand shock by minimizing some function of its long-run effects on several monetary variables (which are not necessarily of direct interest for the analysis); or we could in principle identify the monetary policy shock by imposing minimization of the sum of the squared impact effects on many slow-moving variables, like prices and industrial production indexes.

In this paper we adopt a traditional scheme with $m = q$ to help comparison with VAR results. Nonetheless, we think that the possibility to identify by 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

Coming to estimation, we proceed as follows. First, starting with an estimate $\hat{r}$ of the number of static factors, we estimate the static factors themselves 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: our 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 our estimated factors are $\boldsymbol{f}_t = \hat{A}_n'(x_{1t} x_{2t} \cdots x_{nt})'$.

Second, we set a number of lags $\hat{p}$ and run a VAR($\hat{p}$) 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, we obtain an estimate of a non-structural representation of the common components 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 $\hat{S} = \hat{K}\hat{\mathcal{M}}$, our estimated matrix of non-structural impulse response functions is

$$\hat{C}_n(L) = \hat{A}_n \hat{D}(L)^{-1} \hat{S}. \tag{2.7}$$

Finally, we obtain $\hat{H}$ and $\hat{b}_i(L) = \hat{c}_i(L)\hat{H}$ $i = 1, \ldots, n$ by imposing our identification restrictions on $\hat{B}_m(L) = \hat{C}_m(L)\hat{H}$.

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 can be obtained by a standard block bootstrap technique. The sampling period is partitioned into blocks (large enough to retain relevant lagged auto- and cross-covariances). The blocks and the corresponding data are then reordered by drawing randomly (with reintroduction) and the impulse-response functions for the reordered data are estimated. A distribution for the 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, we cannot enlarge the number of variables that 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, if we enlarge n the number of primitive shocks q and the associated number of identifying restrictions do not change at all. The 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. However, there are two important differences with the model described above. First, 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: we cannot choose a relatively large r without having to impose a large number of economic restrictions in order to reach identification. Second, 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. This feature, besides hampering comparison with VAR results, renders the method difficult to implement in general. 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.[3]

3 Empirical analysis

3.1 Data and data treatment

Our 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. We added a few real exchange rates (see below) and short-term interest rate spreads between US and some foreign countries, and eliminated discontinued series. 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. However, 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

[3]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 some efficiency loss.

Appendix.

3.2 The number of static and dynamic factors

To determine the number of static factors, we used the criteria proposed by Bai and Ng (2002). We set to 25 the maximum number of factors and computed PC_{p1}, PC_{p2}, PC_{p3}, IC_{p1}, IC_{p2}, IC_{p3}. None of the criteria reaches an internal minimum, with the exception of IC_{p2}, which indicates 16 factors. We then set $\hat{r} = 16$ for our preferred model. Bai and Ng estimators were criticized for easily overestimating the number of factors when the idiosyncratic terms are strongly cross-correlated (Onatsky 2008). As a robustness check, we therefore show a few results for specifications with $r = 10$ and $r = 4$ (see section 3.6).

To determine the number of dynamic factors, we used the criteria proposed by Bai and Ng (2007), Amengual and Watson (2007) and Hallin and Liska (2007). We first computed the residuals of a VAR(2) with the first 16 estimated factors, the number of lags being determined as the average of AIC (3 lags) and BIC (1 lag). Second, following Bai and Ng (2007), we found $\hat{q}_3 = 7$ and $\hat{q}_4 = 10$ when using the covariance matrix of such residuals (parameters $\delta = .1$, $m = 1$) and $\hat{q}_3 = 7$, $\hat{q}_4 = 7$ when using the correlation matrix (parameters $\delta = .1$, $m = 1.25$ for $\hat{q}_3$, $m = 2.25$ for $\hat{q}_4$.). Third, following Amengual and Watson (2007) we computed $\hat{BN}^{ICP}(\hat{y}^A)$ with IC_{p1} and IC_{p2}, and found 7 and 4 primitive factors respectively. Finally, we computed the criteria proposed by Hallin and Liska (2007). The logarithmic criterion always produces either 0 or 1 dynamic factor (depending on the penalty function and the initial random permutation). The "non-log" criterion produces 4 to 6 factors. We conclude that the number of dynamic factors is in the interval 4-7. In our preferred model we use 4 dynamic factors; in the robustness analysis of Section 3.6 we show results for a seven-shock specification.

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. In our analysis of the factor model results we assume that US monetary policy does not affect such country specific components of exchange rates, so that (given the orthogonality of the common and the idiosyncratic components) the impulse-response functions of the common components coincide with the impulse-response functions of the variables themselves.

3.3 The benchmark VAR

Before showing the results for the structural factor model, we 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 our 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, we use a standard recursive scheme (see CEE) where the monetary policy shock is the third shock with the above order of variables.[4]

The impulse-response functions are reported in Figure 1 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

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

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 Dornbrusch (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.

The delayed overshooting puzzle is rather robust to inclusion of additional variables in the VAR and different identifying assumptions (Scholl and Uhlig, 2005). On the other hand, within the recursive identification approach, 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 (we do not show this result here) or within the FAVAR approach. However, in both cases the reaction of prices is nearly zero or still positive during the first year.[5] 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.[6] In our reference VAR 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. Figure 2 displays the impulse response functions of the four series included in the VAR. The dotted lines are the 80% confidence bands obtained with the block bootstrap procedure described in Section 2.4. We set the block length to 52 months, large enough to retain relevant autocorrelations.

The most striking result is that both puzzles disappear. The Swiss/US real exchange rate reacts immediately, with an appreciation of about 2.5% in front of a unite variance

[5] 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.

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

shock that increases the federal funds rate by about 0.2 percentage points, 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. However, the point estimate is perfectly consistent with Dornbrusch (1976)'s overshooting theory, where the maximal effect is predicted to occur contemporaneously. To the best of our knowledge, this result has never been obtained before. In addition, the CPI falls after the second month after the shock. The impulse response function is always negative, although the upper confidence band is slightly above the zero line. This result is more clear-cut than the one obtained by BBE. Moreover, industrial production significantly falls for about 20 months, the response displaying the typical inverted hump-shape. Finally, 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 a qualitative point of view, with predictions about the transmission mechanisms of monetary policy arising in standard theoretical models. Specifically, after a contractionary policy shock, prices fall permanently, industrial production falls temporarily and the real exchange rate appreciates in the month the shock occurs.

Let us come now to 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 suggest a sizable role of the monetary policy in affecting the dynamics of both real and nominal variables.

Figure 3 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. Effects are not negligible, but not significant, since confidence bands are unpleasantly large. The point estimates of the conditional UIP (right column) 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%.[7] 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 4 depicts the impulse response functions of four selected nominal 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 our 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.

Figure 5 displays the response of some selected variables related to demand conditions. Overall the figure 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.[8] 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

[7] 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).

[8] We do not show the response of sales since it is identical to that of consumption.

reducing significantly. This behavior is consistent with the goal of keeping the amount of inventories to a target level. Capacity utilization in manufacturing immediately and significantly falls reaching the minimal level at about two quarters after the shock. Housing starts is the real variable that most rapidly reacts to the monetary policy shock with a large negative impact effect.

Figure 6 displays the impulse response of selected labor market variables. Hours and employment immediately and significantly fall with the largest effect observed after one year. The effects are particularly pronounced from a quantitative point of view for hours in the manufacturing sector. The response of vacancies follows that of employment although the impact effect is smaller. On the other hand, consistently with CEE, unemployment, both number of persons and the rate, reacts to the shock with one month of delay and, like employment, reaches the maximal level after one year.

Table 3 reports the impact effects along with the 10th and 90th percentiles of various components of the industrial production and the CPI. Results in Table 3 can be interpreted, to a certain extent, as an informal test of the reliability of the identifying restrictions using the panel information. Indeed restricting the effects on production and prices to zero is justified by the idea that, on the one hand, it takes some time to adjust production to the new monetary conditions, and, on the other hand, prices are sticky. We should therefore see these restrictions satisfied by each disaggregated component. For all the CPI components the impact effects are nearly zero. On the contrary, for sectoral production indexes we observe significant effects, both positive and negative (starred cells). Notice in particular the impact response of the manufacturing sector, which is significantly negative, consistently with the above results for hours and capacity utilization.

This suggests caution about the identification scheme adopted here. Although reasonable and useful to compare VAR and factor model results, recursive identification has been questioned in the literature, and the above disaggregated result casts further doubts. We believe that it would be interesting to explore alternative identification schemes. In particular, given the nature of the model, a criterion exploiting the cross-sectional information would be quite natural. A possibility is to use sign restrictions on disaggregated industrial production and price indexes. We plan to investigate this issue in a further research.

3.6 Robustness

In this subsection we study the robustness of the results to changes in the number of both dynamic and static factors. Tests in section 3.1 suggest a number of dynamic factors between four and seven. We then repeat the analysis previously done using seven dynamic factors. Identification is implemented in just the same way, the only difference being that now we add the other three real exchange rates after the federal funds rate in our recursive identification scheme. Figure 7 displays the impulse response functions of the main macro aggregates. Results are very similar to the four factors case, even if the response of the CPI is somewhat less pronounced. In particular, the responses of the four exchange rates are very similar to those in the benchmark specification: a sizable immediate appreciation is followed by nearly zero responses.

In our second exercise we go back to the 4 dynamic shock specification and study what happens when varying the number of static factors. The response of prices do not change that much, so that we do not show the results. On the other hand, the response of exchange rates changes substantially. Fig 8 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 factors case is particularly interesting in that, when the number of static and dynamic factors is the same, our model is very much like to a FAVAR model. This suggests that a FAVAR including 4 factors would not be able to solve the delayed overshooting puzzle. This result, we believe, empirically highlights the importance of allowing for a number of static factors substantially larger than that of dynamic factors.

Fig 9 displays the responses of the same variables plotted in Figure 7 for the 10 static factor, 4 dynamic factors case. Again responses are very similar to the benchmark specification. In particular the response of both prices and the real exchange rate have the same shapes as in the benchmark case. Overall results seem to be robust to changes in model specification.

4 Conclusions

In this paper we study the effects of monetary policy shocks within a structural factor model approach. The factor model enables us to handle a large amount of information and therefore to avoid an important limitation of structural VAR models. We identify monetary policy shocks 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 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. Our results highlight the importance of using extended information sets and show that the structural factor model is a promising tool for applied macroeconomics. On the other hand, the estimated impulse response functions of disaggregated production indexes cast doubts on the recursive scheme and suggest that alternative identification restrictions should be explored.

Appendix: Data

Transformations: 1=levels, 4= logs, 5= first differences of logs of the original series.

no.series	Mnemonic	Long Label	Transformation
1	DSPIC96	Real Disposable Personal Income	5
2	A0M051	PERSONAL INCOME LESS TRANSFER PAYMENTS	5
3	PCEC96	REAL PERSONAL CONSUMPTION EXPENDITURES	5
4	A0M059	SALES, ORDERS, AND DELIVERIES, SALES, RETAIL STORES	5
5	IPS10	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	5
6	IPS11	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL	5
7	IPS12	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS	5
8	IPS13	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	5
9	IPS18	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	5
10	IPS25	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	5
11	IPS299	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS	5
12	IPS306	INDUSTRIAL PRODUCTION INDEX - FUELS	5
13	IPS307	INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES	5
14	IPS32	INDUSTRIAL PRODUCTION INDEX - MATERIALS	5
15	IPS34	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	5
16	IPS38	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	5
17	IPS43	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	5
18	PMP	NAPM PRODUCTION INDEX (PERCENT)	1
19	MCUMFN	CAPACITY UTILIZATION: MANUFACTURING (NAICS)	1
20	LHEL	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS	5
21	LHELX	EMPLOYMENT: RATIO; HELP-WANTED	4
22	LHEM	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL	5
23	LHNAG	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES	5
24	LHU14	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS	1
25	LHU15	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS +	1
26	LHU26	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS	1
27	LHU27	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS +	1
28	LHU5	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS	1
29	LHU680	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS	1
30	LHUR	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	1
31	CES002	EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE	5
32	CES003	EMPLOYEES ON NONFARM PAYROLLS - GOODS-PRODUCING	5
33	CES006	EMPLOYEES ON NONFARM PAYROLLS - MINING, THOUSANDS	5
34	CES011	EMPLOYEES ON NONFARM PAYROLLS - CONSTRUCTION	5
35	CES015	EMPLOYEES ON NONFARM PAYROLLS - MANUFACTURING	5

no.series	Mnemonic	Long Label	Transformation
36	CES017	EMPLOYEES ON NONFARM PAYROLLS - DURABLE GOODS	5
37	CES033	EMPLOYEES ON NONFARM PAYROLLS - NONDURABLE GOODS	5
38	CES046	EMPLOYEES ON NONFARM PAYROLLS - SERVICE-PROVIDING	5
39	CES048	EMPLOYEES ON NONFARM PAYROLLS - TRADE, TRANSP., UTILITIES	5
40	CES049	EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE	5
41	CES053	EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE	5
42	CES088	EMPLOYEES ON NONFARM PAYROLLS - FINANCIAL ACTIVITIES	5
43	CES140	EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT	5
44	AWHI	AVERAGE WEEKLY HOURS INDEX: TOTAL PRIVATE INDUSTRIES	5
45	CES151	AVERAGE WEEKLY HOURS GOODS-PRODUCING	1
46	CES155	AVERAGE WEEKLY HOURS MANUFACTURING OVERTIME HOURS	1
47	AWHMAN	AVERAGE WEEKLY HOURS: MANUFACTURING	1
48	PMEMP	NAPM EMPLOYMENT INDEX (PERCENT)	1
49	HSBMW	HOUSES AUTHORIZED BY BUILD. PERMITS:MIDWEST	4
50	HSBNE	HOUSES AUTHORIZED BY BUILD. PERMITS:NORTHEAST	4
51	HSBR	HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS	4
52	HSBSOU	HOUSES AUTHORIZED BY BUILD. PERMITS:SOUTH	4
53	HSBWST	HOUSES AUTHORIZED BY BUILD. PERMITS:WEST	4
54	HSFR	HOUSING STARTS:NONFARM (1947-58);TOTAL FARM&NONFARM(1959-)	4
55	HSMW	HOUSING STARTS:MIDWEST	4
56	HSNE	HOUSING STARTS:NORTHEAST	4
57	HSSOU	HOUSING STARTS:SOUTH	4
58	HSWST	HOUSING STARTS:WEST	4
59	PMDEL	NAPM VENDOR DELIVERIES INDEX	1
60	PMI	PURCHASING MANAGERS' INDEX	1
61	PMNO	NAPM NEW ORDERS INDEX	1
62	PMNV	NAPM INVENTORIES INDEX	1
63	A0M007	NEW ORDERS, DURABLE GOODS INDUSTRIES	5
64	A0M027	NEW ORDERS, CAPITAL GOODS INDUSTRIES, NONDEFENSE	5
65	A1M092	MANUFACTURERS' UNFILLED ORDERS, DURABLE GOODS INDUSTRIES	5
66	FM1	MONEY STOCK: M1	5
67	FM2	MONEY STOCK:M2	5
68	FMFBA	MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES	5
69	FMRNBA	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS	5
70	FMRRA	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS	5
71	FCLBMC	WKLY RP LG COM'L BANKS:NET CHANGE COM'L & INDUS LOANS	1
72	CCINRV	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	5
73	FSPCOM	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE	5
74	FSPIN	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS	5

no.series	Mnemonic	Long Label	Transformation
75	FYFF	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE)	1
76	FYGM3	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.	1
77	FYGM6	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.0	1
78	FYGT1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.	1
79	FYGT10	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.	1
80	FYGT5	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.	1
81	FYAAAC	BOND YIELD: MOODY'S AAA CORPORATE	1
82	FYBAAC	BOND YIELD: MOODY'S BAA CORPORATE	1
83	EXRUS	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)	5
84	EXRCAN	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	5
85	EXRJAN	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	5
86	EXRSW	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	5
87	EXRUK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	5
88	PWFCSA	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS	5
89	PWFSA	PRODUCER PRICE INDEX: FINISHED GOODS	5
90	PWCMSA	PRODUCER PRICE INDEX:CRUDE MATERIALS	5
91	PWIMSA	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS	5
92	PMCP	NAPM COMMODITY PRICES INDEX	1
93	PU83	CPI-U: APPAREL & UPKEEP	5
94	PU84	CPI-U: TRANSPORTATION	5
95	PU85	CPI-U: MEDICAL CARE	5
96	PUNEW	CPI-U: ALL ITEMS	5
97	PUC	CPI-U: COMMODITIES	5
98	PUCD	CPI-U: DURABLES	5
99	PUS	CPI-U: SERVICES	5
100	PUXF	CPI-U: ALL ITEMS LESS FOOD	5
101	PUXHS	CPI-U: ALL ITEMS LESS SHELTER	5
102	PUXM	CPI-U: ALL ITEMS LESS MEDICAL CARE	5
103	CES277	AVERAGE HOURLY EARNINGS - CONSTRUCTION	5
104	CES278	AVERAGE HOURLY EARNINGS - MANUFACTURING	5
105	CES275	AVERAGE HOURLY EARNINGS GOODS-PRODUCING	5
106		REAL FOREIGN EXCHANGE RATE: SWISS	4
107		REAL FOREIGN EXCHANGE RATE: JAPAN	4
108		REAL FOREIGN EXCHANGE RATE: UK	4
109		REAL FOREIGN EXCHANGE RATE: CANADA	4
110		US - CANADA INTEREST RATES SPREAD	1
111		US - JAPAN INTEREST RATES SPREAD	1
112		US - UK INTEREST RATES SPREAD	1

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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.

Table 3: Disaggregated IP and CPI, impact effects.

	10th percentile	point estimate	90th percentile
IP TOTAL INDEX	0	0	0
IP PRODUCTS	-0.0046	0.0165	0.0776
IP CONSUMER GOODS	0.0713	0.1180 (*)	0.2290
IP DURABLE CONSUMER GOODS	-0.1333	0.1159	0.3296
IP NONDURABLE CONSUMER GOODS	0.0589	0.1246 (*)	0.2952
IP BUSINESS EQUIPMENT	-0.1555	-0.0993	0.0097
IP FINAL PRODUCTS	0.0061	0.0463 (*)	0.1318
IP FUELS	-0.4729	-0.2554 (*)	-0.0000
IP RESIDENTIAL UTILITIES	0.7649	1.1631 (*)	1.8329
IP MATERIALS	-0.0957	-0.0246	0.0007
IP DURABLE GOODS MATERIALS	-0.2153	-0.0557 (*)	-0.0281
IP NONDURABLE GOODS MATERIALS	-0.1538	-0.0444	0.0159
IP MANUFACTURING	-0.0904	-0.0522 (*)	-0.0337
CPI ALL ITEMS	0	0	0
CPI APPAREL	-0.0111	0.0099	0.0629
CPI TRANSPORTATION	-0.0502	-0.0341	0.0115
CPI MEDICAL CARE	-0.0060	0.0025	0.0245
CPI COMMODITIES	-0.0230	-0.0151	0.0045
CPI DURABLES	-0.0139	0.0094	0.0244
CPI SERVICES	-0.0180	-0.0014	0.0213
CPI ALL ITEMS LESS FOOD	-0.0066	-0.0040	0.0093
CPI ALL ITEMS LESS SHELTER	-0.0116	-0.0090	0.0038
CPI ALL ITEMS LESS MEDICAL CARE	-0.0052	-0.0054 (*)	-0.0007

Figures

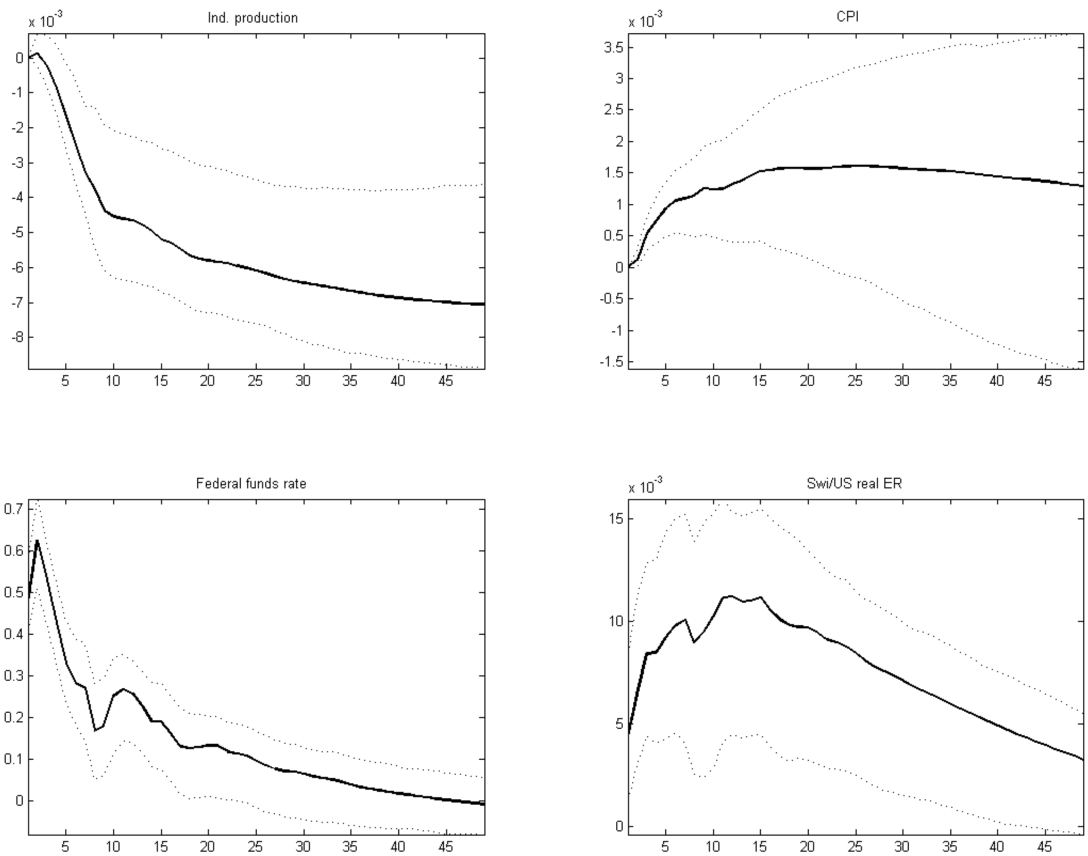

Figure 1: Impulse response functions to a unity variance contractionary monetary policy shock in the VAR. Solid line - point estimates, dotted line - 80% confidence bands.

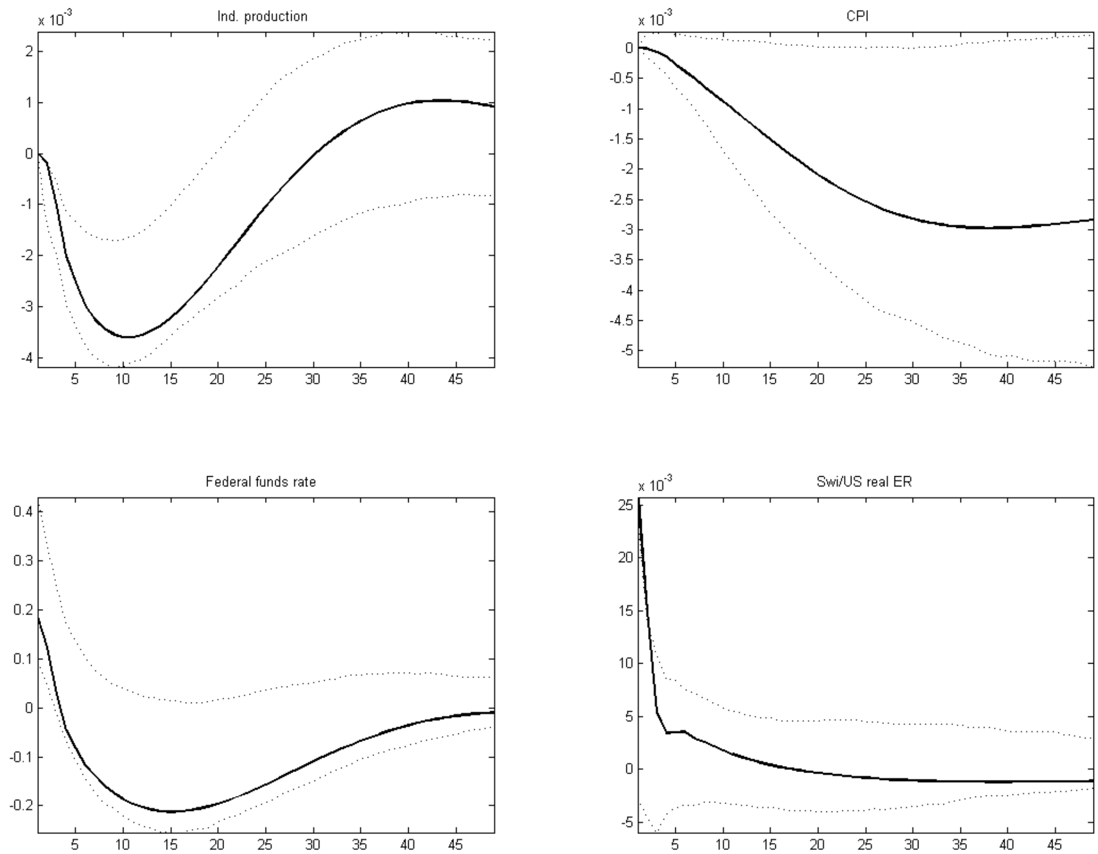

Figure 2: Impulse response functions to a unity variance contractionary monetary policy shock in the benchmark dynamic factor model (16 static factors, 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

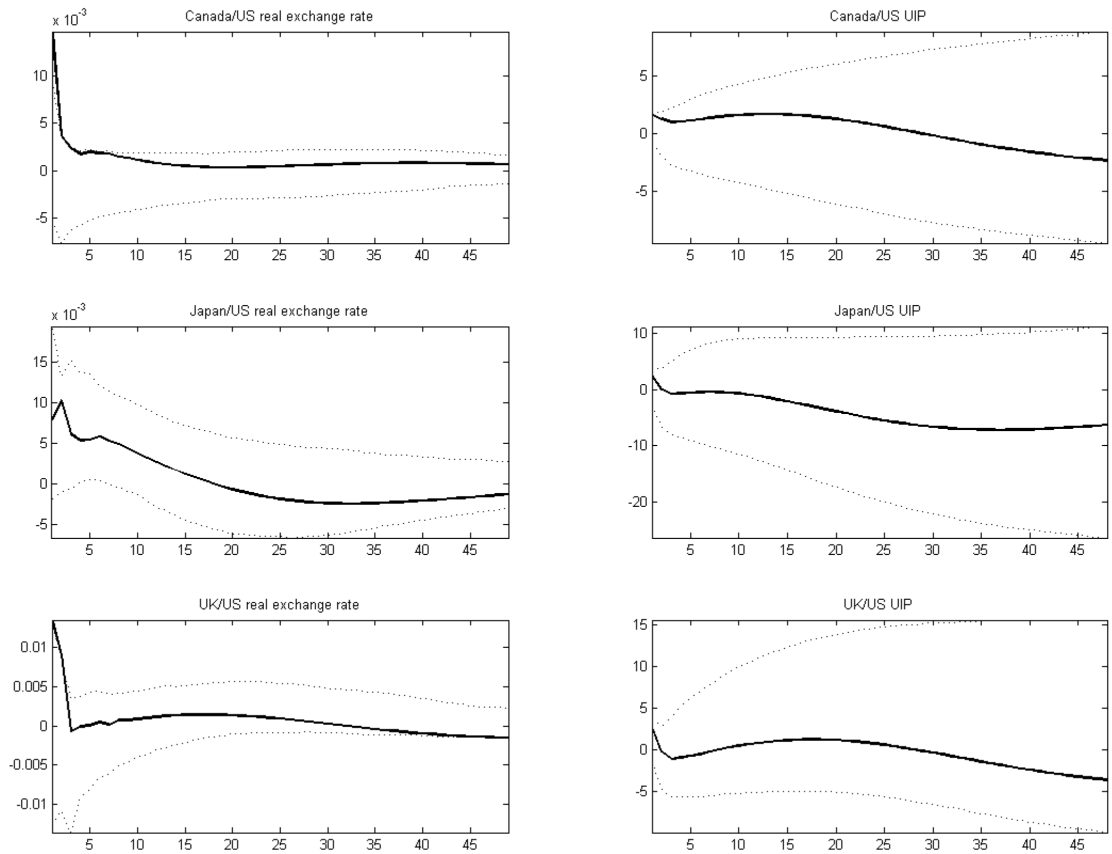

Figure 3: Impulse response functions to a unity variance contractionary monetary policy shock in the benchmark dynamic factor model (16 static factors, 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

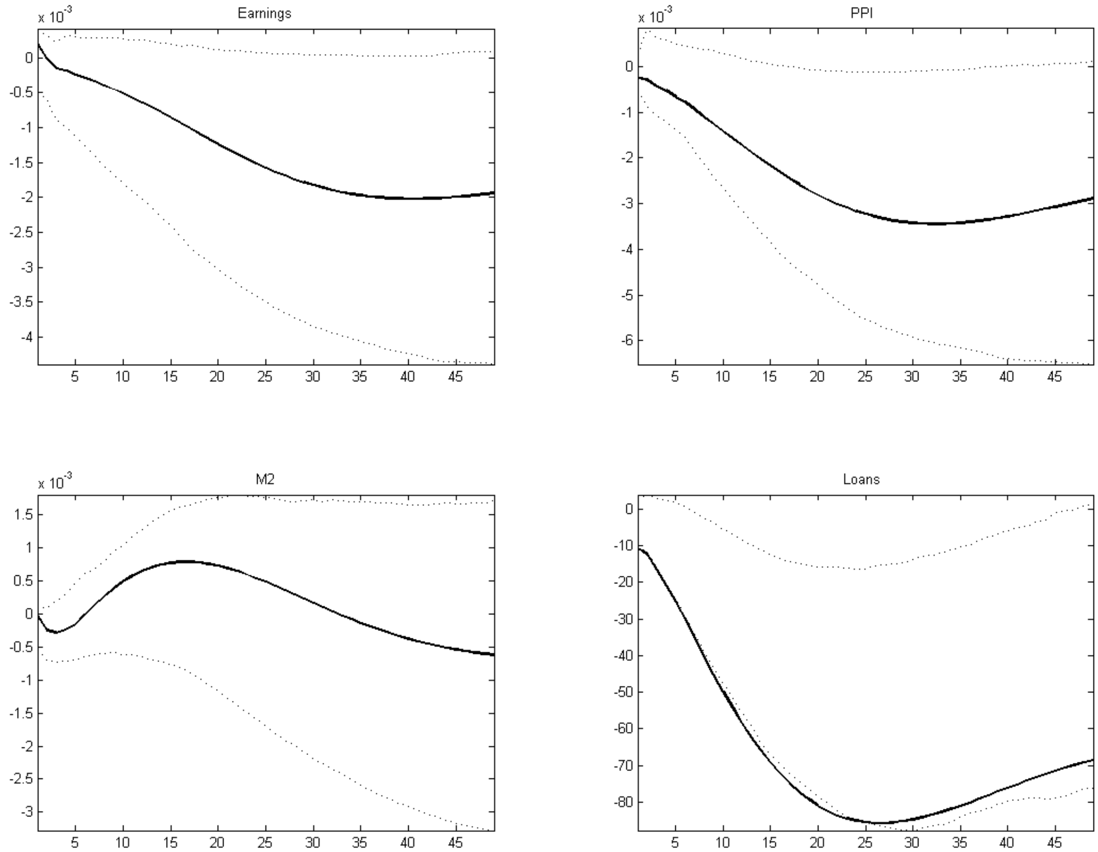

Figure 4: Impulse response functions to a unity variance contractionary monetary policy shock in the benchmark dynamic factor model (16 static factors, 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

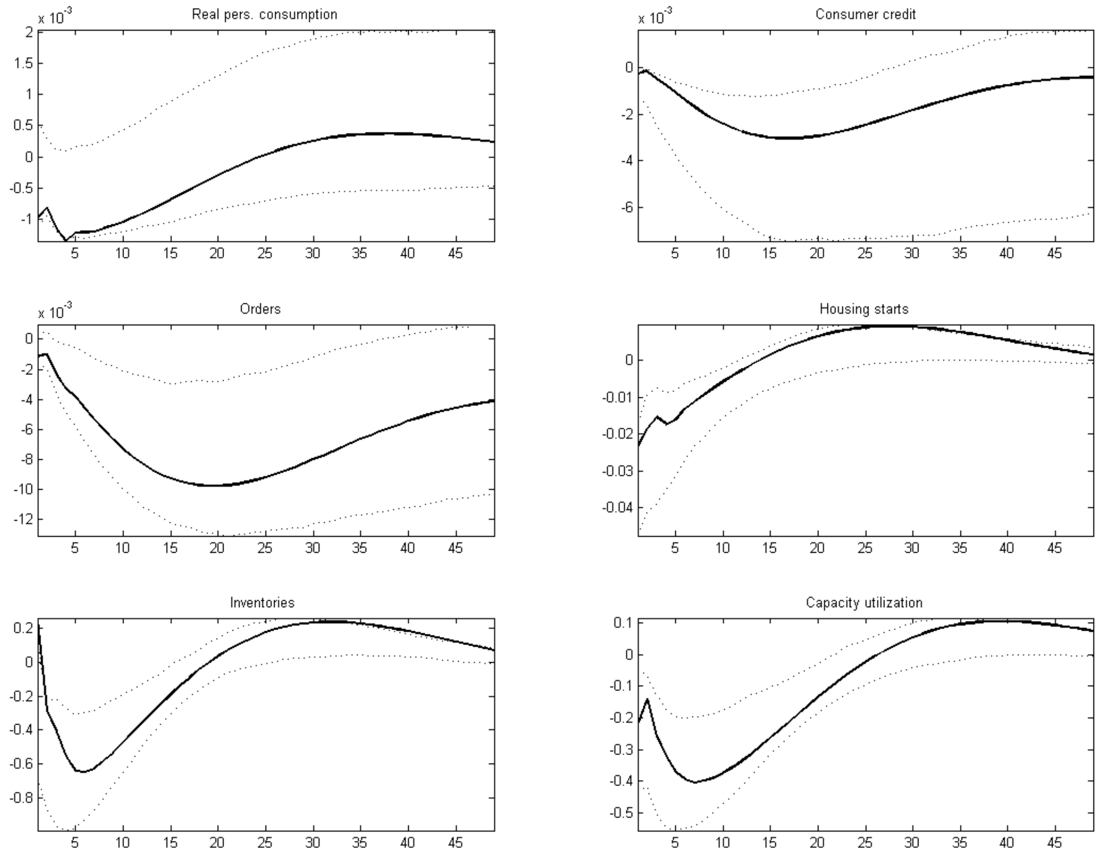

Figure 5: Impulse response functions to a unity variance contractionary monetary policy shock in the benchmark dynamic factor model (16 static factors, 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

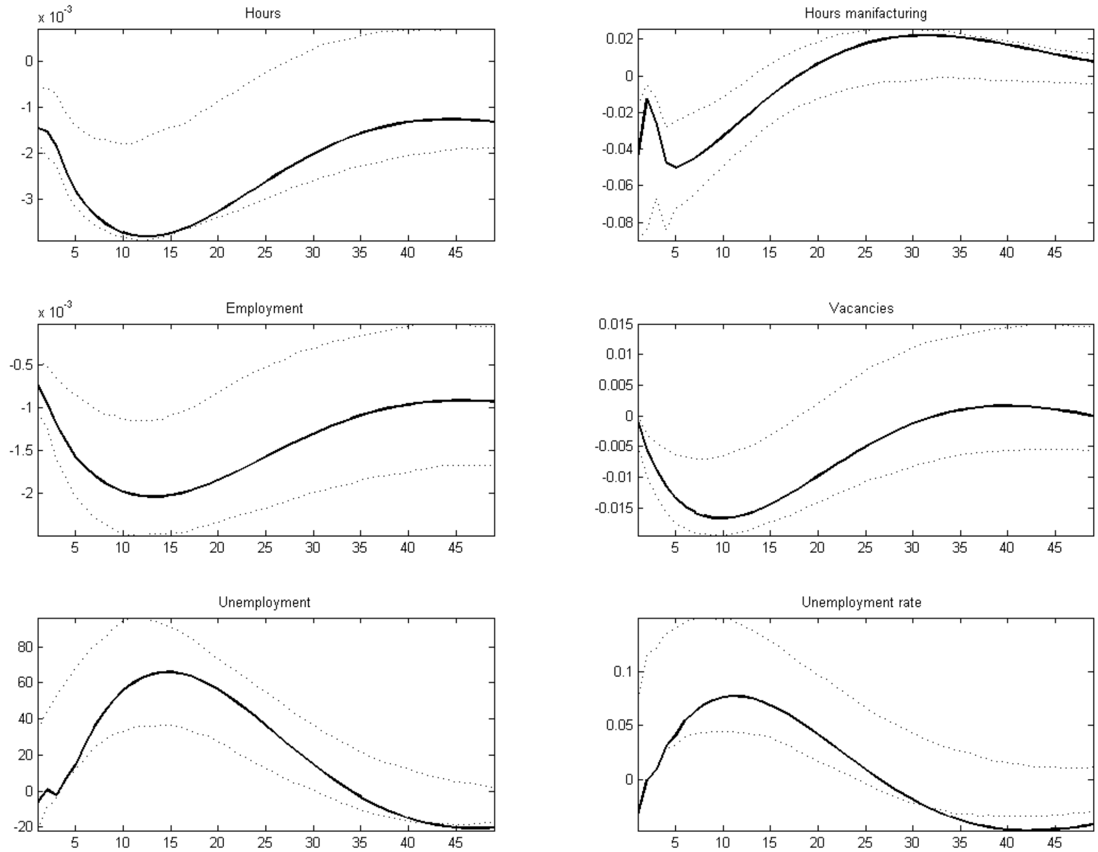

Figure 6: Impulse response functions to a unity variance contractionary monetary policy shock in the benchmark dynamic factor model (16 static factors, 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

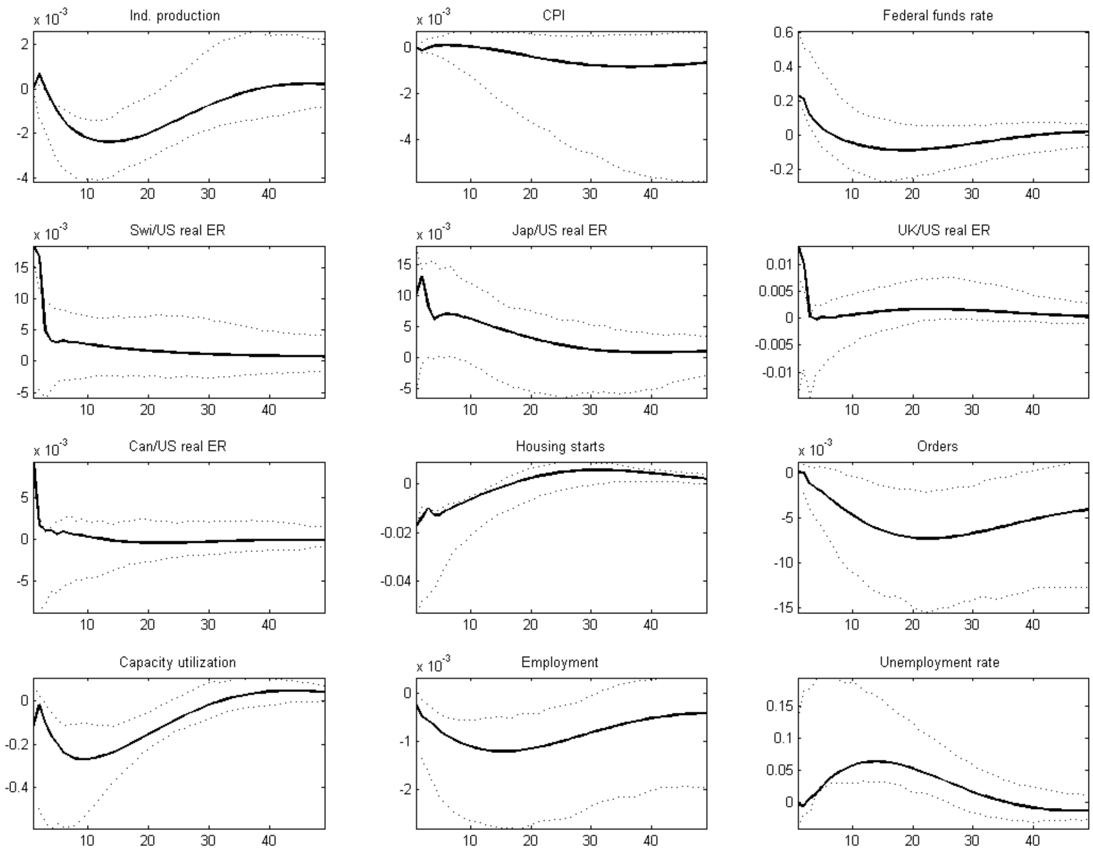

Figure 7: Impulse response functions to a unity variance contractionary monetary policy shock in the dynamic factor model with 16 static factors and 7 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.

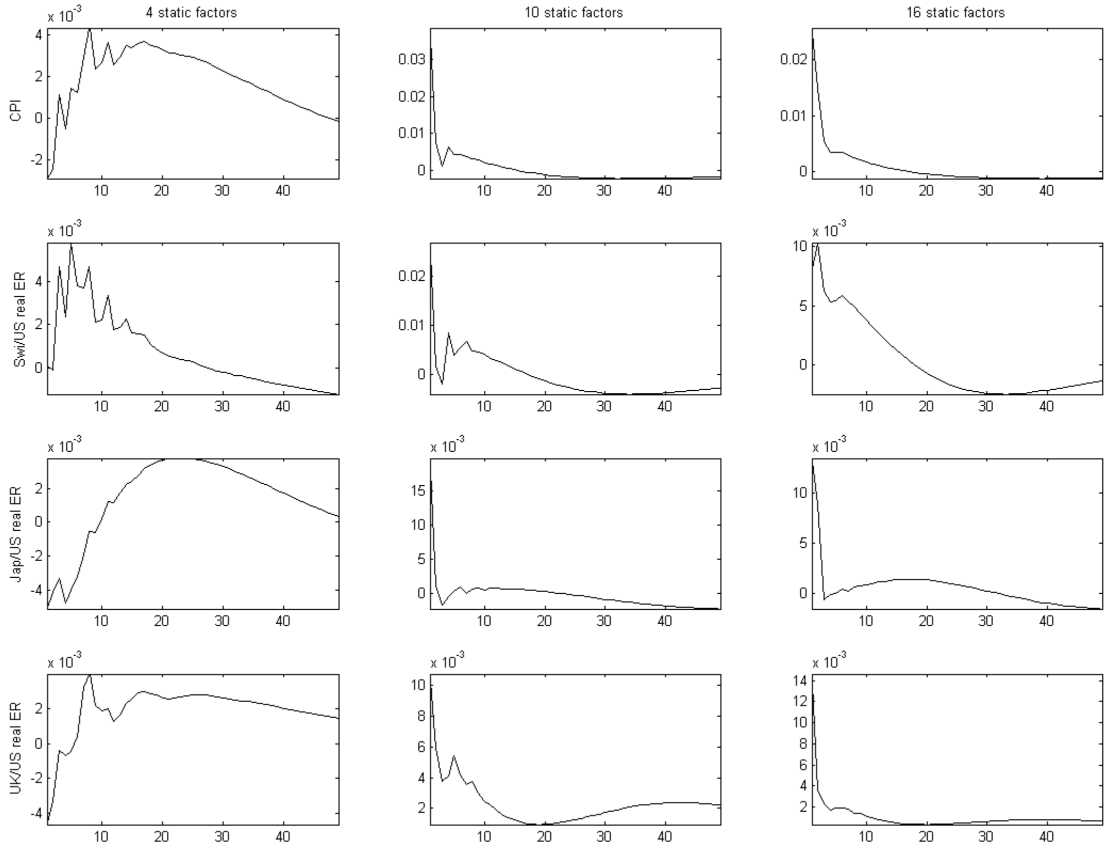

Figure 8: Impulse response functions of real exchange rates to a unity variance contractionary monetary policy shock in the dynamic factor model for a different number of dynamic factors, 4, 10 and 16. Solid line - point estimates.

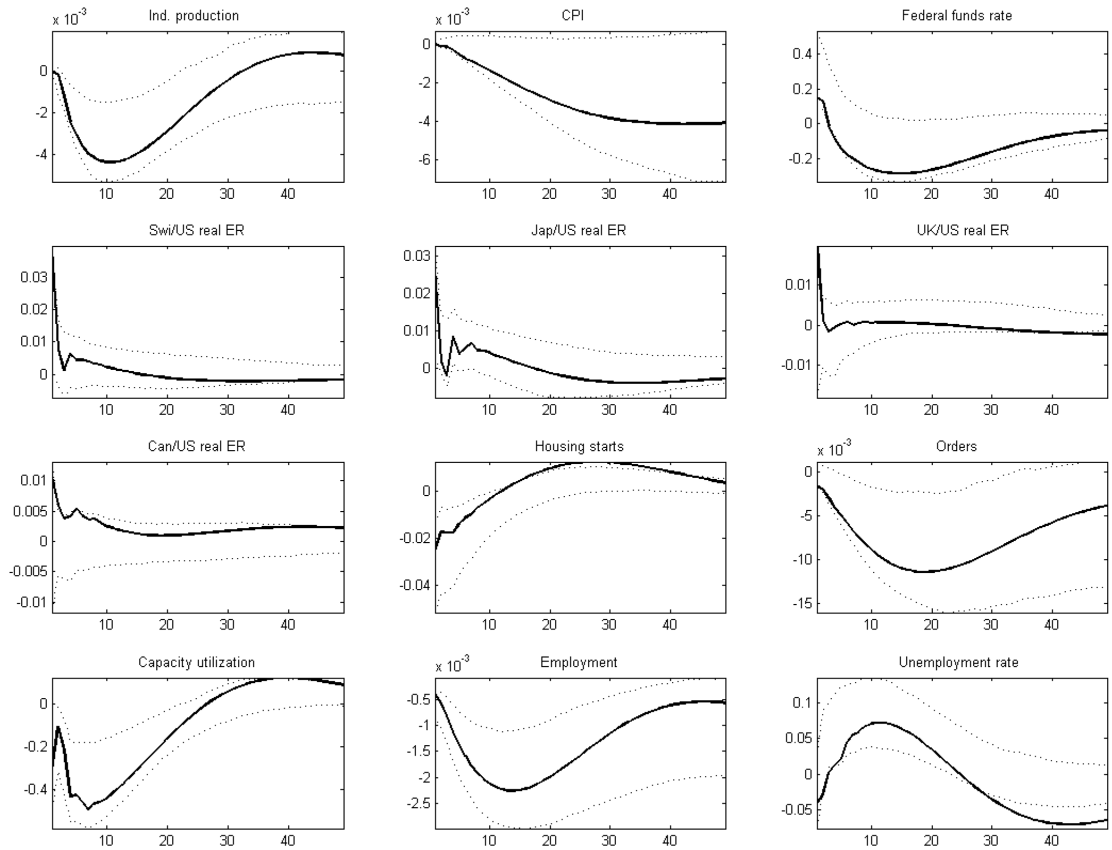

Figure 9: Impulse response functions to a unity variance contractionary monetary policy shock in the dynamic factor model with 10 static factors and 4 dynamic factors). Solid line - point estimates, dotted line - 80% confidence bands.