Inferring Structural Ordering: How does the UK economy respond to international shocks?

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15th May 2016

Abstract

We develop an identification result based on relative variances of the idiosyncratic shocks. The analysis allows to make inferences on the structural ordering of macroeconomic variables in a vector autoregression (VAR) or a Factor-Augmented VAR (FAVAR) context. To illustrate our findings we apply the framework and methods to the study of propagation of international and UK economy wide shocks, based on an extension, initially proposed by Mumtaz and Surico (2009). There is a the FAVAR model developed in Bernanke, Boivin, and Eliasz (2005) in to a small open economy setting. However, the structural ordering implied by the model, whereby UK macroeconomic factors trail the international economic variables, is not supported by the data. The empirical evidence rather reveals an ordering where real activity in the UK emerges at the top of the order, followed by the international economy, and finally the UK policy rate. This suggests characterisation of the UK not as a small open economy, but an (medium-sized) open economy with significant contemporaneous influences on the international economy.

Keywords: international transmission, FAVAR, open economy anomalies, large information, identification of structural VARs.
JEL classification: E52, F41.

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This is an early draft and very much work-in-progress. Please do not quote. Sincere thanks are due to Sean Holly, Toru Kitagawa and Konstantinos Theodoridis for helpful comments and encouraging suggestions. The usual disclaimer applies.

1 Introduction

The objective of this paper is to develop an identification result and to propose inference on the ordering of variables in a recursive structural vector autoregressive (SVAR) model. We apply the results to the study of transmission of shocks and their impact on monetary policy, using a factor-augmented vector autoregression (FAVAR) model proposed by Bernanke et al. (2005) and extended to the small open economy context by Mumtaz and Surico (2009). Following the methodology of FAVAR models, unobserved factors are augmented as variables in a vector autoregressive (VAR) model, where the VAR is then identified using structural restrictions. The resulting SVAR models are widely used for policy analysis and help organize our reading of stylized facts (Christiano et al., 2007; Rubio-Ramírez et al., 2010; Kilian, 2013). Mumtaz and Surico (2009) study the transmission of international shocks to real activity and monetary policy in the UK, using three different identification schemes, and show that their findings are robust across the three chosen structures. We apply our identification result to the same data, the same context, and similar models. To begin, we use frequentist rather than Bayesian inference to allow the data to inform the underlying structure, rather than impose it through a prior. The striking finding is that, the data do not support either of the three alternative SVARs – recursive, nonrecursive and sign restrictions – considered in Mumtaz and Surico (2009). The structures implied by our analysis offer rich new interpretation and open new lines of inquiry.

Three different identification structures are commonly used for SVAR models: recursive schemes (Grilli and Roubini, 1995; Eichenbaum and Evans,1995; Christiano et al., 1999, 2007; Faust and Rogers, 2003; Kilian, 2009; Inoue and Kilian, 2013); nonrecursive schemes (Cushman and Zha, 1997; Kim and Roubini, 2000; Kim, 2001; Uhlig, 2005; Christiano et al., 2007); and sign restrictions (Canova, 2005; Scholl and Uhlig, 2005; Fry and Pagan, 2011; Inoue and Kilian, 2013). Strictly speaking, our identification result applies only to recursive models. However, many nonrecursive or sign-restriction identified SVARs also include structural zeroes. The variables in such models can ordered in such a way as to place most of these zeroes in the upper triangle of the contemporaneous impulse response matrix; see, for example, Giacomini and Kitagawa (2015). This implies corresponding causal ordering restrictions which can also be verified by our identification result.

The identification result is based on relative variation of the variables in the SVAR. In this sense, our work is related to previous literature on identification by relative variances and also to conventional wisdom in SVAR modelling that variables with smaller variances should appear towards the top of the causal order (Rubio-Ramírez et al., 2010; Sims, 2012); see also Lippi and Reichlin (1994). Specifically, we show that, for a SVAR(0) model with no lags, but with recursive contemporaneous causation, and with idiosyncratic shocks that are homoscedastic across the variables, the position at the top of the causal order is taken by the variable with the smallest variance. Once this variable is partialled out, the second position is occupied by the variable with the smallest partial variance matrix; and so on. However, the homoscedasticity assumption may be strong in many applications. We show that, for an SVAR(p) model with recursive contemporaneous dependence, the standard deviation of the idiosyncratic shocks can be inferred from the estimate of the error covariance matrix of a reduced form VAR model estimated from the same variables.

In terms of contemporaneous causal ordering, the FAVARs in Mumtaz and Surico (2009) are structured such that latent factors representing the international shocks come first, followed by the factor(s) capturing the domestic (UK) economy, and finally the UK policy rate. Thus, all the three identification schemes – recursive, nonrecursive and sign restrictions – include zero restrictions implied by the placement of the domestic variables at the end of the causal links, and further that, the short-term ineterst rate rate comes at the end. These structural restrictions can be put to test using the identification result proposed in this paper.

Our empirical results indicate that at least one component of the UK domestic economic shocks (that is, at least one domestic latent factor), comes at the top of the causal chain. Given the assumption of a small open economy, this may appear surprising at first blush. However, our findings indicate that the UK is more like a "medium-sized" open economy, in that shocks to UK asset prices lead some features of the international economy in terms of contemporaneous causal ordering. This observation has important implications for the development of international financial and open economy models for the UK, and potentially other similar economies. Then, this paper contributes to the current debate within the literature as to empirical validation of structural assumptions underlying macroeconomic models; see, for example, Stock and Watson (2015).

The paper is organised as follows. Section 2 sets out our model and methodology, including small open economy FAVARs (Mumtaz and Surico, 2009) and our identification results. The data and our empirical results are discussed in section 3, and section 4 collects our conclusions and implications for future research.

2 Models and methodology

We describe first a FAVAR model based on Bernanke et al. (2005) and extended to the small open economy context by Mumtaz and Surico (2009). Next we describe structural restrictions implied by the three SVARs considered in Mumtaz and Surico (2009). Finally, we develop our identification results, first for the case of homoscedastic innovations, and then extended to the case of a SVAR(p) model where the idiosyncratic errors are heteroscedastic across the variables.

2.1 An open economy FAVAR-SVAR model

Consider a SVAR(p) model

$$A_0 y_t = a + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t,\ t = 1, \ldots, T, \tag{1}$$

where y_t is an $k \times 1$ vector, ε_t a $k \times 1$ vector white noise process, normally distributed with mean zero and variance-covariance matrix $\Sigma = diag\left(\sigma_1^2, \ldots, \sigma_k^2\right)$ is a $k \times k$ positive definite diagonal matrix. Note that we assume the idiosyncratic structural shocks to be uncorrelated, as is common in the SVAR literature. The structural parameters $A_0, A_1, \ldots, A_p$ are (at least partially) unknown $k \times k$ matrices, and a is an unknown $k \times 1$ vector. The initial conditions $y_1, \ldots, y_p$ are given.

Usually the idiosyncratic errors are considered IID standard normal, and the contemporaneous structural matrix, A_0, is left unconstrained; see, for example, Giacomini and Kitagawa (2015). However, we rescale the model to allow for heteroscedastic variances by setting the diagonal elements of A_0 to unity. Then, we write $A_0 = I_k - W$, where I_k is the $k \times k$ identity matrix and W is a $k \times k$ structural matrix with zero diagonal elements. The work in this paper relates to the structure of W.

The reduced form VAR representation of the model (1) is

$$y_t = b + \sum_{j=1}^{p} B_j y_{t-j} + u_t, \tag{2}$$

where $b = A_0^{-1} a$, $B_j = A_0^{-1} A_j$, for $j = 1, \ldots, p$, $u_t = A_0^{-1} \varepsilon_t$, and $E\left(u_t u_t'\right) = \Omega = A_0^{-1} \Sigma \left(A_0^{-1}\right)'$. Under fairly general conditions, the reduced form parameters $b, B_1, \ldots, B_p$ are usually identified. But identification of the underlying structural parameters $a, A_0, A_1, \ldots, A_p$ require assumptions on the structure of the SVAR, typically either recursive or nonrecursive zero restrictions, or sign restrictions. Next, we turn to such identification restrictions in the context of an open economy SVAR model.

2.1.1 Specification of the FAVAR model

Following Bernanke et al. (2005) and Mumtaz and Surico (2009), we consider a data-rich FAVAR setting where there is a large panel of around 400 international macroeconomic variables covering 17 industrialised economies, together with about 200 UK domestic economic variables covering asset prices, commodity prices, liquidity and interest rates. We use a FAVAR to model the interaction between the UK economy and the rest of the world which, following Mumtaz and Surico (2009) and Boivin and Giannoni (2009), we initially treat as the "foreign" block. This

FAVAR aggregates the above around 600 variables into a small number of unobserved factors, and builds a small-scale SVAR model based on these factors, plus the domestic policy rate taken on its own. In the current context, the principal aim of using the FAVAR is to estimate the dynamic responses of a large number of home variables to foreign shocks. The FAVAR allows one to incorporate a large amount of information in the model in a very simple manner and therefore nullify the possibility of omitted variable bias. However, the identification results developed here are equally useful in the context of the main alternative to the FAVAR – the global VAR model (Pesaran et al., 2004; Dees et al., 2007).

For the moment, we consider a model with two blocks, one for the UK, which we call "domestic," and one for the rest of the industrialised world, which we call "foreign". Following Mumtaz and Surico (2009), we first order the blocks.[1] The information about the UK (domestic) and rest of the industrialised world (foreign) are summarised into a small number (L) of unobserved factors, $F_t = \left[F_t^* : F_t^{uk}\right]$, where asterisks denote the foreign economies. The UK short-term interest, R_t, is the only observable factor, and together with the unobserved common components it forms a dynamic system that evolves according to the following transition equation (Bernanke et al, 2005):

$$\begin{bmatrix} F_t \\ R_t \end{bmatrix} = B\left(L\right) \begin{bmatrix} F_{t-1} \\ R_{t-1} \end{bmatrix} + u_t, \tag{3}$$

where in line with the reduced form of the SVAR(p) model (2), $B\left(L\right)$ is a conformable lag polynomial of order p, and u_t is the same as above.

Following Bernanke et al. (2005), the unobserved factors are extracted by a large panel of N indicators, X_t, which contain important information about the fundamentals of the economy. The factors and the variables in the panel are related by an observation equation of the form:

$$X_t = \Lambda^F F_t + \Lambda^R R_t + \upsilon_t, \tag{4}$$

where Λ^F and Λ^R are $N \times L$ and $N \times 1$ matrices of factor loadings, and υ_t is a $N \times 1$ vector of zero mean factor model errors. The FAVAR model of Bernanke et al. (2005) is described by (3) and (4).

In developing a small open economy extension, Mumtaz and Surico (2009) consider a foreign block consisting of four factors to the above model, with $F_t^* = \{\Delta Y_t^*, \Pi_t^*, \Delta M_t^*, R_t^*\}$, where ΔY_t^* represents an international real activity factor, Π_t^* denotes an international inflation factor, ΔM_t^* is an international liquidity

[1] As we demonstrate later, this ordering is problematic, because it is not supported by the data. Specifically, the domestic aggregate factor (UK) appears to be at the top of the causal order. However, domestic policy rate is still at the bottom. Nevertheless, we proceed with this ordering for the moment.

factor, and R_t^* denotes comovements in international short-term interest rates. These international factors are identified through the upper $N \times 4$ block of the matrix Λ^F, which is assumed to be block diagonal. The factors are extracted from panel data on international variables for 17 industrialised economies. Specifically, ΔY_t^* is extracted from data on output and consumption for different countries, Π_t^* from data on prices and wages, ΔM_t^* from monetary aggregates, and R_t^* from yields on short term Treasury bills.

In addition, they add a domestic block, where the dynamics of the UK variables are captured by l domestic factors $F_t^{UK} = \left\{F_t^{1,UK}, \ldots, F_t^{l,UK}\right\}$. These domestic factors are extracted from the full panel of UK series. Whereas Mumtaz and Surico (2009) use the leading four principal components from the UK data and do not ascribe economic interpretation to the factors, we extract separate factors for different aspects of the domestic (UK) economy, and then either pick up specific factors or combine these into aggregates. R_t is treated as the monetary policy instrument (Bernenke et al., 2005).

The FAVAR in Boivin and Giannoni (2009) has a related specification for the factor structure. However, unlike Mumtaz and Surico (2009), Boivin and Giannoni do not impose zero restrictions on the factor loadings in the international block of the VAR. In turn, such zero restrictions allow identification of different foreign shocks using a number of alternative identification strategies, which we discuss below. Our model is different from Mumtaz and Surico (2009) in imposing zero restrictions also in the factor structure in the UK block. This is important in our case because our empirical results indicate that at least one of the domestic factors lies at the top of the contemporaneous causal order, and it is then important to identify the corresponding domestic sector(s).

There is rotational indeterminacy in the above factor model (4), so that it is not econometrically identified without a normalisation. Following Bernanke et al. (2005), Mumtaz and Surico (2009) use the standard normalization implicit in principal component factors. We do the same, but in addition, we also extract factors using common correlated effects (Pesaran, 2006) and dynamic factors (Sargent and Sims, 1977; Stock and Watson, 1989).

The dynamics of each domestic variable in X_t is a linear combination of all UK factors, which are linked to the international factors through the transition equation (3). This implies that the response of any such UK variable to a shock in the transition equation (3) can be calculated using the estimated factor loadings, Λ^F and equation (4). This completes the description of the FAVAR reduced form.

2.1.2 Specification of the SVAR(p) model

We need to impose constraints to identify the underlying contemporaneous structural matrix ($A_0 = I_k - W$) of the SVAR(p) model (1). Mumtaz and Surico (2009) consider three different identification schemes, based on recursive ordering, nonrecursive ordering, and a mixture of sign and zero restrictions. Specifically, they order the variables in the FAVAR as follows: $\left[\Delta Y_t^*, \Pi_t^*, \Delta M_t^*, R_t^*, F_t^{UK}, R_t\right]$.

In the recursive scheme, the the contemporaneous impulse response matrix, or the impact matrix, A_0^{-1}, is lower triangular, implying that the rest of the world does not react to UK domestic conditions within the period. Further, on average, the short-term interest rates in the foreign economies react contemporaneously to world activity, inflation, and liquidity but these international factors react to R_t^* with at least one lag. This first assumption is retained across all identification schemes. One major empirical contribution of this paper is to demonstrate that the above causal ordering is not supported by the data. A vast literature on closed and open economies has identified the monetary policy shock by ordering last a short-term interest rate in recursive structural VARs; we demonstrate later that this assumption is supported by the data.

The recursive scheme makes further assumptions, specifically that the contemporaneous causal ordering runs from ΔY_t^* to Π_t^*, and then progressively through $\Delta M_t^*, R_t^*$, and F_t^{UK}, and finally to R_t. This implies the following recursive structural implication in the reduced form VAR errors:

$$\begin{pmatrix} u_{\Delta Y^*} \\ u_{\Pi^*} \\ u_{\Delta M^*} \\ u_{R^*} \\ u_{F^{UK}} \\ u_R \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \times & 1 & 0 & 0 & 0 & 0 \\ \times & \times & 1 & 0 & 0 & 0 \\ \times & \times & \times & 1 & 0 & 0 \\ \times & \times & \times & \times & 1 & 0 \\ \times & \times & \times & \times & \times & 1 \end{bmatrix} \begin{pmatrix} \varepsilon_{\Delta Y^*} \\ \varepsilon_{\Pi^*} \\ \varepsilon_{\Delta M^*} \\ \varepsilon_{R^*} \\ \varepsilon_{F^{UK}} \\ \varepsilon_R \end{pmatrix}. \tag{5}$$

The marks "$\times$" represent freely estimated parameters. As emphasized in Mumtaz and Surico (2009), the recursive identification in small-scale models is typically associated with a number of anomalies such as the price and liquidity puzzles, and the exchange rate and forward discount puzzles. These empirical facts are anomalies because they are inconsistent with the predictions of a number of, though not all, theories. A possible interpretation of the anomalies is that the recursive scheme is unsuited for recovering correctly a policy shock.

In order to improve the identification of the monetary shock, several authors have proposed alternative schemes ranging from nonrecursive to sign restrictions. The success of the alternative schemes in ameliorating the anomalies has been mixed so far. As an alternative, Mumtaz and Surico (2009) consider the following nonrecursive scheme:

$$\begin{pmatrix} u_{\Delta Y^*} \\ u_{\Pi^*} \\ u_{\Delta M^*} \\ u_{R^*} \\ u_{F^{UK}} \\ u_R \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \times & 1 & 0 & 0 & 0 & 0 \\ \times & \times & 1 & \times & 0 & 0 \\ 0 & 0 & \times & 1 & 0 & 0 \\ \times & \times & \times & \times & 1 & 0 \\ \times & \times & \times & \times & \times & 1 \end{bmatrix} \begin{pmatrix} \varepsilon_{\Delta Y^*} \\ \varepsilon_{\Pi^*} \\ \varepsilon_{MD^*} \\ \varepsilon_{MS^*} \\ \varepsilon_{F^{UK}} \\ \varepsilon_R \end{pmatrix}. \tag{6}$$

Following Sims and Zha (2006), the third and fourth rows identify money demand and money supply shocks in the rest of the world, respectively. There are considerable contemporaneous causal implications of the nonrecursive scheme (6). The transmission of shocks originate from world activity and then pass on to world inflation. World money demand and money supply occupy middle positions in the causal order, but their relative ordering is ambiguous. The shocks then pass on to the domestic economy, followed finally by the policy rate. The methods proposed here can be used to validate these causal assumptions.

The third SVAR uses both zero and sign restrictions:

$$\begin{pmatrix} u_{\Delta Y^*} \\ u_{\Pi^*} \\ u_{\Delta M^*} \\ u_{R^*} \\ u_{F^{UK}} \\ u_R \end{pmatrix} = \begin{bmatrix} 1 & - & - & - & 0 & 0 \\ - & 1 & + & + & 0 & 0 \\ + & \times & 1 & - & 0 & 0 \\ + & \times & + & 1 & 0 & 0 \\ \times & \times & \times & \times & 1 & 0 \\ \times & \times & \times & \times & \times & 1 \end{bmatrix} \begin{pmatrix} \varepsilon_{AD^*} \\ -\varepsilon_{AS^*} \\ \varepsilon_{MD^*} \\ \varepsilon_{MS^*} \\ \varepsilon_{F^{UK}} \\ \varepsilon_R \end{pmatrix}, \tag{7}$$

where "+" and "−" represent positive and negative effects, respectively. Unlike the recursive and nonrecursive schemes, world aggregate demand and aggregate supply shocks are now identified by sign restrictions; see Mumtaz and Surico (2009) for further discussion.

This model also contains causal implications that can be tested using our framework. Specifically, the ordering of the foreign factors are undetermined, but they precede the domestic UK economy, which in turn is followed by the short term interest rate. Such causal interpretations emerge in any SVAR(p) model that has zero restrictions. The variables can be ordered, as in Giacomini and Kitagawa (2015), to place the maximum number of zero rows or columns above the diagonal of the contemporaneous impulse response matrix A_0^{-1}. The corresponding causal ordering can then be verified using our identification scheme, to which we turn next.

2.2 Identification of structural ordering

Consider the SVAR(p) model (1), written in terms of the structural matrix W:

$$y_t = a + Wy_t + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t,\ E\left(\varepsilon_t \varepsilon_t'\right) = \Sigma = diag\left(\sigma_1^2, \ldots, \sigma_k^2\right),$$

where W is a $k \times k$ matrix with zero diagonal elements. The reduced form is the following:

$$\begin{aligned} y_t &= \left(I_k - W\right)^{-1} a + \sum_{j=1}^{p} \left(I_k - W\right)^{-1} A_j y_{t-j} + u_t, \\ E\left(u_t u_t'\right) &= \left(I_k - W\right)^{-1} \Sigma \left(\left(I_k - W\right)^{-1}\right)'. \end{aligned}$$

Our maintained assumption is a recursive scheme, formalised as follows.
Assumption 1 (Recursive Structure): *There exists some permutation of the variables in y_t, say $y_t^{[P]} = \left(y_t^{[1]}, \ldots, y_t^{[k]}\right)$, for which the corresponding structural matrix $W^{[P]}$ is a lower triangular $k \times k$ matrix with zero diagonal elements. That is, $W^{[P]} = \left(\left(w_{ij}^{[P]} : w_{ij}^{[P]} = 0 \text{ if } j \geq i\right)\right)_{i,j=1,\ldots,k}$.*

In many contexts and models, the recursive structure may not hold for all the variables in the SVAR(p) model, but only for a selection of variables. This is precisely the context in which our identification results can be useful in validating the causal implications of nonrecursive schemes or any other schemes with zero restrictions. However, even if we know that Assumption 1 holds for some permutation, the order of variables is unknown. The results here are for identification of the true order of variables in the recursive ordering.

One useful result follows immediately from Assumption 1.
Lemma 1. $\left(I_k - W\right)^{-1} = I_k + W$.
Proof of Lemma 1. *Since $W^{[P]}$ is a square matrix, we have the infinite series expansion, $\left(I_k - W^{[P]}\right)^{-1} = I_k + W^{[P]} + \sum_{j=2}^{\infty} \left(W^{[P]}\right)^j$. By Lemma 1.2 in Banerjee and Roy (2014: p.23-24), for any lower triangular matrix A, $A^m = 0$ for any $m > 1$. Since $W^{[P]}$ is lower triangular by* ***Assumption 1****, the result $\left(I_k - W^{[P]}\right)^{-1} = I_k + W^{[P]}$ follows immediately. However, since the structure of both matrix inversion and addition are preserved under permutations, we further have $\left(I_k - W\right)^{-1} = I_k + W$.*

2.2.1 A chicken-and-egg thought experiment

Let us consider the simple case with $k = 2$. Thurman and Fisher (1988) analyse Granger causality between egg-type chicken (as compared to broiler chicken) and production of eggs using annual data for the U.S. Their analysis ignores potential nonstationarity, but this is of minor significance for our thought experiment, which relates to contemporaneous (or Rubin-type) causation. We motivate our simple experiment using data for 1961-2004 from USDA (2005) on annual growth rate of chicken (y_C) and eggs (y_E). First, we assume $p = 0$ and homoscedasticity of the innovations: $\sigma_C^2 = \sigma_E^2 = \sigma^2$. Under recursive structure (**Assumption 1**), and ignoring the time subscript, the true model is either

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{bmatrix} 0 & 0 \\ w & 0 \end{bmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}, \ E\left(\varepsilon\varepsilon'\right) = \sigma^2 I,$$

or,

$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{bmatrix} 0 & w \\ 0 & 0 \end{bmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix}, \ E\left(\varepsilon\varepsilon'\right) = \sigma^2 I.$$

But, which one is it? It is clear that, if chicken precedes eggs in causal ordering (the former model), then $V(y_C) = \sigma^2 \leq \sigma^2(1 + w^2) = V(y_E)$, with the equality holding if and only if $w = 0$. On the other hand, if y_C follows y_E in causal ordering then, $V(y_C) \geq V(y_E)$. It turns out that the variation in growth rate of chicken is about 3.75 times that of eggs, so under the maintained hypothesis of homoscedasticity and no temporal dynamics, eggs must contemporaneously cause chicken.

However, the above analysis ignores potential differences in the variance of idiosyncratic errors (that is, $\sigma_C^2 \neq \sigma_E^2$), as well as temporal dynamics ($p > 0$). Using methods described below, we obtain estimates $\widehat{\sigma}_C = 0.0014$ and $\widehat{\sigma}_E = 0.0065$ using a reduced form VAR(1) model for y_C and y_E. Then, we can write

$$\begin{aligned} \begin{pmatrix} y_{Ct}/\widehat{\sigma}_C \\ y_{Et}/\widehat{\sigma}_E \end{pmatrix} &= \begin{pmatrix} a_C/\widehat{\sigma}_C \\ a_E/\widehat{\sigma}_E \end{pmatrix} + W \begin{pmatrix} y_{Ct}/\widehat{\sigma}_C \\ y_{Et}/\widehat{\sigma}_E \end{pmatrix} + B \begin{pmatrix} y_{C,t-1}/\widehat{\sigma}_C \\ y_{E,t-1}/\widehat{\sigma}_E \end{pmatrix} + \begin{pmatrix} \varepsilon_C/\widehat{\sigma}_C \\ \varepsilon_E/\widehat{\sigma}_E \end{pmatrix}, \\ W &= \begin{bmatrix} 0 & w\frac{\widehat{\sigma}_E}{\widehat{\sigma}_C} \\ 0 & 0 \end{bmatrix} \ or \ \begin{bmatrix} 0 & 0 \\ w\frac{\widehat{\sigma}_C}{\widehat{\sigma}_E} & 0 \end{bmatrix}. \end{aligned}$$

We are now back to the homoscedasticity case, and now contemporaneous causation can be inferred from the estimated error covariance matrix of the VAR model

$$\begin{pmatrix} y_{Ct}/\widehat{\sigma}_C \\ y_{Et}/\widehat{\sigma}_E \end{pmatrix} = \begin{pmatrix} a_C^* \\ a_E^* \end{pmatrix} + B \begin{pmatrix} y_{C,t-1}/\widehat{\sigma}_C \\ y_{E,t-1}/\widehat{\sigma}_E \end{pmatrix} + \begin{pmatrix} \varepsilon_C^* \\ \varepsilon_E^* \end{pmatrix}.$$

Conducting the above inferences, we find that the error standard deviation for chicken is about 20 times as large as that for eggs. So, we can conclude that eggs contemporaneously cause chicken. However, estimates of the above VAR(1) model also indicate that chicken Granger cause eggs, and not the other way round.

2.2.2 Main results

With the basic intuition from the chicken-and-egg thought experiment in place, we can now obtain the identification results. The key intuition is that causal ordering can be inferred from the relative variances. This is not surprising. There are results on identification of macroeconomic variables based on relative variances; see xx and also Lippi and Reichlin (1994) for a related discussion. In the literature on SVARs, this is in line with conventional wisdom that the variable with the smaller volatility comes at the top of the causal order realtive to a variable with larger variance; see also Rubio-Ramírez et al. (2010) and Sims (2012). The following proposition formalises the above result and extends it to the case $k > 2$.

Proposition 1. *Consider the SVAR(p) model (1) with $k > 2$, with no lag structure ($p = 0$), homoscedasticity of the innovations ($\sigma_1^2 = \ldots = \sigma_k^2 = \sigma^2$), and where* ***Assumption 1*** *holds. Then the variable with the smallest variance ($y^{[1]}$) comes at the top of the causal order. Construct the partial covariance matrix of the other variables, after partialling out $y^{[1]}$. The variable with the smallest partial variance ($y^{[2]}$) occupies the second position in the causal order. This iterative procedure recovers the causal order $y_t^{[P]} = \left(y_t^{[1]}, \ldots, y_t^{[k]}\right)$ for the entire vector y_t.*

Proof of Proposition 1. *The proof is by induction. First consider the case $k = 3$. Consider the triangular structure*

$$W = \begin{bmatrix} 0 & 0 & 0 \\ \theta & 0 & 0 \\ \upsilon & w & 0 \end{bmatrix};\ E\left(yy'\right) = \sigma^2 \begin{bmatrix} 1 & \theta & \upsilon \\ \theta & 1+\theta^2 & \theta\upsilon + w \\ \upsilon & \theta\upsilon + w & 1 + \upsilon^2 + w^2 \end{bmatrix}.$$

It is clear that the variable with the smallest variance comes at the top of the causal order. However, the relative order of the other two variables is not clear. Partialling out the first first variable, we have

$$\begin{aligned} E\left(y^{[-1]}\left(y^{[-1]}\right)'\right) &= \sigma^2 \left\{ \begin{bmatrix} 1+\theta^2 & \theta\upsilon + w \\ \theta\upsilon + w & 1 + \upsilon^2 + w^2 \end{bmatrix} - \begin{pmatrix} \theta \\ \upsilon \end{pmatrix} \begin{pmatrix} \theta & \upsilon \end{pmatrix} \right\} \\ &= \sigma^2 \begin{bmatrix} 1 & w \\ w & 1 + w^2 \end{bmatrix}. \end{aligned}$$

It is now clear that the second position in the causal order is taken by the second variable. Hence, the procedure recovers the correct causal order. Now, we run the induction. To be completed.

Let us now generalise to the case of potential heteroscedasticity and $p > 0$. Suppose we knew the standard deviations (or variances) of the innovations for each variable in the SVAR(p). Then, one can simply scale each variable by the corresponding standard deviation and covert the model to the homoscedastic case. **Proposition 1** can then be applied to infer on the causal order. The next result shows how the standard deviations can be estimated.

Proposition 2. *Consider the SVAR(p) model (1) with any number of variables and any lag structure. The innovations are potentially heteroscedastic. Denote the singular value decomposition of the reduced form error covariance matrix* $E(u_t u_t') = \Omega$ *in (2) as* $\Omega = TST'$*, where* S *is the diagonal matrix containing the eigenvalues of* Ω*, and the columns of* T *constitute the corresponding eigenvectors. Then, under* ***Assumption 1*** *(recursive structure), the standard deviations of the idiosyncratic errors constitute the absolute values of the diagonal elements of the matrix* $TS^{1/2}$*. Further, we make the Gaussian (or any other) assumptions necessary to obtain a consistent estimator* $\widehat{\Omega}$*. Then, the idiosyncratic error standard deviations are consistently estimated by the corresponding diagonal elements of* $\widehat{T}\widehat{S}^{1/2}$*.*

Proof of Proposition 2. *Note that, by* ***Assumption 1*** *and* ***Lemma 1****,* $\Omega = (I_k - W)^{-1} \Sigma \left((I_k - W)^{-1}\right)' = (I_k + W)\Sigma(I_k + W)'$*. Now, since the singular value decomposition is unique upto the signs of the eigenvectors, which are the column vectors of* T*. Also,*

$$\begin{aligned}\Omega &= TST' = \left(TS^{1/2}\right)\left(TS^{1/2}\right)' \\ &= (I_k + W)\Sigma(I_k + W)' = \left[(I_k + W)\Sigma^{1/2}\right]\left[(I_k + W)\Sigma^{1/2}\right]'.\end{aligned}$$

Further, the final expression simplifies as

$$\left[(I_k + W)\Sigma^{1/2}\right] = \begin{bmatrix} \sigma_1 & \sigma_2 w_{12} & \dots & \sigma_k w_{1k} \\ \sigma_1 w_{21} & \sigma_2 & \dots & \sigma_k w_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_1 w_{k1} & \sigma_2 w_{k2} & \dots & \sigma_k \end{bmatrix}.$$

However, while the signs of the eigenvectors are not identified, they can be fixed by the observation that diagonal elements of $\left[(I_k + W)\Sigma^{1/2}\right]$ *are positive. This implies that diagonal elements of* T *must be positive as well, since the diagonal elements of* S*, which are eigenvalues of a symmetric positive definite matrix* Ω *are positive. Hence, in drawing the correspondence between* $\left(TS^{1/2}\right)$ *and* $\left[(I_k + W)\Sigma^{1/2}\right]$*, one needs to make sure that the diagonal elements of* T *are non-negative. If any of these elements are negative, we flip the sign of the entire corresponding column, and denote the matrix transformed thereby as* T^**. Now, by* *the uniqueness of the above representation, that is,* $T^*S^{1/2} = \left[(I_k + W)\,\Sigma^{1/2}\right]$, *we see that the diagonal elements of* $T^*S^{1/2}$ *are the standard deviations of the idiosyncratic innovations. In terms of consistency, all the above steps go through when* Ω *is replaced by its consistent estimator* $\widehat{\Omega}$, *and the singular value decomposition is based on this estimator. Thus, we can obtain consistent estimators* $\widehat{\sigma}_1, \ldots, \widehat{\sigma}_k$.

A Proposition with more explicit asymptotic results will be added later. Finally, we have the identification result for the order of the arbitrary heteroscedastic SVAR(p) model.

Proposition 3. *Consider the SVAR(p) model (1) with* $k > 2$, *with arbitrary lag structure (*$p = 0$*), arbitrary heteroscedasticity of the innovations, and where* ***Assumption 1*** *holds. Scale each variable by its standard deviation estimated using* ***Proposition 2****. That is:* $y_{[S]1t} = y_{1t}/\widehat{\sigma}_1, \ldots, y_{[S]kt} = y_{kt}/\widehat{\sigma}_k$. *Estimate the error covariance matrix from the reduced form VAR(p) model based on the standardised variables. Then the variable with the smallest variance (*$y_{[S]}^{[1]}$*) comes at the top of the causal order. Construct the partial covariance matrix of the other variables, after partialling out* $y_{[S]}^{[1]}$. *The variable with the smallest partial variance (*$y_{[S]}^{[2]}$*) occupies the second position in the causal order. This iterative procedure recovers the causal order* $y_{[S]t}^{[P]} = \left(y_{[S]t}^{[1]}, \ldots, y_{[S]t}^{[k]}\right)$ *for the entire vector* y_t.

Proof of Proposition 3. *The proof is a simple consequence of* ***Proposition 1*** *and* ***Proposition 2****, noting that* ***Proposition 2*** *addresses the issue of potential heteroscedasticity and also the lag structure which is already conditioned upon. Then,* ***Proposition 1*** *needs to simply be applied to the partial covariance matrix of the scaled variables, where the effect of the lag structure is partialled out. Then, the steps in* ***Proposition 1*** *identifies the true underlying causal structure of the variables.*

Having obtained our identification results and inference in the general case, we can now proceed to our application. Standard errors can be obtained by the application of the wild bootstrap; the parametric bootstrap is also available here (xxxx). If the structural assumptions are supported by the data, one can then proceed to estimation of a corresponding SVAR(p) model by imposing the structure. These results take the literature forward by allowing us to verify some of the structural assumptions inherent in the SVAR literature, and therefore helps in identifying specific shocks: monetary policy shocks, demand shocks, and so on. Validation of structural assumptions underlying macroeconomic models is a matter of considerable importance; see also Stock and Watson (2015).

3 Data and results

We use the same data as Mumtaz and Surico (2009), who kindly provided the data on their website, and the same context. The methods and models are also similar, except for two important details. First, our objective is primarily to validate the structural implications of the different models. For this purpose, we develop identification results and corresponding inferences. Second, we use similar inferences but in a frequentist, rather than Bayesian, framework. Our main new results relate to identification of causal order, and these results can be translated into Bayesian inferences. In principle, such Bayesian inferences offer more precise evaluation of model uncertainty, in this case relating to different identifying structural assumptions. However, there is also a cost. Bayesian inferences are subject to specification of prior information. Hence, one should carefully evaluate what information, relating to the validity of the structural assumptions, arise from the data and what comes from the prior. Here, we wish to abstract from these issues and therefore conduct frequentist inferences. All computations are done using Stata 14.1.

3.1 Data

We use quarterly data from 1974Q1 to 2005Q1. The data set spans the UK and 15 other OECD countries and 600 data series. We refer to the UK as the "domestic" economy. The "foreign" countries are Canada, United States, Germany, France, Italy, Belgium, Netherlands, Portugal, Spain, Finland, Sweden, Norway, Austria, Australia, and Japan. The foreign block includes most of the UK's main trading partners and the major industrialised economies across the world. There are minor variations from Mumtaz and Surico (2009) in the choice of countries, and we also make only a limited choice of variables to obtain precise interpretation of the unobserved factors. We point to these variations later, as and when they arise.

There is another crucial difference. Mumtaz and Surico (2009) extract the factors Λ^F in (4) by principal components analysis. We also use principal component factors, but also in addition extract factors by common correlated effects (Pesaran, 2006), which is useful in large N large T settings, and dynamic factor models (Sargent and Sims, 1977; Stock and Watson, 1989), which is useful for explicitly modeling temporal dynamics.

All variables are individually subjected to augmented Dickey-Fuller unit root tests (Dickey and Fuller, 1979) and suitably converted into stationary series. This implies that, in some cases, data for different countries are subjected to different transformations to stationarity. One can also use panel data tests for stationarity or unit roots (Hadri, 2000; Im et al., 2003), which we have not done. The stationary series are then standardised before being subjected to factor extraction. Our central analysis is based on estimated dynamic factors, because in our view, they represent most precisely the temporal variation in macroeconomic aggregates; we view this as crucial to our implementation of VAR-type models. However, we also verify that the findings are robust to the choice of factor extraction methods.

3.1.1 "Foreign" countries

For each "foreign" country, we use data on real activity, inflation, money and interest rates. For real activity, we use year on year growth rate of per capita income across 11 countries to extract the factors; less Belgium, Netherlands, Portugal and Sweden.

Unit root tests indicate inflation to be nonstationary in most countries. Hence, inflation is measured by quarterly change in year on year growth of the consumer price index in 18 countries, including all of the above countries, but also including Luxembourg, Greece and Ireland.

The series on money consist of a range of monetary aggregates from narrow to broad, but we use M3 for most countries, except M2 for Japan, the Netherlands and Norway, and M1 for Austria. Year on year growth rates are nonstationary for most countries, and hence quarterly change of growth rates are used, except for Australia, Japan and Sweden, for which year on year growth rate is stationary. We use data on 11 monetary authorities, less Belgium, Finland, France, Italy and Portugal, and including the Euro Area.

We have data on a wide range of short-term interest rates for the countries, and use quarterly changes in yields on 3 month Treasury Bills in most cases, except for Belgium, France and Germany, for which we use quarterly changes in the headline interest rate. The extracted factors are based on data for 14 countries, less Canada and Norway, but including China.

The extracted factors by the three methods are very similar and show nice dynamics (Figure 1). There is a small lead in the dynamic factor, which is because it is a one-quarter ahead prediction. As discussed before, we use the one-quarter ahead dynamic factor predictions as our measure of unobserved factor, and this is because the dynamics is a key component in our methodology to infer on contemporaneous causal structure. These dynamic factors constitute our data on $F_t^* = \{\Delta Y_t^*, \Pi_t^*, \Delta M_t^*, R_t^*\}$.

3.1.2 UK ("domestic") country factors

The data for the UK are very similar in composition to that of the "foreign" block. Mumtaz and Surico (2009) collected many different real activity indicators, inflation series including components of the retail price index, narrow and broad money, and a set of asset prices such as house prices and the effective exchange rate. In addition to these macro variables, they included a large number of disaggregated

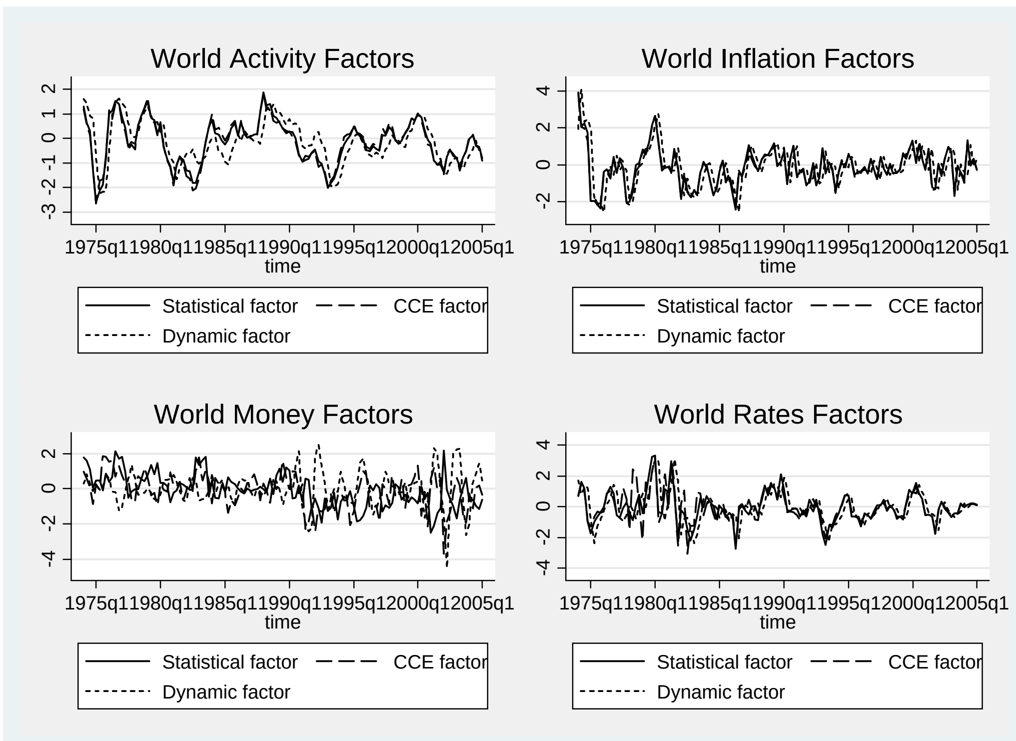

Figure 1: Extracted "Foreign" Factors

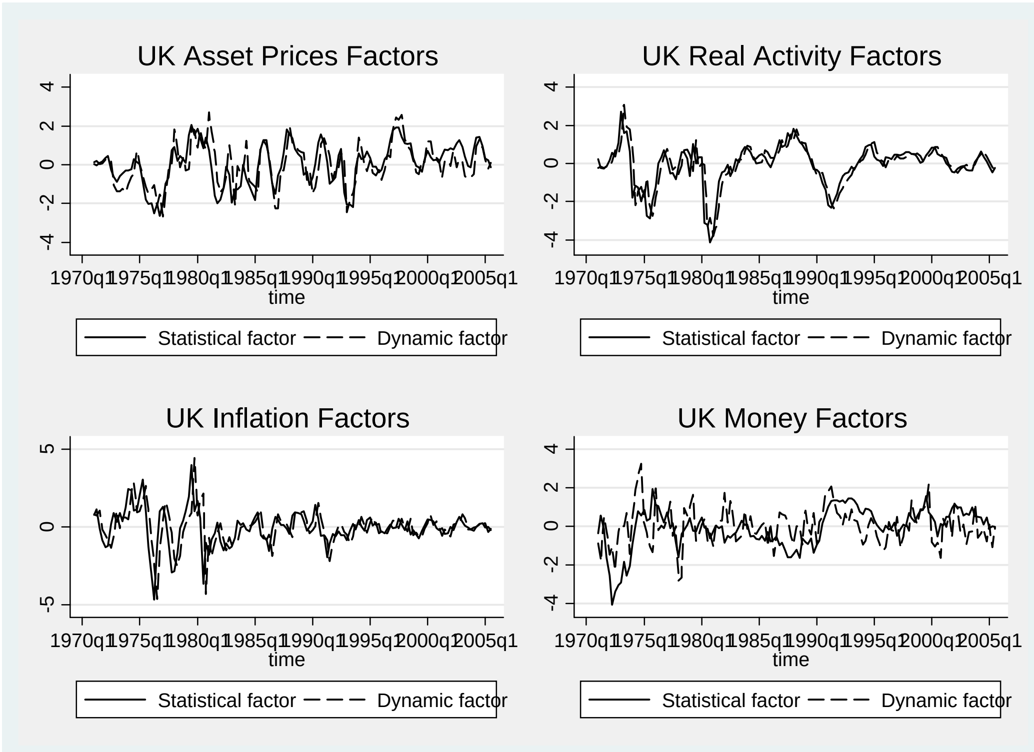

Figure 2: Extracted "Domestic" Factors

deflator and volume series for consumers' expenditure. The Office for National Statistics (ONS) publishes over 140 subcategories of consumer expenditure data in value, volume, and deflator terms, going back to the 1960s (ONS, 2007). This provided a ready-made collection of consistent disaggregated price (and volume) data over a long time period. We make use of only part of the above data. We also use data on the short term interest rate, yields on the UK 3-month Teasury Bills, and take quarterly differences to achieve stationarity; this constitutes our data on R_t.

First, loosely following the "foreign" block above, we extract factors separately for asset prices, real activity, inflation and money (liquidity). Here we use only principal components factors and dynamic factors; common correlated effects (Pesaran, 2006) is not used because the data are strictly not in the nature of panel data, because there is variation across different measures of the same kind of activity, but not across different countries or regions. Figure 2 plots the extracted factors for the four blocks.

The factors show nice dynamics and agree with economic perception. Next, we combine the four predicted dynamic factors as above into a single dynamic

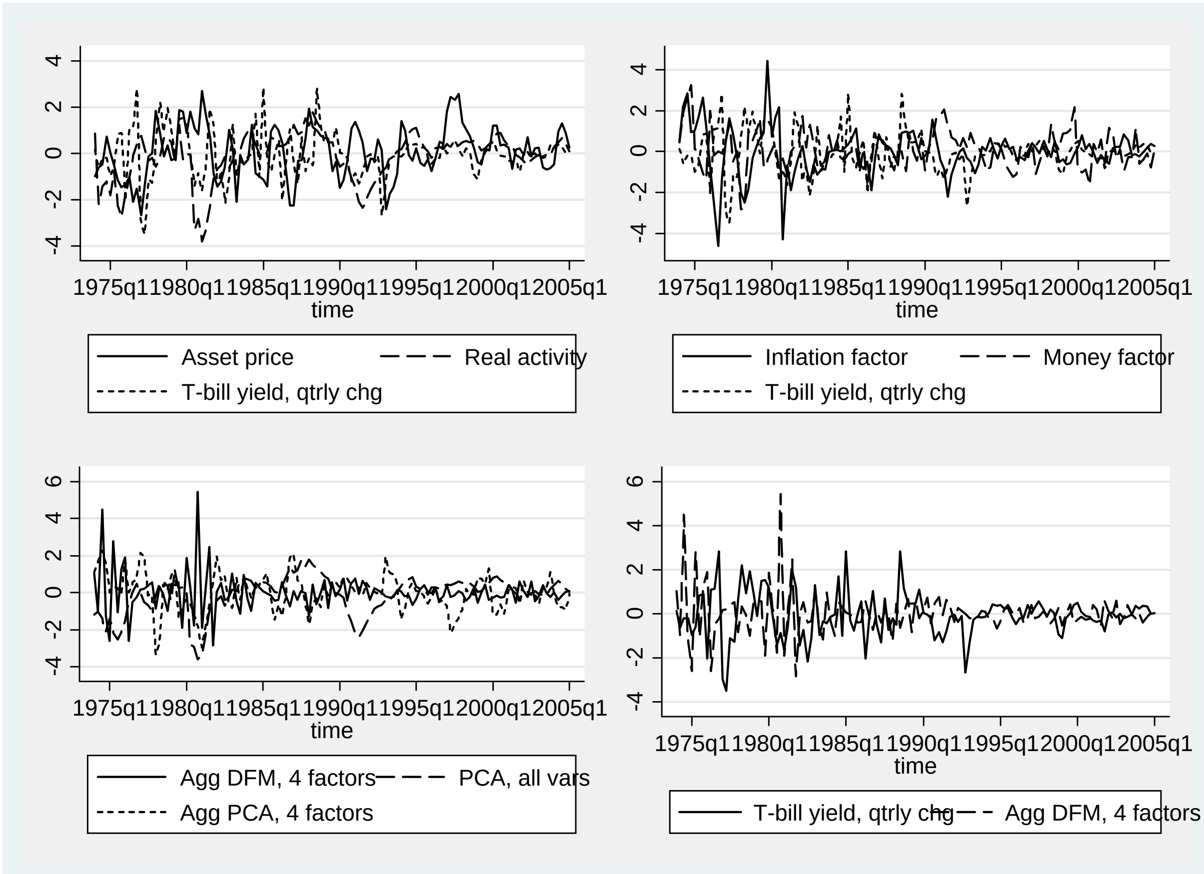

Figure 3: UK ("Domestic") Policy Rate and Aggregate Economy Factors

factor. We plot this aggregate dynamic factor against the policy (interest) rate and the collection of constituent factors (Figure 3). In the following analysis, we first consider the above dynamic factor (of constituent factors) as the measure F_t^{UK} of UK economic activity.

Thus, we have a collection of factors and data, $\left\{\Delta Y_t^*, \Pi_t^*, \Delta M_t^*, R_t^*, F_t^{UK}, R_t\right\}$, as inputs towards further analysis.

3.2 Inference on ordering

Based on the above collection of variables, we now proceed towards evaluation the validity of the structural causal interpretations of the different models: recursive (5), nonrecursive (6) and sign and zero restrictions (7). As discussed above, the main structural implication common to all the three models is that the foreign block, $F_t^* = \{\Delta Y_t^*, \Pi_t^*, \Delta M_t^*, R_t^*\}$, comes at the top of the causal ordering, followed by the aggregate UK factor (F_t^{UK}), and finally the UK short term interest (policy) rate (R_t).

We start with the reduced form VAR in (2). The first stage lag selection is quite crucial, because we want to model most of the temporal dependence while leaving remaining contemporaneous dependence between the variables in the errors. However, lag selection statistics are very mixed. SBIC indicates 1 lag, HQIC 4 lags, FPE 6 lags and AIC incates at least 9 lags. We make a subjective judgment and include 3 lags; our results are verified as robust to 2- and 4-lag VARs in the first stage.

Based on the estimated error covariance matrix, we then compute idiosyncratic error standard deviations using **Proposition 2**. Next, we scale the variables using the estimated standard deviation and re-estimate the reduced form VAR. This time, lag selection strongly indicates 1 lag. We collect the estimated error covariance matrix and use **Proposition 3** to infer on the causal structure implied by the data. The following structure is supported:

$$F_t^{UK} \longrightarrow \Pi_t^* \longrightarrow \Delta M_t^* \longrightarrow R_t^* \longrightarrow \Delta Y_t^* \longrightarrow R_t.$$

In line with theory and past work, the "domestic" policy rate is placed unambiguously at the end of the causal chain. This implies that monetary policy shocks can be well-identified from the structural VARs. However, neither of the three SVAR models considered – recursive (5), nonrecursive (6) and sign and zero restrictions (7) – is supported by the data. The main observation is that the "domestic" factor, F_t^{UK}, comes at the top of the causal structure, which constitutes a violation of each of the above models. Why is this so? It can be hypothesized that the position of the UK economy within the world economy is not quite like a small open economy, but rather a "medium-sized" economy. Then, there are some shocks from the UK economy that drive the dynamics of the world economic variables rather than the other way round.

Be that as it may, we estimate a SVAR model based on the modified recursive scheme as follows:

$$\begin{pmatrix} u_{F^{UK}} \\ u_{\Pi^*} \\ u_{\Delta M^*} \\ u_{R^*} \\ u_{\Delta Y^*} \\ u_R \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \times & 1 & 0 & 0 & 0 & 0 \\ \times & \times & 1 & 0 & 0 & 0 \\ \times & \times & \times & 1 & 0 & 0 \\ \times & \times & \times & \times & 1 & 0 \\ \times & \times & \times & \times & \times & 1 \end{bmatrix} \begin{pmatrix} \varepsilon_{F^{UK}} \\ \varepsilon_{\Pi^*} \\ \varepsilon_{\Delta M^*} \\ \varepsilon_{R^*} \\ \varepsilon_{\Delta Y^*} \\ \varepsilon_R \end{pmatrix}. \tag{8}$$

Obviously, this causal structure is supported by the data. The estimates offer good interpretation. To be written up.

3.3 Estimation of an extended model

Next, the question arises as to which features of the UK "domestic" economy might contemporaneously lead the world economy. We suspect this might be the UK asset prices. Therefore, we segregate the "domestic" factors to allow for more intricate dynamics. Our *a priori* reasoning is validated by the data. Indeed, UK asset prices contemporaneously affect world economies. We also estimate a recursive model based on this causal structure. To be completed.

3.4 Impulse responses

To be completed.

4 Conclusion

In this paper, we

New findings

New directions of future research

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