Monetary Policy and Identification in SVAR Models: A Data Oriented Perspective

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January 2010

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Abstract

There is an ongoing debate on how to identify monetary policy shocks in SVAR models. Graphical modelling exploits statistical properties of data for identification and offers a data based tool to shed light on the issue. The information set of the monetary authorities, which is essential for the identification of the monetary shock seems to depend on availability of data in terms of higher frequency with respect to the policy instrument.

Keywords: Monetary Policy, SVAR, Graphical Modelling
JEL *classfication*: C32, E50.

[*] I am grateful to Sergio Destefanis, Emanuel Gasteiger, Giovanni Melina, Marco Reale, Lucio Sarno and Granville Wilson for helpful comments. The usual disclaimer applies.
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Introduction

Studies utilising the structural vector-autoregression (SVAR) approach for the analysis of monetary policy, frequently assume that the monetary authority's information set includes contemporaneous observations of goods market variables, that is, the policy instrument is endogenous to the contemporaneous value of such variables. In addition, a block lower triangular structure based on a Cholesky decomposition is adopted to obtain identification (see Christiano et al. (2005), amongst others). A different perspective, for instance, is offered by Kim and Roubini (2000). They argue that the information set of the monetary authorities depends on availability of data in terms of higher frequency with respect to the policy instrument and adopt a structural decomposition, where the matrix of the contemporaneous relationships derived to obtain identification is sparse.

Graphical Modelling (GM) is a relatively recent tool, which allows to obtain identification of SVARs, (see Oxley et al. (2009)). GM is a data oriented method based on the analysis of partial correlations among variables which give rise to a conditional independence graph (CIG). In a subsequent step, all the information embodied in the relationships among the random variables in the system is utilised in a systematic way in order to obtain identification. This procedure allows reducing the number of potential SVARs originating from a unique reduced form.

The aim of the paper is to provide a data oriented perspective on the ongoing identification debate, which gives support to one of the main views existing in the literature.

Graphical Modelling and SVAR

In this section we will first illustrate the general ideas behind the GM approach for then describing its extension to the SVAR framework.

The first step of the procedure is to compute the partial correlation between any two variables given all the remaining variables, which can be tested using appropriate statistics. This will give rise to the CIG as in Figure 1A, where random variables are represented by nodes and a significant partial correlation by a line called edge. In this case, for example, there is a significant partial correlation between A and B given C.

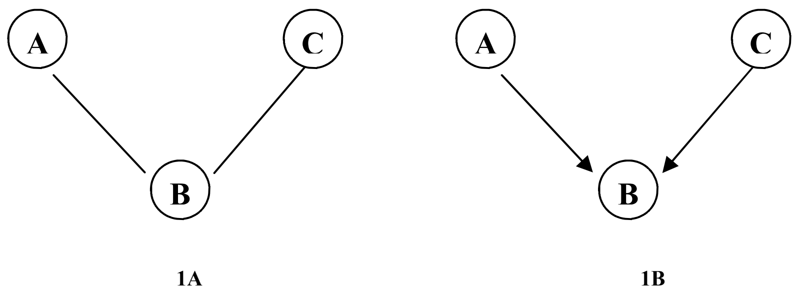

Figure 1: CIG and an hypothetical corresponding DAG

In the linear least square context, the variables included in a CIG can be characterized by relationships in terms of linear predictability, obtaining a Directed Acyclic Graph (DAG). In the DAG in figure 1B, for example, A has predictive power on B. What we can observe is the CIG, where every edge can assume two possible directions, therefore there are 2^n possible DAGs, where n is the number of edges. There are two statistically based general rules, which allow to reduce the number of potential DAGs. First, the moralization rule that considering for example the CIG in figure 1A, allows to exclude the DAG in Figure 1B, in which A and C have predictive power on B, since, statistically, a significant partial correlation between A and C should be observed in the CIG in figure 1A. Second, any DAG has to satisfy the principle of acyclicality, that allows to completely determine the distribution of a set of variables. Figure 2 shows a CIG with a corresponding DAG which can be excluded given its cyclicality.

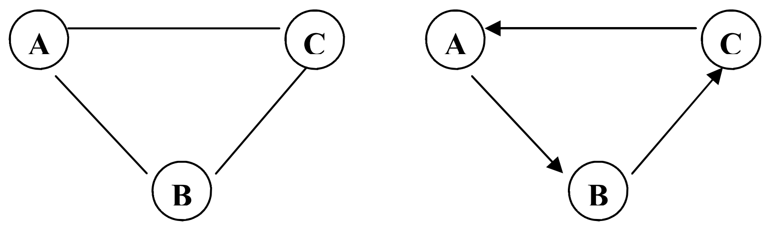

Figure 2

In the process of obtaining plausible DAGs from an observed CIG, it might also be possible that some of the links captured by the CIG are due to moralization and hence must be eliminated in a corresponding DAG. Such demoralization process, in most cases, can be assessed by considering some quantitative rules.

The SVAR can be represented by a DAG, where current and lagged variables are represented by nodes and dependence by arrows. The first step in specifying the SVAR, is to determine the lag order through the minimization of an order selection criteria such as the Akaike (AIC), Hannan and Quinn (HIC) and Schwarz (SIC).

Once the lag order is determined, in order to construct the CIG among contemporaneous variables conditioned on all the remaining contemporaneous and lagged variables, we need to derive the sample partial correlation between the contemporaneous variables, calculated from the inverse $\hat{W}$ of the sample covariance matrix $\hat{V}$ of the whole set of variables as:

$$\hat{\rho}\left(x_{i,t,}x_{j,t}\left|\{x_{k,t-w}\}\right.\right) = -\hat{W}_{rs} / \sqrt{(\hat{W}_{rr}\hat{W}_{ss})}$$

, where $\{x_{k,t-w}\}$ is the whole set of variables excluding the two variables considered and where r and s index the variables $x_{i,t}$ and $x_{j,t}$ in the matrices $\hat{V}$ and $\hat{W}$.

The critical value utilised to test for the significance of the sample partial correlations is calculated by making use of the relationship between a regression t-value and the sample partial correlation. It is given by:

$$\frac{z}{\sqrt{(z^2 + v)}}$$

, where v are the residual degrees of freedom obtained as a regression of one variable on all the remaining variables and z represents a critical value at a chosen significance level of the standard normal distribution. Whenever a sample partial correlation is greater than the critical value, a link in the CIG is retained. Next, one considers all the admissible DAGs for an evaluation from a likelihood perspective.

Often, different competing SVARs may be likelihood equivalent, i.e. they may yield the same information criterion. Hence, in order to determine the contemporaneous relationships needed for identification, the partial correlation between contemporaneous and lagged variables are also computed, using only lagged values with significant partial correlation. In this circumstance it is possible to obtain an evaluation of the contemporaneous relationships based on information criterion.

In order to obtain identification of the structural shocks, we assume that the correlation matrix of the residuals, in the SVAR chosen, is diagonal. A first diagnostic check is to inspect the significance of such correlations. Moreover, as this procedure typically imposes over-identifying restrictions, a χ^2 likelihood-ratio test may be conducted as well.

The Empirical Analysis

The solution of a Dynamic Stochastic General Equilibrium (DSGE) model can be approximated by a restricted VAR. It seems natural to utilise, in an unrestricted VAR, the same variables generally utilised in a DSGE model. A commodity price index is also added to solve the price puzzle.

We therefore consider the log of real GDP, the producer price index (all commodities), the implicit GDP deflator and the federal funds rate, utilising quarterly US data over the period 1959:1-2006:4, extracted from the FRED's database of the Federal Reserve Bank of St. Louis. All data except the federal funds rate are seasonally adjusted.

As a robustness check, we analyse two different versions of the model. The first version just includes variable levels, as in Christiano et al. (2005). In the second version a deterministic trend is added, as in Bernanke (1986), amongst others. All variables have been tested for unit roots and cointegration with unrestricted coefficient and restricted trend. The variables are all integrated of order 1 and indicate the presence of one cointegrated vector, therefore, identification based on levels would also be valid in case we consider the trends as stochastic. In both models AIC indicates a lag order of 4, while SIC and HIC suggest 2 lags. We prefer to use 4 lags, since the consequences of overestimation of the order are less serious than underestimation, see Kilian (2001). In order to construct the CIG, we compute the partial correlations between variables at 10% significance level. Both models show the same connections and give rise to the CIG in figure 3.

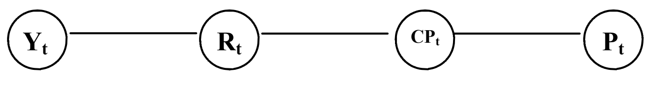

Figure 3: CIG deriving from both models

The interest rate (R_t) is connected to output (Y_t) and commodity price (CP_t), and there is a further connection between CP_t and the price level (P_t). We need to establish to which variable the interest rate is endogenous, if any, and the direction in the relationship between CP_t and P_t. We have 2^3 possible SVAR. They are shown in figure 4.

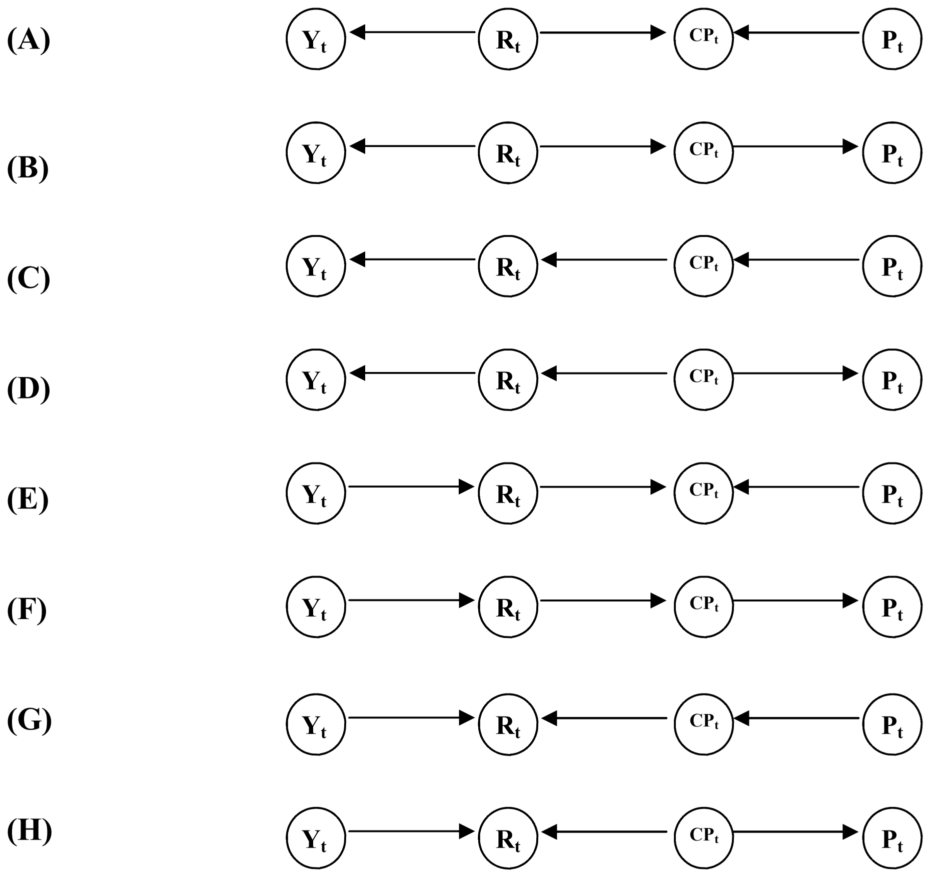

Figure 4: DAGS deriving from the CIG in figure 3

DAGS (A), (E), (G), and (H) can be excluded following the moralization rule. We need to evaluate the four remaining potential SVARs. Table 2 shows AIC, HIC and SIC of the four remaining SVARs, for the model in levels and with deterministic trend. The contemporaneous relationship indicated in the DAG (C) are, for both models, the best performing from a likelihood perspective.

MODEL	AIC	HIC	SIC
B	646.47	675.32	717.67
C	623.78	652.63	694.98
D	628.76	657.61	699.96
F	640.15	669.00	711.36
model in levels			

MODEL	AIC	HIC	SIC
B	639.26	668.11	710.47
C	614.95	643.80	686.15
D	621.82	650.67	693.02
F	631.20	660.04	702.40
model with deterministic trend			

Table 3: Information Criteria of the possible SVAR

R_t is solely endogenous to CP_t. and has a contemporaneous effect on Y_t, which is a economically plausible at quarterly frequency and a common assumption in DSGE models. P_t drives CP_t and is economically plausible, if we think that P_t can be a proxy of the unit costs which impact on CP_t. These results indicate that the monetary authority's decision may not depend on contemporaneous output and GDP deflator. Moreover, the information set of the monetary authority seems to be conditioned by the availability of data in terms of frequency, given that the producer price index is available at monthly frequency, while GDP and GDP deflator are available at quarterly frequency with a delay. Results also indicate that the Cholesky decomposition, where every variable is connected to all the other variables, may not be appropriate for identification.

Table 4 shows the correlation of the structural errors for model (C), with a critical value at 5% equal approximately to 0.146. They are all statistically not different from zero.

	u^Y	u^R	u^{CP}	u^P
u^Y	1.000			
u^R	0.015	1.000		
u^{CP}	-0.035	-0.027	1.000	
u^P	-0.099	0.047	0.000	1.000
model in levels				

	u^Y	u^R	u^{CP}	u^P
u^Y	1.000			
u^R	0.014	1.000		
u^{CP}	-0.021	-0.034	1.000	
u^P	-0.107	0.054	0.000	1.000
model with deterministic trend				

Table 4: Correlation between structural errors.

We also fail, as expected, to reject the likelihood-ratio test for the three over-identifying restrictions with a p-value equal to 0.39 for the model in levels and 0.19 for the model with deterministic trend.

Conclusions

Our results appear to be more in line with Kim and Roubini (2000), than with alternative views. It is our hope that this paper also shows that GM, when integrated with economic priors, can represent a valid identifying scheme.

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