Does information help recovering fundamental structural shocks from past observations?*

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Abstract

This paper asks two questions. First, can we detect empirically whether the shocks recovered from the estimates of a structural VAR are fundamental? Second, can the problem of non-fundamentalness be solved by considering additional information? The answer to the first question is "yes" and that to the second is "under some conditions".

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1 Introduction

Structural Vector Autoregressive Models (SVAR) are a very useful tool in applied macroeconomics since they are simple, flexible and robust to model misspecification (see Stock and Watson (2001) for a discussion). Moreover, under some conditions, the linearized solution of dynamic stochastic general equilibrium models (DSGE) can be approximated by a finite autoregressive model (VAR) so that SVARs can be used to match models to data.

Predictions from different DSGE models can be compared empirically using the VAR tool with which a linear combination of the structural shocks can be easily estimated as residuals of OLS regressions and then identified by imposing a set of restrictions. If such restrictions are verified by a broad class of models, different predictions of models within that class can be compared by looking at the estimated shocks and their coefficients (impulse response functions).

However, if the structural model has a Moving Average (MA) component, the VAR representation is admissible only under some conditions which may not be verified by the structural model. In that case, there is no hope to recover the structural shocks from VAR estimation. This point was first made by Hansen and Sargent (1991) and Lippi and Reichlin (1993) and recently brought back in the macroeconomic debate by Chari et al. (2005), Christiano et al. (2005) and Fernandez-Villaverde et al. (2005).

This paper asks whether it is possible to verify empirically if the shocks of interest are indeed in the span of the present and past of the variables considered in the SVAR model. Moreover, we ask whether, in case the shocks are not in that span, we can recover them from the span of the present and past of the variables in a larger model obtained by adding auxiliary variables to the ones we want to focus on.

We will go through the analysis via an empirical application where we use aggregate and sectoral data for US manufacturing industries to study the effect of technology shocks on hours worked, in the spirit of Gali (1999) and Christiano et al. (2004).

2 SVAR and their critics

Suppose that the equilibrium solution of a "true" structural model links a number m of observable variables to a number q of structural shocks:

$$X_t^* = B^*(L)u_t^* \tag{2.1}$$

where X_t^* is an m-dimensional vector of observable macroeconomic variables, u_t^* is a q-dimensional vectors of shocks, white noise with unit variance, whose propagation is captured by $B^*(L) = B_0^* + B_1^*L + B_2^*L^2 + ...$, an $m \times q$ matrix of moving average filters. In general, the number of shocks, q, can be equal to or different from the number of observable variables m.

The objective of the econometrician is to make inference on the responses of the observable variables X_t^* to the shocks, i.e. the impulse response function:

$$B_h^* = \partial X_{t+h}^* / \partial u_t^*, h = 0, 1, 2, ...$$

SVAR modelling consists in two steps. First, model (2.1) is approximated by a VAR representation:

$$A^*(L)X_t^* \simeq \varepsilon_t^* \tag{2.2}$$

where $A^*(L) = A_0 + A_1^*L + ... + A_p^*L^p$ is an $m \times m$ filter of finite length p, A_0 is normalized to be lower triangular, and ε_t^* is an m-dimensional vector of orthogonal innovations.

The second step consists in inverting and rotating the VAR representation (2.2). Denoting by R a rotation matrix ($R'R = I_m$), from

$$X_t^* = [A^*(L)^{-1}R] \quad [R'\epsilon_t^*]$$

we get the Impulse Response, $B^*(L) \simeq A^*(L)^{-1}R$, to the structural shocks u_t^*.

For inverting the VAR representation, prerequisite is the existence of a filter $N(L) = N_0 + N_1L + N_2L^2 + ...$ such that: $N(L)B^*(L) = I_m$. In this case we have:

$$N(L)X_t^* = N(L)B^*(L)u^*(L) = u_t^*$$

i.e. the structural shocks u_t^* can be extracted from present and past observations $(X_t^*, X_{t-1}^*, ...)$. In this case, the filter $A^*(L)$ and the innovations ϵ_t^*, in the finite VAR representation (2.2), are an approximation of $RN(L)$ and Ru_t^*, respectively. Notice that for such filter to exists, the number of structural shocks, q, should be less or equal to the number of observable macroeconomic variables m. Following the SVAR tradition, we will assume from now on that there are as many shocks as variables ($m = q$), but the discussion holds, with minor modifications, for $m > q$[1].

The ability of a SVAR to recover structural shocks and their propagation mechanism relies crucially on the ability of the VAR representation (2.2) to approximate the model solution (2.1). There are three possible situations in which such approximation does not work:

1. The roots of det$B^*(L)$ are on the unit circle. In this case, known as non-invertibility, the VAR representation does not work since an infinite number of lags of the observables $p = \infty$ is needed to recover the structural shocks. This situation might occur, for example, if some variables are over-differenced (see for example Christiano et al., 2004).

2. The roots of det$B^*(L)$ are inside the unit circle. In this case, the system is said to be non-fundamental, (see Hansen and Sargent, 1991; Lippi and Reichlin, 1993), and the impulse response functions cannot be recovered even with an infinite past of the observable variables ($p = \infty$).

3. The roots of det$B^*(L)$ are outside the unit circle. In this case the number of lags (p) necessary to recover the structural shock maybe very large. This might happen, for example, when some state variables are not included in the set of observable variables, (see for example Chari et al., 2005; Cooley and Dwyer, 1998).

From now von we will discuss case 2 (non-fundamentalness) which is the worse case.

[1]If there are more shocks than variables, $m < q$, there is no hope to recover the structural shocks from a finite of number of variables.

3 A well known empirical example

We consider, as an example, the empirical model introduced by Gali (1999) which is a VAR on aggregate labor productivity (y_t) and aggregate labor input, hours (h_t), whose corresponding structural MA representation is:

$$\underbrace{\begin{pmatrix} \Delta y_t \\ \Delta h_t \end{pmatrix}}_{X_t^*} = \underbrace{\begin{pmatrix} b_{11}^*(L) & b_{12}^*(L) \\ b_{21}^*(L) & b_{22}^*(L) \end{pmatrix}}_{B^*(L)} \underbrace{\begin{pmatrix} u_{1t}^* \\ u_{2t}^* \end{pmatrix}}_{u_t^*.} \tag{3.3}$$

Here u_{1t}^* is the technology shock and u_{2t}^* is the non technological shock. We are interested in the responses of hours worked to productivity shocks since this allows us to assess the empirical relevance of price stickiness in the economy. In particular, the contemporaneous response of hours to productivity shocks is expected to be negative in a sticky price economy and positive in a flexible price economy (see for example Gali, 1999; Christiano et al., 2004; Chari et al., 2005).

The system is identified by assuming that only technological shocks can affect the long run level of productivity

$$b_{12}^*(1) = \lim_{s\to\infty} \partial y_{t+s}/\partial u_{2t}^* = 0.$$

4 Is non-fundamentalness detectable?

Let us consider a system in which the set of variables of interest X_t^* is augmented with blocks of additional variables, $X_{1t}, ..., X_{kt}$. The general representation is:

$$\begin{pmatrix} X_t^* \\ X_{1t} \\ ... \\ X_{kt} \end{pmatrix} = \begin{pmatrix} B^*(L) & \Psi^*(L) \\ B_1(L) & \Psi_1(L) \\ ... & ... \\ B_k(L) & \Psi_k(L) \end{pmatrix} \begin{pmatrix} u_t^* \\ v_t \end{pmatrix} \tag{4.4}$$

where v_t are additional structural shocks, orthogonal to the shocks of interest u_t^*. The model (2.1) implies the restriction $\Psi^*(L) = 0$, i.e. that the additional shocks v_t are specific to the added variables. In a compact form the system (4.5) can be rewritten as:

$$\begin{pmatrix} X_t^* \\ X_t \end{pmatrix} = \begin{pmatrix} B^*(L) & 0 \\ B(L) & \Psi(L) \end{pmatrix} \begin{pmatrix} u_t^* \\ v_t \end{pmatrix}$$

where $X_t = (X_{1t}, ..., X_{kt})'$ is a vector of additional variables of dimension n, $B(L) = (B_1(L), ..., B_k(L))'$ and $\Psi(L) = (\Psi_1(L), ..., \Psi_k(L))'$.

Non-fundamentalness can be easily detected by looking at this larger system. Precisely, if u_t^* is fundamental with respect to X_t^*, then the structural shocks can be recovered from the past of the observables, $u_t^* = N(L)X_t^*$. This implies:

$$X_{it} = B_i(L)N(L)X_t^* + \Psi_i(L)v_t.$$

Since v_t is orthogonal to X_t^*, then X_{it} depends only on the past of X_t^* . It hence follows that X_{it} does not Granger cause X_t^* (Sims, 1972). This proves the following[2]:

Proposition If any of X_{it},$i = 1, ..., n$, Granger causes X_t^*, then u_t^* is non-fundamental with respect to X_t^*.

Non-fundamentalness can hence be detected empirically by checking wether the block of interest X_t^* is (weakly) exogenous with respect to potentially relevant additional blocks of variables that are likely to be driven by sources that are common with the variables of interest. This is a quite stringent condition; we will further discuss it later.

We can check the condition above for Gali (1999)'s model (3.3) on aggregate hours and productivity by looking at sectoral information. Precisely, we test for block exogeneity of the aggregate manufacturing X_t^* variables with respect to sectoral variables $X_{it} = (\Delta y_{it}, \Delta h_{it})'$ which represents the bivariate vector of the growth rate of labor input and labor productivity for the two-digit manufacturing sectors, $i = 1, ..., 18$. Our data are annual and consist of measures hours of all persons and output per hour (source: Bureau of Labor Statistics). The sample is 1949-2000.

Results are reported in Table 1.

Table 1: Granger Causality Test

		F-test	p-value			F-test	p-value
Non Durable Sectors				**Durable Sectors**			
Food & Kindred Prod.	(SIC 20)	1.58	0.81	Lumber & Wood Prod.**	(SIC 24)	13.85	0.01
Textile Mills Prod.**	(SIC 22)	14.18	0.01	Furniture & Fixtures	(SIC 25)	6.87	0.14
Apparel &Related Prod.	(SIC 23)	6.83	0.15	Stone, Clay & Glass **	(SIC 32)	15.23	0.00
Paper & Allied Prod.	(SIC 26)	2.18	0.70	Primary Metal Ind.	(SIC 33)	6.19	0.19
Printing & Publishing	(SIC 27)	6.52	0.16	Fabricated Metal Prod.	(SIC 34)	5.18	0.27
Chem. & Allied Prod.	(SIC 28)	3.73	0.44	Ind. Machinery,Comp.Eq.	(SIC 35)	6.51	0.16
Petroleum Refining**	(SIC 29)	11.34	0.02	Electric & Electr. Eq.	(SIC 36)	0.63	0.96
Rubber & Plastic Prod.	(SIC 30)	5.62	0.23	Transportation Equip.	(SIC 37)	3.59	0.46
				Instruments**	(SIC 38)	20.42	0.00
Misc. Manufacturing	(SIC 39)	1.71	0.79				

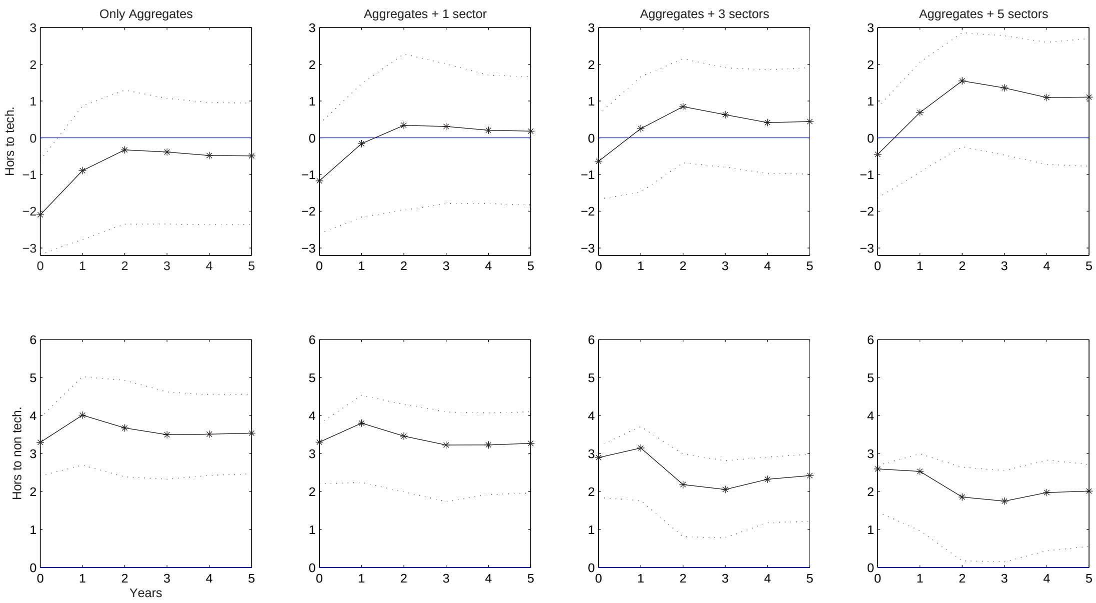
For five sectors (25% of the total) the hypothesis of weak erogeneity is rejected, hence non-fundamentalness of the system (3.3) is detected. The Grange-causing sectors, ordered according to their F-stat associated to the Granger causality test, i.e. starting from the sectors with respect to which the aggregate manufacturing are less likely to be weakly exogenous, are: Instruments, Stone, Clay & Glass, Textile Mills Products, Lumber & Wood Products and Petroleum Refining.

If we augment the aggregate VAR model with the k sectors most likely to Granger-cause the aggregate manufacturing system, the shape of the estimated response of output to the technology shock changes.

Let us include, recursively, sectors starting from those for which the aggregate manufacturing system is less likely to be weakly exogenous:

[2]This result was first introduced by Forni and Reichlin (1996) in the case data follow a factor structure.

Figure 1: **Impulse response functions of hours**



$$\begin{pmatrix} X_t^* \\ X_{i_1 t} \\ ... \\ X_{i_k t} \end{pmatrix} = \begin{pmatrix} B^*(L) & 0 \\ B_{i_1}(L) & \Psi_{i_1}(L) \\ ... & ... \\ B_{i_k}(L) & \Psi_{i_k}(L) \end{pmatrix} \begin{pmatrix} u_t^* \\ v_{i_1 t} \\ ... \\ v_{i_k t} \end{pmatrix} \tag{4.5}$$

We identify the system by imposing that sectoral shocks have no contemporaneous effects on the aggregate $\Psi_{i_k}(0) = 0$ for all k and by requiring, as usual, that only technological shocks can affect the long run level of productivity

$$b_{12}^*(1) = \lim_{s \to \infty} \partial y_{t+s} / \partial u_{2t} = 0$$

Figure 1 reports the estimated responses of hours worked to technology (upper panel) and non-technology (lower panel), for four different system and for $k = 0, 1, 3, 5$. We start from a system with only aggregated measures of hours and productivity ($k = 0$, first column) and then we add the Instruments sector ($k = 1$ second column), the Instruments, Stone, Clay & Glass, Textile Mills Product sectors ($k = 3$, third column), and finally all the Granger causing sectors at 5% level ($k = 5$, fourth column).

The impulse response functions computed by estimating the VAR only with aggregate manufacturing sectors show a contemporaneous ($k = 0$) decline of hours worked in response to a technology shock. This result is in line with the finding of Gali (1999) and has been considered as evidence of substantial price stickiness in the US economy. However, when we add more and more sectors the response of hours worked to technology shocks are shifted upward while the response to non technology shocks are shifted downward.

Figure 2: **Contemporaneous response of hours to technology shock**

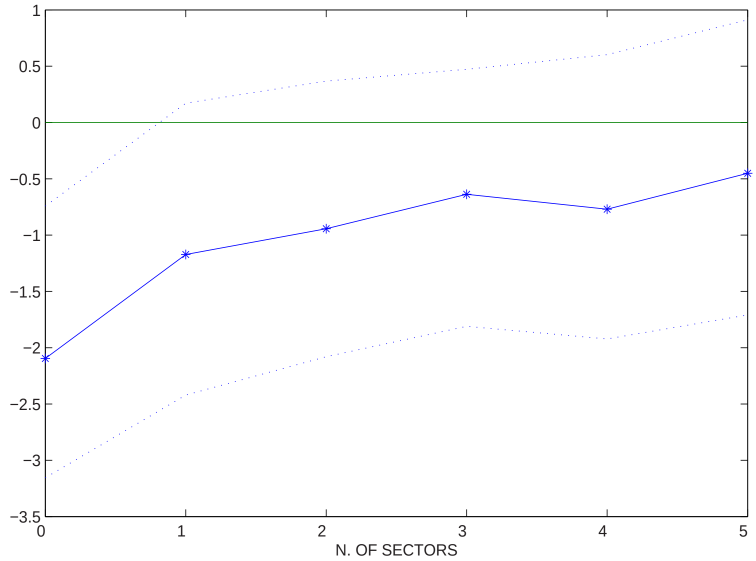


Figure 2 plots the contemporaneous response of hours to technology against the size of the system. Clearly, as we add the Instruments sector, the contemporaneous impulse response becomes insignificant. Point estimates increases monotonically approaching zero when we add all five Granger-causing sectors.

5 Does large information help?

In the previous Section we have seen that large information can help detecting non-fundamentalness and, for our example, adding extra information actually changes the shape of the impulse response function thereby changing the interpretation of the results in a key dimension. Here we ask the question of whether, in general, by enlarging the econometrician information set, we can solve the non-fundamentalness problem. In terms of our empirical application, we would like to understand if the shocks recovered by augmenting the system with sectoral variables are the fundamental shocks u_t^*. In general, larger information does not necessarily solve the problem of non-fundamentalness. This is easily seen by computing the roots of the moving average of system (4.5):

$$\det \begin{pmatrix} B^*(z) & 0 \\ B(z) & \Psi(z) \end{pmatrix} = [\det B^*(z)][\det \Psi(z)]$$

where $B(L) = (B_1(L), ..., B_k(L))$. If some roots of $B^*(z)$ are inside the unit circle then the larger system will have roots outside the unit circle as well, unless some roots of $\det B^*(z)$ cancel with those of $\det \Psi(z)$. This implies that, in general, the whole system is not fundamental if the small system is not. Therefore, taking into account additional information, does not help solving the non-fundamentalness problem in general.

However, information helps under some conditions. Let us illustrate them in the case of finite moving average to the shocks of interest. The discussion holds for the more general case, but implies a heavier notation.

Suppose that (4.5) satisfies the following restriction: $B(L) = B_0 + B_1 L + ... + B_s L^s$, i.e. the effect of all shocks in zero after s periods. The system can hence be rewritten as:

$$X_t = \mathbf{B}\mathbf{U}_t^* + \Psi(L)v_t$$

where $\mathbf{B} = (B_0, B_1, ..., B_s)$, $\mathbf{U}_t^* = (u_t^{*\prime}, ..., u_{t-s}^{*\prime})'$.

Let us start from the assumption that $v_t = 0$, i.e. that the system is driven by q shocks only. In this case, if $\mathbf{B}'\mathbf{B}$ is of full rank, we have:

$$\mathrm{Proj}[\mathbf{U}_\mathrm{t}^*|\mathrm{X_t}] = \left(\mathbf{B}'\mathbf{B}\right)^{-1}\mathbf{B}'X_t = \left(\mathbf{B}'\mathbf{B}\right)^{-1}\mathbf{B}'\mathbf{B}\mathbf{U}_t^* = \mathbf{U}_t^*$$

and we can recover U_t^*, and hence u_t^*, from the present of X_t. This is to say that u_t^* is fundamental with respect to X_t^*.

As Forni et al. (2005) have shown, fundamentalness with respect to $(X_t^*, X_t)'$ is a less stringent condition if the system size is larger than the number q of the relevant shocks. In this case, to extract u_t^* from the present and past of all variables of the observables, we just need the full-rank condition above. The latter ensures that the dynamic of the panel is sufficiently rich so that, by exploiting the cross-sectional dynamic, it is possible to recover the lags of the common shocks.

Let us now consider the more realistic case in which $e_t = \Psi(L)v_t \neq 0$. In this case, sufficient conditions for recovering the U^* can be established by studying the properties of the system as we increase the number of auxiliary variables we consider. This analysis is provided in details by Forni et al. (2005).

Let us here reformulate the problem for our case. We have:

$$\mathrm{Proj}[\mathbf{U}_\mathrm{t}^*|\mathrm{X_t}] = \left(\mathbf{B}'\Sigma_e^{-1}\mathbf{B} + I_{q(s+1)}\right)^{-1}\mathbf{B}'\Sigma_e^{-1/2}\mathbf{B}\mathbf{U}_t^* + \left(\mathbf{B}'\Sigma_e^{-1}\mathbf{B} + I_{q(s+1)}\right)^{-1}\mathbf{B}'\Sigma_e^{-1/2}e_t$$

where $\Sigma_e = \mathrm{Cov}(e_t)$. To recover U_t^* we need two conditions. Precisely:

A1) $\mathbf{B}'\mathbf{B}/n$ is of full rank for n large.

A2) $\|\Sigma_e/n\|$ small for n large.

Assumption A1 ensures that the shocks of interest are pervasive throughout the cross-section and that they generate heterogenous dynamics. Assumption A2 ensures that the remaining shocks do not propagate "too much" and can therefore be considered as idiosyncratic, sectoral shocks or as measurement error.

Under A1 and A2, as the cross-sectional dimension n goes to infinity, we have:

$$\left(\mathbf{B}'\Sigma_e^{-1}\mathbf{B} + I_{q(s+1)}\right)^{-1}\mathbf{B}'\Sigma_e^{-1/2}e_t \to 0$$

and hence

$$\mathrm{Proj}[\mathbf{U}_\mathrm{t}^*|\mathrm{X_t}] \to \mathbf{U}_t^*$$

.

These conditions imply that the shocks u_t^*'s are asymptotically, for n large, fundamental. In other words, by adding extra information we can eventually recover the structural shocks.

How realistic are condition A1 and A2? For the empirical example we are considering here, with aggregate and sectoral variables, the conditions are satisfied provided that sectoral variables Granger-cause the aggregate.

Assumption A2 is satisfied since, by construction, sectoral shocks v_t's do not affect aggregate manufacturing measures, i.e. $\Psi^*(L) = 0$. For assumption A1 to be satisfied, the macro shocks, which are our shocks of interest, must affect all sectors and this implies that the sectoral variables Granger-cause the aggregates. Evidence on the latter is given by results on Granger causality reported in Table 1 above.

Therefore, the reliable result is the one produced by the system augmented by the Granger-causing sectors and this indicates that there is no evidence of hours worked going down in response to technological shocks.

In a more general case, conditions A1 and A2 are satisfied if data can be represented by an approximate factor model (Forni et al., 2005). A large literature has brought evidence that these models are a good empirical representation of large panels of macro data and of sectoral or regional data (Giannone et al. (2004), Stock and Watson (2005), Bernanke et al. (2005), Forni et al. (2005)). The estimation and identification theory for shocks and impulse responses is developed by Forni et al. (2005) so that these models can be easily used for structural analysis and they are a valid alternative to SVAR analysis when information may help solving the problem of non-fundamentalness.

6 Dealing with the curse of dimensionality problem

The discussion of the previous Section implies that we may have to consider many auxiliary variables and this leads to the possibility of running out of degrees of freedom. In our empirical illustration, for example, modelling all sectors together implies considering a system of 38 equations (= 2×18 sectors + 2 aggregates) with only 51 observations in time.

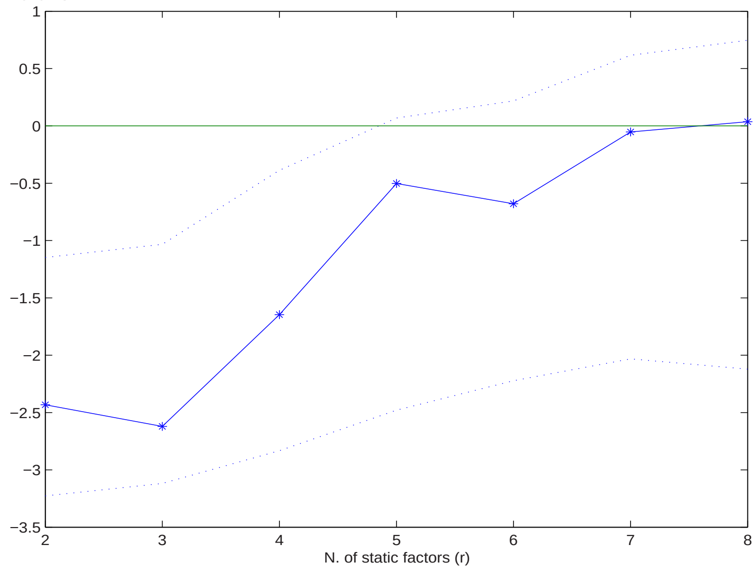
A solution to this problem is provided by the dynamic factor literature. In fact, under the assumptions A1 and A2 defined in the previous Section, the system has an approximate Factor Structure (see Forni et al., 2005) whereby the variables are driven by few pervasive shocks and n idiosyncratic ones. This implies that all the relevant information can be captured by few common factors which can be extracted as appropriate aggregates of the observables (see Forni et al., 2000; Stock and Watson, 2002).

Precisely, under A1 and A2 the following representation holds:

$$\begin{pmatrix} X_t^* \\ X_t \end{pmatrix} = \begin{pmatrix} \Lambda^* \\ \Lambda \end{pmatrix} F_t + \Psi(L) v_t$$

where $F_t = DF_{t-1} + Cu_t^*$. F_t is $r \times 1$ and u_t is $(q \times 1)$, $D(L)$ is $(r \times r)$ finite stable filter and C is $r \times q$ matrix. Hence $B^*(L) = \Lambda^* D(L)^{-1} C$ and $\Psi(L)v_t$ is an idiosyncratic

Figure 3: **Contemporaneous response of hours to technology shock: factor model estimation**



component, poorly cross-sectionally correlated.[3]

The common factors F_t can be estimated by the first r principal components of (X_t^*, X_t'). The parameters Λ, Λ^*, D, C can hence be estimated by ordinary least squares considering the estimated factors as they were know (see Forni et al., 2005, for details). Once parameters are estimated, we can impose the identification restriction $b_{21}^*(1) = 0$ as in the traditional SVAR literature[4].

Figure 3 plots the contemporaneous response of hours to technology shocks for different values of r, the number of common factors. For $r = 2$, results are very similar to those obtained only with aggregate manufacturing labor input and labor productivity. This is due to the fact that the span of the first two principal components is very close to the span of the aggregate manufacturing measure, since principal components are a weighted average of sectoral variables. Notice that, as we add more common factors (r increases), we capture more sectoral information and the contemporaneous response of hours to productivity increases monotonically.

This confirms the result that the negative contemporaneous response of hours to technology is an artifact due to the presence of non-fundamentalness, i.e. we cannot extract the fundamental structural shocks on the basis of the aggregate growth rate of labor and labor input alone. Enlarging the information set of the econometrician, we have a larger chance of capturing the structural shocks and indeed the contemporaneous response of hours becomes not significantly different from zero.

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[3] This model has been also applied by Giannone et al. (2004, 2005). Notice that a number of common factors r larger than the number of common shocks q captures dynamic heterogeneity: $r = q(s + 1)$ in the finite MA example of the previous section.

[4] A closely related approach consists on augmenting the system X_t^* with the first r principal components of X_t (Bernanke et al., 2005; Stock and Watson, 2005). Results using that approach confirm the findings we report here

7 Lessons for applied work

The discussion above suggests some lessons for applied work. Even when the object of interest is a small system, one should check for the possibility of non-fundamentalness by augmenting it with auxiliary variables. Variables which have forecasting power (Granger-cause) for the variables of that system or factors capturing the information from a large data set should be included in the estimation. The auxiliary variables, beside being Granger-causing the key variables, must have strong commonality with them and small idiosyncratic dynamics, weakly cross-sectionally correlated.

The shocks of interest will be recoverable as long as they are "pervasive". This implies that, in general, it is easier to recover "large" shocks which affect all variables (key and auxiliary ones as well) than small ones.

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