On the identification of non-normal shocks in structural VAR

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Abstract

In the structural Vector Autoregressive model, sometimes the economic restrictions for the identification of the non-normal shocks reveal limitations. We propose a method based on tail dependency to identify the non-normal structural shocks in Vector Autoregression models. Our approach is mainly based on two steps: i) the non-normal residuals are decorrelated and ii) the uncorrelated residuals are further rotated in order to obtain independence using a tail dependency matrix.Unlike economic identification, we do not label the shocks a priori, but we assign labels ex-post based on economic judgement. We show how our approach is able to identify all the shocks using a Monte Carlo study. Finally, we apply our method to two different VARs, all estimated on US data: i) a monthly trivariate model which studies the effects of oil market shocks, and finally ii) a VAR that focuses on the interaction between monetary policy and the stock market. In the first case, we validate the results obtained in the economic literature. In the second case, we cannot confirm the validity of the identification scheme based on combination of short and long run restrictions which is used in part of the empirical literature.

Keywords: Identification; Independent Component Analysis; Impulse Response Function; Vector Autoregression.
JEL classification: C32

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1 Introduction

Over the last decade, the popularity of Structural Vector AutoRegression (SVAR) models has more than persisted in empirical macroeconomics and finance. Many argue that recent events can hardly be explained by models that are based on Gaussian Shocks structure(Mishkin (2015). This has been shown by recents literature that high frequency changes in distributions of innovations is clearly present in finance and macro time series. For instance, the presence of large shocks or student-t distributed shocks: see Chib and Ramamurthy (2014), Cúrdia et al. (2012) or stochastic volatility processes (see Justiniano and Primiceri (2008), Fernández-Villaverde and Rubio-Ramírez (2007)) or high and low frequency regime changes (Sims and Zha (2006), Liu et al. (2011)).

Recently, Lindé et al. (2015) show strong evidence that both low and high frequency changes in volatility are important. In most cases, identification of shocks can be achieved by applying a suitable rotation to the residuals of the VAR using short-run or long-run restrictions motivated by economic theory.[1] Departing from this *economic* identification, we focus on a rather structural interpretation of the VAR by exploiting the statistical properties of the innovation terms.

We propose a new methodology to identify non-normal structural shocks based on tail dependency. Our approach consists of two main steps: i) the non-normal residuals are decorrelated and ii) using a tail dependency matrix, the uncorrelated residuals are further rotated in order to reduce tail dependency. We apply our approach to simulated data and macroeconomics framework. Therefore, the frequency of the time series and their degree of non-normality are important to achieve an accurate identification.

The intuition for our method is summarized as follows. Under Gaussianity, we reach identification of shocks by orthogonalizing the realizations. This implies that their linear relations are equal to zero. However, in case of tail events, we face non linear relations between realizations which is common in finance. Tail observations of the variables are related differently than in the rest of the ellipse. In this case, data could exhibit tail dependence, despite the orthogonalization of the residuals. This bias arises when no distinction is made between calm periods and crisis/post-crisis periods. For example, the stock market moves after a variation of the Federal fund rate during a calm period, but may not follow during a crisis period, as shown in Figures 1a and 1b. If these tail events appear, then the shocks can be identified by the rotation of the ellipse to reduce the dependence among them.

To perform this identification, we exploit a higher order moments matrix to reduce tail dependency. In contrast to *economic* identification literature, where the shocks are *ex-ante* labelled, we assign labels *ex-post* based on economic theory.

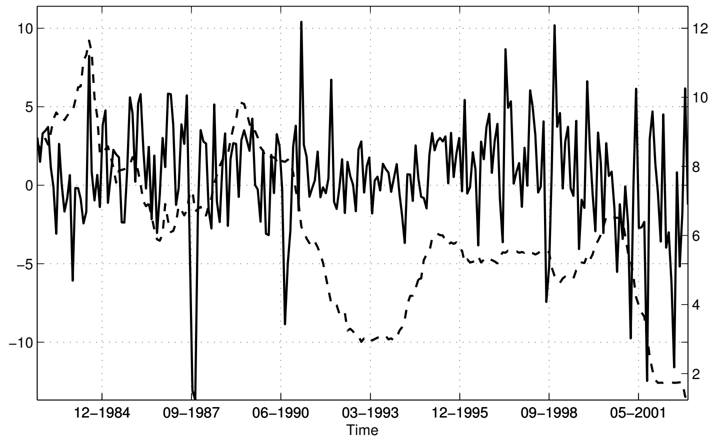
Empirically, we apply our method to two different VAR models to identify structural shocks: i) three different oil shocks using a monthly VAR (Kilian, 2009) and ii) *monetary policy* shock using monthly VAR (Bjørnland and Leitemo, 2009).

In the first case, we succeed in disentangling all structural shocks and we obtain similar results to those of Kilian (2009). In the second case, compared to Bjørnland and Leitemo (2009), we find a smaller and not significant effect of the *monetary policy* shock on real stock prices during the period examined. Therefore, we cannot confirm the identification scheme based on a combination of short and long run restrictions used in their analysis. Adding their economic restriction, SVAR is over-identified.

[1] For a recent review, see Kilian (2013).

Figure 1: Federal fund rate and S&P500 stock price Index

(a)



(b)

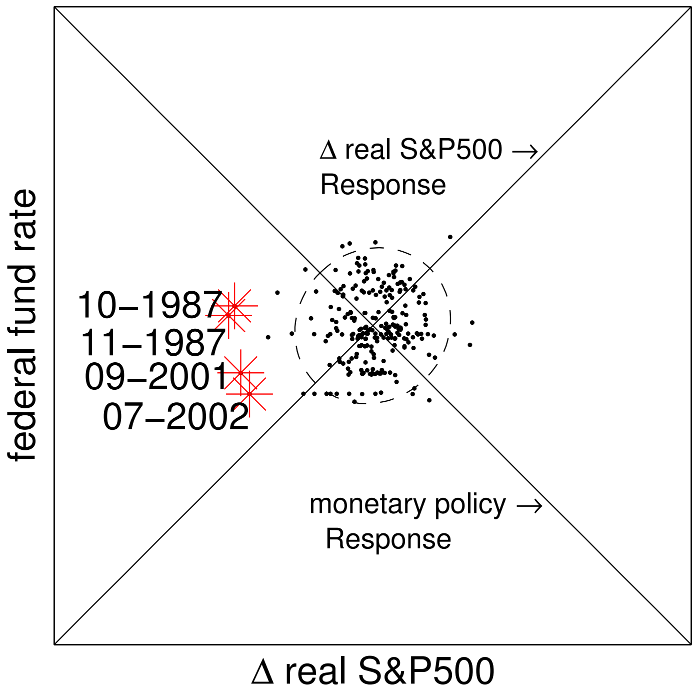


Figure 1a contains two time series from January 1983 to December 2002: monthly change of real S&P500 stock price (Solid line) and federal fund rate (Dashed line). Scatter plot 1b shows the realizations of the series. The dashed contour represents the 95% confidence level for uncorrelated bivariate normal distribution. The tail events are represented by cross symbols and corresponding dates (10-1987, 11-1987, 09-2001 and 07-2002).

From a methodological perspective, this paper is related to a well developed *economic* identification literature. In a pioneering work, Sims (1980), uses a recursive identification scheme (through the Cholesky decomposition) to impose zero constraints on the short-run impact matrix of a VAR model. Under such a scheme, the ordering of chosen variables determines those responding to a given shock upon impact, and those having a one period delayed response. Bernanke (1986), Shapiro and Watson (1988) and Blanchard and Quah (1989) extend this recursive identification scheme identifying the model through long-run restrictions; see Galì (1999) and Christiano et al. (2006) for various applications. Short-run and/or long-run restrictions are primarily applied to exactly identified SVAR models. "Exact" identification imposes strict assumptions on the number of zero restrictions and their location in the impact matrix. Such identifying assumptions may be inconsistent with the identification of many shocks. Hence, the restrictions used for identifying structural shocks cannot be tested in the usual way. Blanchard and Diamond (1992, 1994); Uhlig (2005) use *a priori* assumptions on signs of structural parameters to identify the structural shocks.

Alternatively, several studies base the identification on the *statistical* properties of the innovation term. Kuttner (2001) uses proxies and instrumental variables to achieve identification. Recent works exploit the change of volatility of the residuals: Rigobon (2003) and Rigobon and Sack (2003) use heteroskedasticity and Normandin and Phaneuf (2004) consider conditional heteroskedasticity. This Identification of shocks based on regime shifts in volatility is more standard in macroeconomics. The technique applied in this paper shares the same assumptions and properties: i) Constant transmission of shocks across regimes, independent of the shock volatility, ii) Independence of shocks (= uncorrelated shocks in Gaussian world) and iii) N-1 non-Gaussian shocks or N-1 changes in volatility.

Another strategy is to specify an encompassing model that includes (as special cases) various alternative structural models implied by different economic models, allowing tests for over-identifying restrictions. The advantage of this approach is that it avoids conditioning on one specific model that may be incorrect. Of course, this type of SVAR model no longer admits a Cholesky representation and must be estimated by numerical methods using the generalized method of moments (GMM). Bernanke and Mihov (1998) use this strategy to model the market for bank reserves as part of a study of US monetary policy. In related work, Lanne and Lütkepohl (2010) model the errors as a mixture of normal distributions.

Finally, Hyvärinen et al. (2010) and Moneta et al. (2013) introduce the concept of independence based on the non-Gaussianity of the data. However, they reach the "exact" identification by imposing a recursive identification scheme. Recently, Lanne et al. (2015) have used a similar approach, but adopting a maximum likelihood estimator of the non-Gaussian SVAR model and follow the identification scheme proposed by Ilmonen and Paindaveine (2011) and Hallin and Mehta (2015). By doing our method, there is no need to specify a specific distribution of the innovations.

The rest of this paper is laid out as follows. Section 2 presents a Vector Autoregressive model (VAR) framework and our estimation procedure. Section 3 is devoted to the Monte Carlo study. Section 4 is dedicated to the empirical evidence for the validity of the method. In the final section (Section 5) the conclusions are drawn.

2 Methodology

Model setup

Let $\mathbf{y}_t$ be an $n \times 1$ vector of stationary variables that evolves over time according to a VAR model:

$$\mathbf{A}(L)\mathbf{y}_t = \boldsymbol{u}_t$$

where $\mathbf{A}(L) = I_n - A_1 L - A_2 L^2 - ... - A_p L^p$ is a matrix lag polynomial, and the error term $\boldsymbol{u}_t$ is independent and identically distributed (*i.i.d.*) with mean zero and covariance matrix $\boldsymbol{\Sigma}_u$. Furthermore, let us assume that the error term $\boldsymbol{u}_t$ is a linear combination of the structural macroeconomic shocks $\boldsymbol{\varepsilon}_t$, so that $\boldsymbol{u}_t = \mathbf{B}\boldsymbol{\varepsilon}_t$, where $\mathbf{B}$ is an $n \times n$ matrix and $\boldsymbol{\varepsilon}_t$ follows a distribution with mean zero and covariance matrix $\mathbf{I}_n$. $\boldsymbol{\varepsilon}_t$ also satisfies the following assumptions: i) at least unconditional moments up to order 4 are finite, i.e. $\mathrm{E}[\boldsymbol{\varepsilon}_t^k] < \infty$, for $k \leqslant 4$ and ii) $\boldsymbol{\varepsilon}_t$ is composed of mutually independent processes.

When VAR models are used for macroeconomic analysis, the focus is on the response of the variables, $\mathbf{y}_t$, to the structural shocks, $\boldsymbol{\varepsilon}_t$, which is the impulse response functions: $\mathbf{C}(L) = \mathbf{A}(L)^{-1}\mathbf{B}$. In practice, the autoregressive polynomial, $\mathbf{A}(L)$, is estimated by OLS, while there exist different ways to estimate matrix $\mathbf{B}$.

It should be notice that, in low dimensional setting, the VAR is not able to recover the space of structural shocks, which are defined in the MA representation. This is when you have non-fundamentalness (Lippi and Reichlin, 1993; Alessi et al., 2011). A solution can be using Blaschke factors (Lippi and Reichlin, 1993; Forni et al., 2014), another is by using factor models (Forni and Gambetti, 2010) or large VARs (Banbura et al., 2010).

The focus here is on how to estimate the matrix $\mathbf{B}$, and the main strategy involves imposing economically meaningful restrictions on the response of the variables to the structural shocks. Whatever of these restrictions is imposed, the identification problem can be rewritten in two steps: a statistical step, and an economic step. The statistical step involves finding the invertible matrix $\mathbf{R}$ such the set of vectors, $\boldsymbol{\nu}_t = \mathbf{R}^T\boldsymbol{u}_t$, are mutually orthogonal, while the economic step involves finding an invertible matrix $\mathbf{H}$, that satisfies the economic restrictions (economic assumption), so that $\mathbf{B} = \mathbf{RH}$.

In this section, we introduce an alternative method to estimate matrix $\mathbf{B}$, which relies mainly on statistical restrictions. Our identification strategy consists in estimating the matrix $\mathbf{B}$ such that the estimated structural shocks $\boldsymbol{\varepsilon}_t$ are statistically independent. The reason for imposing independence comes from economics, which assumes that the structural shocks are *independent* sources of macroeconomic fluctuations.[2]

The idea of *independent* sources is well known in statistics, see Hyvärinen et al. (2010), while it is relatively new in economics.[3]Compared to the standard method used in economics, our approach imposes a stronger statistical restriction, but it does not require any economic assumption a priori. The crucial point here is the distribution of the structural shocks, about which economic theory is silent, meaning that it does not make any distributional assumption. If the shocks are normally distributed, then uncorrelation implies independence. How-

[2]For a brilliant and early discussion on independent shocks and aggregate fluctuations in economy theory, see Jovanovic (1987).

[3]There exist few applications in economics based on statistical independence. Barigozzi and Moneta (2015) use a factor model to identify common functional factors spanning the space of Engel curves.

ever, when $\boldsymbol{\varepsilon}_t$ is Gaussian, and so is $\mathbf{y}_t$, then $\mathbf{y}_t$ generally have non-unique moving average representations (MA) (Gourieroux and Monfort, 2014). If, instead, $\boldsymbol{\varepsilon}_t$ is not Gaussian, then uncorrelation does not imply statistical independence, and furthermore under some regularity conditions it admits a unique MA representation (Lii and Rosenblatt, 1982; Findley, 1986, 1990; Cheng, 1992; Breidt and Davis, 1992; Gouriéroux and Zakoian, 2014). In other words, our method is useful in a framework with non-normal residuals, and in this framework our method identifies the unique matrix $\mathbf{B}$ such that the structural shocks are statistically independent.

Statistical independence is defined using probability density functions: let $p_i(\varepsilon_{i,t})$ be the probability density function (pdf) of the i-th entry of $\boldsymbol{\varepsilon}_t$, and let $p(\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t})$ be the joint pdf of $\varepsilon_{1,t}$, $\varepsilon_{2,t}$, $\ldots$, $\varepsilon_{n,t}$, then if the shocks are statistically independent the following relation holds: $p(\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t}) = \prod_{i=1}^{n} p_i(\varepsilon_{i,t})$. In other terms, the shocks are statistically independent if and only if information on the value of the $\varepsilon_{i,t}$ does not provide *any* information on the value of $\varepsilon_{j,t}$ for $j \neq i$, and vice-versa.

In practice, the literature on Independent Component Analysis (ICA) has suggested different methods to impose statistical independence, (Jutten and Herault, 1991; Hyvärinen et al., 2001). For example, Hyvärinen (1998) minimizes the mutual information, or equivalently by maximizes the negentropy, a measure of non-Gaussianity, (Hyvärinen et al., 2001). Since estimating marginal pdfs is not trivial, Cardoso and Souloumiac (1993) consider the kurtosis, or fourth-cumulant.

The method of Cardoso and Souloumiac (1993) exploits the fact that if the entries of a random vector are mutually independent, then all the cross-cumulants (i.e. the coefficients of the Taylor series expansion of the characteristic function) of order higher than two are equal to zero. In particular, Cardoso and Souloumiac (1993) prove that the entries of a random vector are maximally independent if their associated fourth-order cumulant tensor, which is an $n \times n$ matrix, is maximally diagonal.[4]

Finally, the most popular estimation methods to achieve independence in statistics are: the Fast Fixed-Point Algorithm (FastICA) (Hyvärinen and Oja, 2000; Hyvärinen et al., 2001), Second-Order *Blind* Identification (Belouchrani et al., 1997) and Joint Approximate Diagonalization of Eigenmatrices (JADE) (Cardoso and Souloumiac, 1993). These methods are based on two steps: i) the data are transformed so that the covariance matrix is the identity matrix and ii) the uncorrelated transformed variables are further rotated in order to obtain independence.

Estimation

In this part, we present our identification procedure:

1. The coefficients of the the VAR are estimated using a Multivariate Least Trimmed Squares (MLTS) estimator (Croux and Joossens, 2008). The motivation for using MLST rather than standard OLS is that when the shocks are non-normal, then it performs better than OLS, in terms of computational and robustness to outliers. Moreover, a simple L1-estimate equation by equation may lose the dependence structure between the errors term.

[4]Cumulant tensors are the multivariate generalization of univariate kurtosis and the higher-order generalization of covariance matrices.

2. The estimated residuals $\widehat{\boldsymbol{u}}_t$ are centered and decorrelated. To decorrelate $\widehat{\boldsymbol{u}}_t$ we use whitening. Let $\mathbf{D}$ be a diagonal matrix containing the eigenvalues of the covariance matrix of $\widehat{\boldsymbol{u}}_t$ in decreasing order, and let $\mathbf{V}$ be the matrix of the associated eigenvectors, then whitening decorrelates the residuals as:

$$\widehat{\boldsymbol{\nu}}_t = \mathbf{V}^{-1}\mathbf{D}^{-1/2}\mathbf{V}^T\widehat{\boldsymbol{u}}_t.$$

The term $\mathbf{V}^{-1}\mathbf{D}^{-1/2}\mathbf{V}^T$ is the matrix used to orthogonalize the innovation terms (hence $\mathbf{R}$). The reason why we choose whitening is that the eigenvector $\mathbf{V}$ is identified up to a sign. An alternative strategy to decorrelate $\widehat{\boldsymbol{u}}_t$ is to apply principal component analysis, that is to set $\mathbf{R} = \mathbf{D}^{-1/2}\mathbf{V}^T$. However, decorrelation by principal component analysis can generate permutations of the uncorrelated residuals. In order to observe the residuals in the original space, the decorrelated residuals are set back into original space using $\mathbf{V}^{-1}$.

3. The uncorrelated residuals, $\widehat{\boldsymbol{\nu}}_t$, are rotated in order to get a vector of independent shocks: $\boldsymbol{\varepsilon}_t = \mathbf{H}^T\boldsymbol{\nu_t}$ with $p(\boldsymbol{\varepsilon}_t) = \prod_{i=1}^n p_i(\varepsilon_{i,t})$.

   Borrowing from Ricci and Veredas (2012) who used the following simple measure in different context, we project (ν_{it}, ν_{jt}) onto the 45-degree line (i j):

$$Z_t = \frac{1}{\sqrt{2}}(\nu_{it} + \nu_{jt})$$

   and the tail interquantile range is performed:

$$IQR^{(ij)\xi} = Q^{(ij)\xi} - Q^{(ij)\xi}$$

   where $Q^{(ij)\xi}$ is the ξ^{th} quantile of projection. The larger ξ is, the further we explore the tails. This measure is a pairwise dependency between ν_{it} and ν_{jt}. The main useful features are: i) it is exact for any cut-off point of the tail, ii) it does not depend on specific distributional assumptions, iii) it is simple and no optimizations are needed, iv) it can be computed for tails that are fatter, equal or thinner than those of the Gaussian distribution, and v) it performs well in small samples.

   In this regard, let $\mathbf{Q}(\boldsymbol{\nu}_t) = s_g(\xi)\mathbf{IQR}^{\xi}$ be the $n \times n$ matrix of Interquantile ranges of $n \times 1$ projections of the $\boldsymbol{\nu}_t$ normalized by a factor $s_g(\xi)$ such that under Gaussianity and linear uncorrelation the matrix is equal to the identity matrix.[5] Let $\tilde{\mathbf{D}}$ be a diagonal matrix containing the eigenvalues of the covariance matrix of $Q(\boldsymbol{\nu}_t)$ in decreasing order, and let $\tilde{\mathbf{V}}$ be the matrix of the associated eigenvectors, then the independent shocks are:

$$\widehat{\varepsilon}_t = \tilde{\mathbf{V}}^{-1}\tilde{\mathbf{D}}^{-1/2}\tilde{\mathbf{V}}^T\widehat{\boldsymbol{\nu}}_t.$$

4. Once the third step is applied, $\boldsymbol{\varepsilon}_t$ are identified up to a permutation or a sign with $\mathbf{RH}$. To avoid permutation, the rows of the matrix $\mathbf{H}$ are ordered in such a way that each ε_{it} is tied to a given variable y_{it} after the estimation. Each element on the diagonal should be the largest in absolute value compared to the elements of its row (i.e. $\|C_{ii}\| > \|C_{ji}\|$ for all $i < j$). Another way of putting, it is that the ordering can be determined using the

[5] $\mathbf{Q}(\boldsymbol{\nu}_t)$ is equivalent to $\mathbf{TailCoR}^{\xi}$ that is explained on Ricci and Veredas (2012). The only main difference is the standardized step.

Kurtosis of each elements of $\boldsymbol{\varepsilon}_t$, if the elements do not have homogenous characteristics such as the degree of freedom. Regarding the sign, the transformation $\mathbf{RH}$ is then unique up to sign, but we choose a matrix $\mathbf{B} = \mathbf{JRH}$ for which the highest value in each row is positive where $\mathbf{J}$ is $n \times n$ sign matrix. We obtain the impulse response function by estimating $(\mathbf{I} - \mathbf{A}L)^{-1}\mathbf{B}$.

3 Monte Carlo Study

In this Section, we perform a Monte Carlo simulation exercise in order to study the finite-sample properties of our identification method (henceforth, *Blind* identification). The data are generated by using a bivariate VAR model, namely:

$$\mathbf{y}_t = \mathbf{A}\mathbf{y}_{t-1} + \boldsymbol{u}_t,$$

where $\mathbf{A}$ is generated in such a way that the lowest root is equal to 1.25,[6] and the shocks $\boldsymbol{u}_t$ are linear combinations of independent Student-t distributions. More precisely, $\boldsymbol{u}_t = \mathbf{H}\boldsymbol{\varepsilon}_t$, where $\varepsilon_{1t} \sim t(\alpha)\sqrt{(\alpha-2)/\alpha}$ and $\varepsilon_{2t} \sim t(\alpha)$, and $\mathbf{H}$ is a rotation matrix with rotation angle $\theta = \frac{\pi}{8}$.

The aim of the exercise is to understand the properties of our model when estimating the impulse response functions of $\mathbf{y}_t$ to $\boldsymbol{\varepsilon}_t$, i.e. $\mathbf{C}(L) = (\mathbf{I} - \mathbf{A}L)^{-1}\mathbf{RH}$, that is under which conditions our method can successfully recover $\mathbf{C}(L)$. In other words, we want to understand whether we can use the *Blind* identification explained above when working with quarterly or monthly macroeconomic data.

There are two key aspects that we need to understand: i) how far from normality should our data be for our method to work and ii) how large should the sample size be in order to have enough "tail events".[7] Therefore, we run simulations for different degrees of freedom $\alpha = \{5, 7, 9, 10, 15, 50\}$ for the Student-t distribution, and for different sample sizes $T = \{150, 250, 500, 1000\}$.

Figure 2 shows the boxplots of the estimation of the elements of the rotation matrix $\mathbf{H}$ obtained with 1000 draws and with a sample size of 500 observations.[8] The degrees of freedom are represented on the x-axis, and the value of the estimated elements on the y-axis, where the true H_{ij} is depicted by dots in each sub figure.

We further proceed with the analysis of the impulse response functions (IRF). As an illustrative example, Figure 3 shows the median estimated IRF (solid line) together with the 2.5% and 97.5% quantiles (shaded area), as well as the true IRF (dashed line). Again, results are obtained with 1000 draws and for a sample size of 500 observations. As can be seen, the quantiles are larger under Gaussianity (Figure 3b) than under heavy tails (Figure 3a), thus confirming the result of Figure 2 that our method is capable of correctly identify the IRF only under heavy tails.

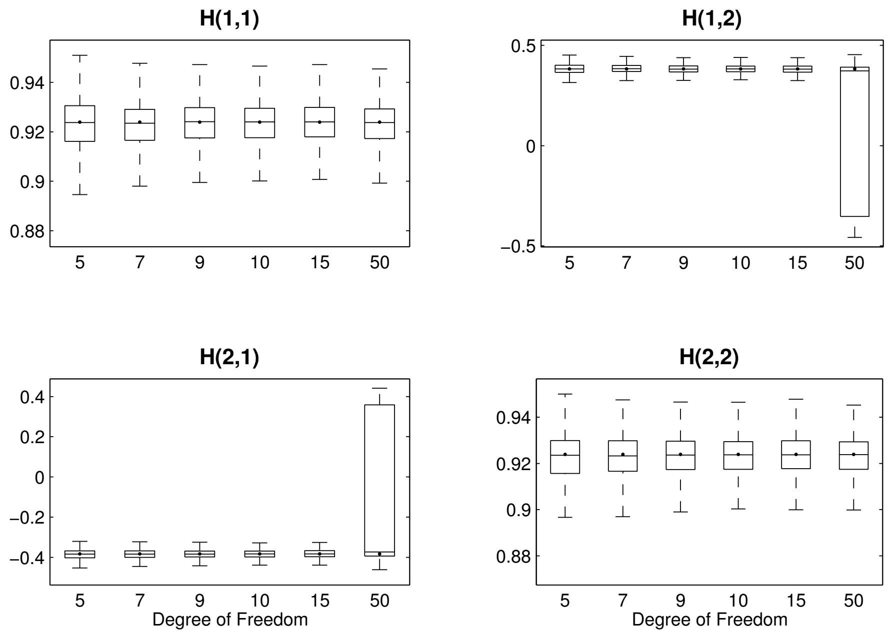
Table 1 shows the Mean Square Error (MSE) of the estimation of $\mathbf{C}(L)$ for different parameter configurations. Let $\widehat{C}^d_{ij,h}$ be the estimated i, j, element of $\mathbf{C}(L)$ at horizon h obtained at the *d-th* draw, and let $C_{ij,h}$ be the true value of the element i, j, at horizon h,

[6] We set autoregressive matrices such that the VAR process is stationary.

[7] Note that, in this exercise, different sample sizes are used and they are not meant to show the consistency of our method, rather they are meant to allow to understand in which framework our approach can be useful.

[8] Results for other configurations are similar and available upon request.

Figure 2: BOXPLOT OF THE MATRIX **H**



This Figure contains the boxplots of the estimation of the elements of **H**. On the x-axis are represented the degrees of freedom, and on the y-axis the coefficients of $\mathbf{H}(i, j)$.

then the entries of Table 1 are:

$$\text{MSE}(h) = \frac{1}{1000n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{d=1}^{1000} (\widehat{C}_{ij,h}^{d} - C_{ij,h})^2.$$

As we can see from Table 1, the MSE increases with α – the closer to normality, the worse the estimation – and is decreasing in T – the larger the sample size, the better the estimation. Note, however, that for $\alpha \geq 10$, even with $T = 1000$, the IRF are poorly estimated. Moreover, even with $\alpha = 5$, which means heavy tails, if the sample size is not large enough (more than $T = 150$), the IRF are not well estimated. All in all, these results emphasize that if *Blind* identification is to be used to identify structural macroeconomic shocks, we need both a relevant departure from normality, and a sample size large enough as reported in Table 1. This means that *Blind* identification may be useful if applied on monthly data, but can hardly be successful with quarterly data.[9]

[9] Obviously, for larger horizons the mean squared error tends to decrease. This is entirely due to the statistical properties of the generated series, that $\mathbf{C}(L)$ is square summable filter.

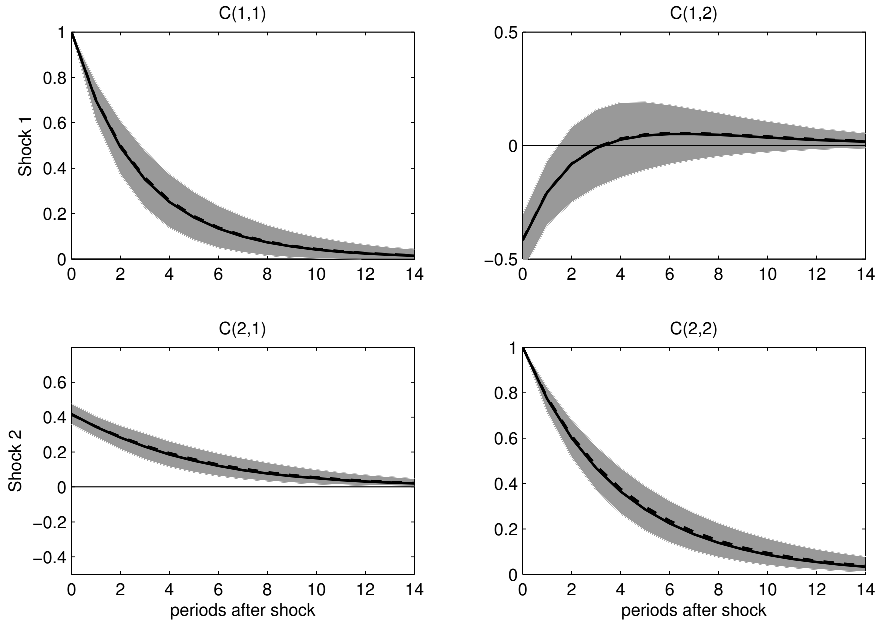
Table 1: IRF Mean Square Error

	h \ α	5	7	9	10	15	50
$T = 150$	1	.027	.040	.083	.095	.125	.171
	2	.019	.026	.048	.055	.068	.094
	4	.014	.017	.025	.028	.030	.041
	8	.005	.006	.008	.008	.008	.001
	15	.001	.001	.001	.001	.001	.001
$T = 250$	1	.016	.022	.043	.073	.101	.174
	2	.011	.014	.026	.042	.057	.095
	4	.009	.010	.016	.022	.029	.044
	8	.004	.005	.006	.007	.009	.012
	15	.001	.001	.001	.001	.001	.001
$T = 500$	1	.006	.010	.024	.035	.074	.154
	2	.004	.006	.013	.018	.036	.074
	4	.003	.004	.007	.009	.015	.027
	8	.001	.002	.002	.003	.004	.006
	15	.000	.000	.000	.000	.000	.000
$T = 1000$	1	.002	.003	.007	.017	.035	.135
	2	.002	.002	.004	.010	.019	.072
	4	.002	.002	.003	.005	.008	.025
	8	.001	.001	.001	.001	.002	.004
	15	.000	.000	.000	.000	.000	.000

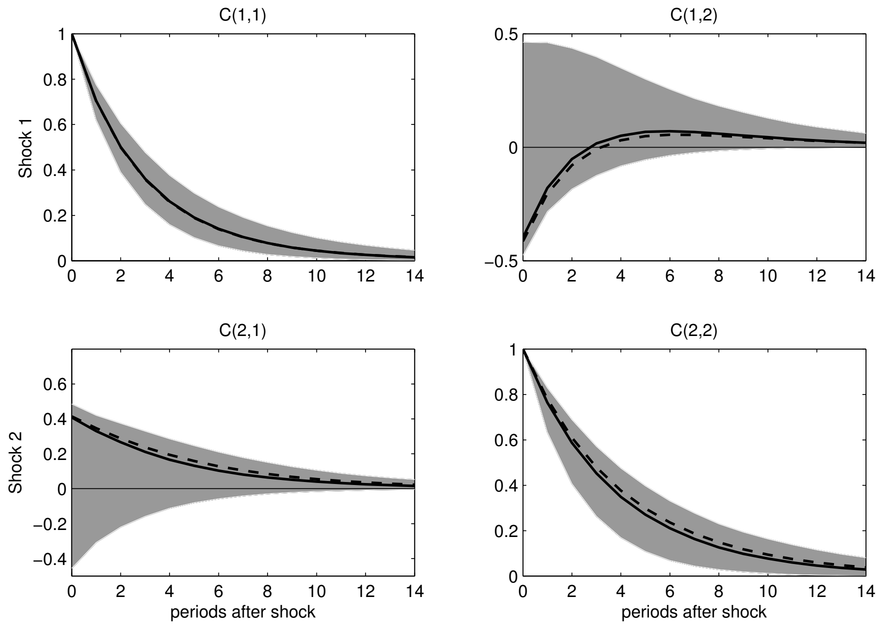
The Table reports IRF Mean Square Error (MSE) estimation for all combinations at horizons (h): 1, 2, 4, 8, and 15. Results are shown for 150,250,500, and 1000 observations (T) and for 4, 5, 8, 10, 15, and 50 degrees of freedom (α).

Figure 3: Impulse response function Simulated

(a) Bivariate Independent Student-t with 5 degree of freedom



(b) Bivariate Independent Student-t with 50 degree of freedom



This Figure contains the median estimated IRF (Solid line) together with 2.5% and 97.5% quantiles (Shaded area), as well as the true IRF (Dashed line). Results are shown for a sample size of 500 observations, and for 5 and 50 degrees of freedom.

4 Empirical Evidence on the US economy

In this section, we apply our methodology for the identification of structural macroeconomic shocks using two different data sets. In the following examples, we illustrate the settings in which there is usually *uncertainity* about the "correct" economic restrictions needed to identify structural shocks. *Blind* identification is a valuable tool as it by-passes the problem of choosing a set of economic restrictions since it mainly exploits the statistical properties of the shocks.

Blind identification is applied on two different VARs, all estimated on US data: i) a monthly trivariate model which studies the effects of oil market shocks (section 4.1); and finally ii) a VAR that studies the interaction between monetary policy and the stock market (section 4.2).[10]

4.1 Crude Oil Market: the effects of demand and supply shocks

Blind identification is able to identify all the structural shocks. Moreover, as we mentioned in Section 3, we achieve a more accurate estimation using a large sample. For this reason, we apply our method on the oil market.[11] In particular, Kilian (2009) identifies all structural shocks using a monthly model. The author concludes that *oil demand* shocks and *oil supply* shocks explain part of the fluctuations in the real oil price and the response of US output.

Following Kilian (2009), the VAR is estimated on i) the percentage change in world crude oil production, ii) an indicator of global activity, and iii) the real price of crude oil imported by the United States,[12] using monthly data from January 1973 to December 2007, where the VAR includes 24 lags.

The shocks are identified by assuming that crude oil production does not respond within the month to both *global oil demand* shocks and *oil market-specific demand* shocks; global activity is affected within the month by *oil supply* shock, but not by *oil market-specific demand* shock; real oil prices respond immediately to *oil supply* shock and *global oil demand* shock. On the contrary, *Blind* identification relies only on imposing independence among structural shocks.

The Table 2 reports the summary of descriptive statistics statistics for the innovations term extracted from the VAR. The checkmark indicates that the null hypothesis (the data are normally distributed) can be rejected at the 5% level. The innovations term are clearly non-Gaussian with the first one that is skewed on the left.

Figure 4 shows the IRF of the three shocks. Notice that, *a priori*, with *Blind* identification we cannot label shocks. Indeed, while when we use economic identification the assumption made for identification provide labels for the shocks, in *Blind* identification labels can be assigned *ex-post* only based on the shape of the IRF. This is the reason why in Figure 4 "shock 1" is not labelled as an *oil supply* shock.

[10] In appendices A and B, we apply our identification method to other illustrative examples in small sample size and with quarterly series. In appendix A, we show that *Blind* identification, in spite of quarterly series, is successful even for small samples if the tail events are large. However, in appendix B, we present an example based on a small sample where not all structural shocks are completely identified due to the uncertainty of their estimation.

[11] For an extended review, see (Hamilton, 2003; Kilian, 2008).

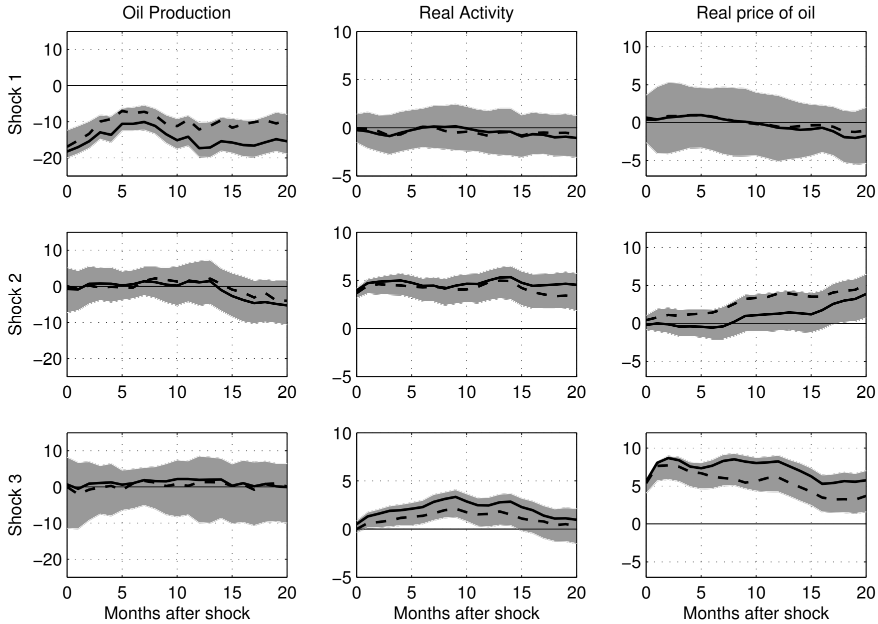
[12] The data for global real activity was downloaded from Kilian's webpage, (Kilian, 2009), while the global crude oil production indicator and the oil price were downloaded from the US Department of Energy.

Table 2: Summary Statistics of Innovations terms: Curde Oil Market

	Mean	Std. Dev.	Skew.	Kurt.	Jarque-Bera test
Innovations 1	-0.99	18.24	-1.044	10.28	✓
Innovations 2	0.25	3.99	0.05	5.88	✓
Innovations 3	-0.05	5.67	0.05	6.46	✓

The Table reports the summary of descriptive statistics statistics for the innovations term extracted from the VAR. The checkmark indicates that the null hypothesis (the data are normally distributed) can be rejected at the 5% level.

Figure 4: Impulse Response Function: Global Crude Oil Market



The Figure contains the impulse response function for a horizon up to 20 months after the shock. The IRFs are estimated both with *economic* identification (Dashed line), and with *Blind* identification (Solid line). The confidence intervals with 90% confidence intervals are constructed based on 1,000 bootstrap replications (Grey shaded area).

After a negative "shock 1", global oil production declines by 20% followed by a partial reversal within the first year, while real activity and real oil price exhibit a small and not significant reaction. Kilian (2008) interprets this shocks as an *oil supply* shock.

A positive "shock 2" leads to a permanent, and significant, expansion of global real economic activity, and to a limited, and significant, variation of global oil production after 15 quarters. A positive "shock 2" also causes a large, permanent, and statistically significant increase in the real price of oil after 15 quarters. Kilian (2008) interprets this shock as an *aggregate demand* shock.

A positive "shock 3" has an immediate and persistent positive effect on the real price of oil up to 8%, a temporary and significant positive effect on real economic activity up to 4%, and a non significant effect on oil production. Kilian (2009) interprets this shock as an *oil market-specific demand* shock.

To sum up, the results obtained with *Blind* identification are similar to those obtained with *economic* identification, few differences emerged, and these differences are given i) by a slightly larger effect of *oil supply* shocks on oil production; ii) by a smaller effect of *aggregate* *demand* shocks on real price of oil; and finally, iii) by a slightly larger effect of *oil market-specific demand* shock on real activity and on real price of oil. All in all, our results validate the *economic* identification scheme of Kilian (2009).

4.2 Interdependence between US monetary policy and the stock market

In this sub-section, there is disagreement in the identification schemes used in VAR models leading to different results. We follow the strand of empirical studies on the effect of *monetary policy* on stock prices. Lee (1992) and Thorbecke (1997), who impose short-run restrictions to identify *monetary policy* shocks, find that *monetary policy* shocks contribute for a small fraction in the variation of stock prices. On the contrary, Lastrapes (1998) and Rapach (2001), who identify *monetary policy* shocks using long-run restrictions, and Bjørnland and Leitemo (2009), who use a combination of short and long-run restrictions, conclude that *monetary policy* shocks have a considerably stronger effect on the stock market. Finally, Rigobon and Sack (2004) find strong short-run effects of *monetary policy* shocks on the stock market using an identification technique based on heterosckedasticity.

To summarize, the literature uses different economic assumptions to disentangle *monetary policy* shocks from the stock market. In this ideal framework with likely non-Gaussianity, *Blind* identification may help to disentangle the various shocks.

Following Bjørnland and Leitemo (2009), we use a monthly VAR model, from January 1983 to December 2002, that includes five variables in the following order: the log of the industrial production, the annual inflation rate, the annual change in the log of commodities prices, the monthly change of log of stock prices (S&P500) and the federal funds rate.[13] The VAR is estimated four lags on the variables included, and *economic* identification is achieved by assuming that *monetary policy* has no long-run effect on real stock prices, which is a common long-run neutrality assumption,(Bjørnland and Leitemo, 2009; Binswanger, 2004).

The Table 3 reports the summary of descriptive statistics statistics for the innovations term extracted from the VAR. The checkmark indicates that the null hypothesis (the data are normally distributed) can be rejected at the 5% level. The innovations term 4 and 5 are clearly non-Gaussian and slightly skewed.

Figure 5 shows the IRF obtained with the two different identification schemes. The solid line and the shaded grey area are, respectively, the point estimate and 68% confidence intervals for the *statistic* IRF. The black dashed line and the grey dashed lines are, respectively, the point estimate and 68% confidence intervals for the *economic* IRF. We build the confidence bands using 1,000 bootstrap replications. We do not directly label shocks a priori as discussed in section 4.1. In the following discussion, the main focus is the IRF to the so-called "shock 4" (*stock market* shock) and "shock 5" (*monetary policy* shock).[14]

As a consequence of positive "shock 4", real stock prices increase by 1%, industrial production increases immediately by 0.1%, and the interest rate increases by only 2 basis points. However, there is no significant effect on the inflation rate. A possible interpretation of this

[13] Bjørnland and Leitemo (2009) detrend industrial production and include inflation rate using first difference to avoid non stationarity. The S&P500 is deflated by using GDP Deflator. We obtain the following time series from the Federal Reserve of St. Louis: industrial production (INDPRO) and federal funds rate (FEDFUNDS). The monthly GDP deflator has been interpolated with CPI (CPIAUCSL) and PPI (PPIFGS), (Bernanke et al., 1997) and used to compute annual inflation rate. For the commodity price, we use the Dow Jones Spot Average (Symbol_DJSD) from Global Financial Data and stock prices from Robert Schiller's webpage, (Shiller, 2005).

[14] Bjørnland and Leitemo (2009) identify only two shocks. The Figure with all IRFs are in appendix C.

Table 3: SUMMARY STATISTICS OF INNOVATIONS TERMS: US MONETARY POLICY AND THE STOCK MARKET

	Mean	Std. Dev.	Skew.	Kurt.	Jarque-Bera test
Innovations 1	0.04	0.45	0.38	4.18	✓
Innovations 2	0.00	0.13	-0.29	3.92	✓
Innovations 3	0.02	3.05	0.19	3.10	✓
Innovations 4	-0.04	3.28	-0.40	4.93	✓
Innovations 5	-0.03	0.21	-0.42	6.85	✓

The Table reports the summary of descriptive statistics statistics for the innovations term extracted from the VAR. The checkmark indicates that the null hypothesis (the data are normally distributed) can be rejected at the 5% level.

shock is to label it as *news* shock that may give information about the future economic condition and could contribute to the business cycles, (Beaudry and Portier, 2006; Bjørnland and Leitemo, 2009). However, it should be noted that the response via *Blind* identification has a smaller impact on interest rate than the *economic* identification.

Turning to "shock 5", an unexpected rise in the interest rate leads to a decrease in industrial production after 2-3 quarters and to a decrease of inflation. This is consistent with the results of the large empirical literature on the effects of *monetary policy* shocks, (Christiano et al., 1999). However, contrary to Bjørnland and Leitemo (2009), real stock prices do not decline after an unexpected rise in the interest rate.

In conclusion, the results lead to reject the identification scheme based on the long-run restriction starting from a VAR with constant coefficient. In this framework, economic restrictions result as an over identification of SVAR.

There are two arguments that support of our results: i) a single event can distort Bjørnland and Leitemo (2009)'s estimation responses. Furlanetto (2011) extends the analysis of Rigobon and Sack (2004) using a larger sample, from 1988 to 2007 and focuses on the stability over time of the results. He shows that the previous results are mainly driven by a single episode market crash in 1987, see Figure 1b. He estimates again using post-1988 data and finds that the estimated policy response is much smaller and not significant.[15] These results are consistent with our finding. ii) Monetary policy does not affect the level of assets prices, but their cycles. Recently, Rey (2015) finds that monetary policy is a determinant of the global financial cycle. The global financial cycles are associated to a boom and bust of assets prices (fluctuations) and this cycle commoves with the volatility (VIX) that is a measure of risk aversion.

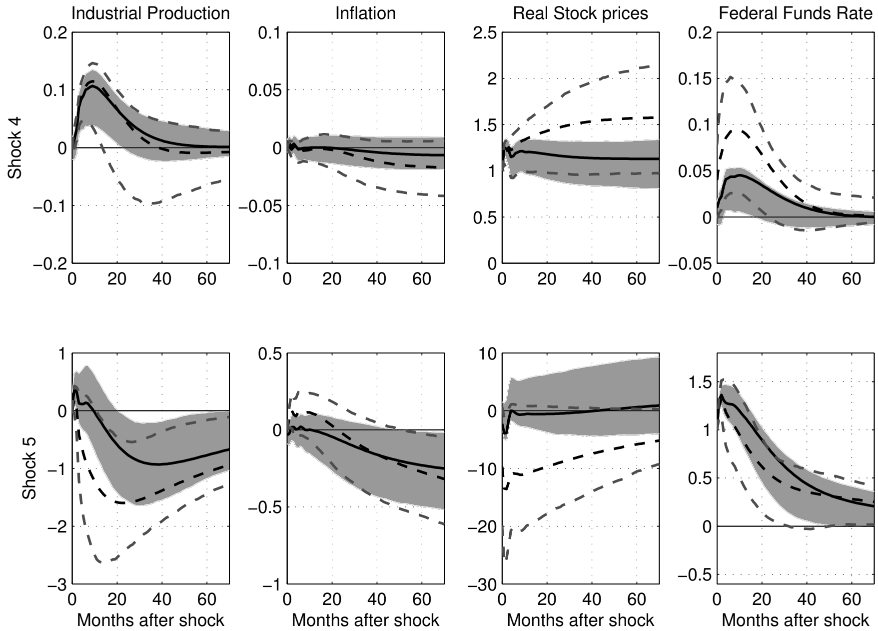
5 Conclusion

The *economic* identification approach, despite its success in a large number of cases, reveals limitations in the identification of the non-normal shocks in SVAR.

To overcome this limitation, we propose an approach for the identification of structural shocks based on tail dependency. Borrowing from statistics, we use a methodology mainly based on two steps to identify all non-normal structural shocks: i) the non-normal residuals are decorrelated and ii) the uncorrelated residuals are further rotated in order to obtain independence using a fourth order matrix. Furthermore, unlike *economic* identification assumptions

[15] Alternatively, Galí and Gambetti (2014) proceed with a time varying coefficient VAR to study the dynamics of the response.

Figure 5: Impulse Response Function: *Stock market* and *Monetary policy* shocks



The Figure contains the impulse response function for a horizon of up to 70 months after the shock. The IRFs are obtained with the two different identification schemes: the solid line and the shaded grey area are, respectively, the point estimate and 68% confidence intervals (1,000 replications) for *Blind* identification, while the black dashed line and the grey dashed lines are, respectively, the point estimate and confidence intervals for the *economic* identification.

which provide labels for the shocks *ex-ante*, *Blind* identification labels can be assigned post-estimation. The validity and performances of the method is verified with a Monte Carlo study. The length of the "period" of available data and their degree of non-normality are shown to be relevant for an accurate estimation.

Finally, we apply our method to two different illustrative examples: i) effects of oil market shocks and ii) interaction between monetary policy and stock market. Our main finding is that we validate overall the *economic* identification scheme of Kilian (2009). In the second empirical illustrative, real stock prices do not respond to *monetary policy* shocks over the period 1983-2003. In other terms, we do not confirm the identification scheme based on combination of short and long run restriction which is adopted in some parts of the economic literature (Bjørnland and Leitemo, 2009). Once again the weakness of ex-ante shocks labelling is revealed.

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A News shocks and the business cycle

A recent influential paper by Beaudry and Portier (2006) drew the attention of economic literature on an old debate on whether the change in expectation of economic agents generates economic fluctuation, (Pigou, 1927). One of the issues in this literature is which set of macroeconomic restrictions is appropriate to identify *news* shocks, where the literature has assumed either that the *news* shocks have delayed effects on productivity, or that they are the only ones having long-run effects on productivity. As we explained in the introduction, when there is uncertainty about the "correct" economic restrictions needed to identify structural shocks, *Blind* identification achieves identification by exploiting mainly the statistical properties of the shocks.

To study the effect of *news* shocks on the business cycle, following Forni et al. (2014), we estimate a bivariate VAR on Total Factor Productivity (TFP) and on the S&P500 by using quarterly data from 1948Q1 to 2013Q4, where the VAR is in levels and it includes 5 lags.[16] We first estimate an unrestricted VAR, and then we identify the *news* shock with both economic restrictions and with *Blind* identification, where *economic* identification is obtained under the assumption that the *news* shock does not have a contemporaneous impact on TFP.

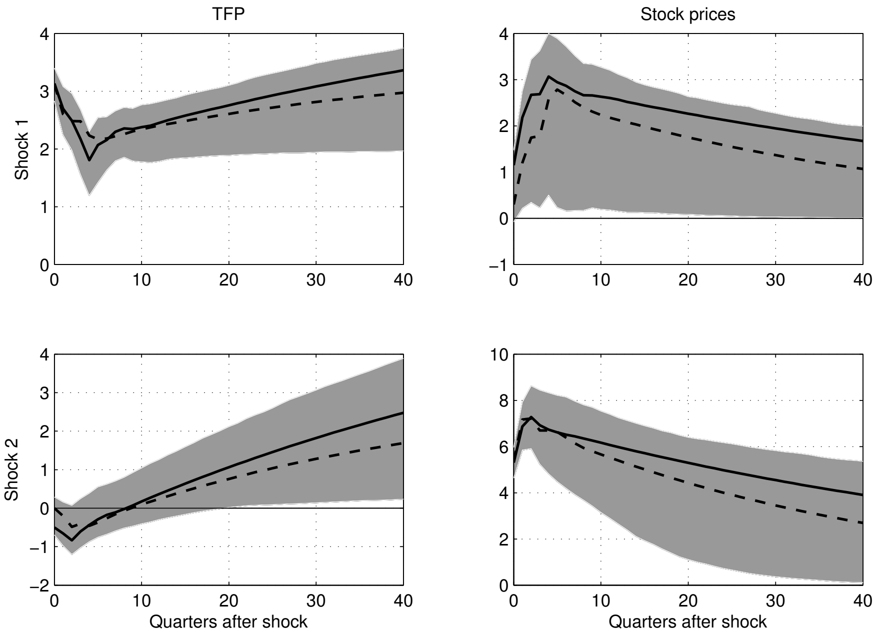
Figure 6 shows the IRF obtained with the two different identification schemes: the dashed line is the *economic* IRF, while the solid line and the shaded grey area are, respectively, the point estimate and 90% confidence intervals for the *statistics* IRF. We construct the confidence bands using 1,000 bootstrap replications.

The main focus is the IRF to the so-called "shock 2" (*news* shock). As we explain in the previous section 4.1, the shocks are not labelled.

After a positive "shock 2", TFP reacts with some delay, while real stock prices increases at impact up to 7% after 3-4 quarters. Overall, the estimated IRF with *Blind* identification are similar to those obtained with *economic* identification, thus validating the *economic* identification scheme.

[16]Total Factor Productivity (adjusted by the capital utilization) is obtained from Fernald (2014), while the S&P500 (deflated by the GDP Deflator) was downloaded from Robert Shiller's webpage, (Shiller, 2005). Both series are standardized by the civilian non-institutional population retrieved from Federal Reserve of St. Louis (mnemonic CNP16OV) and all the variables are in logarithm. This standardization is necessary to compare our results with those of Beaudry and Portier (2006) and Forni et al. (2014).

Figure 6: Impulse Response Function: *News* shocks and the business cycle



The Figure contains the impulse response function for a horizon of up to 40 quarters after the shock. The IRFs are estimated both with *economic* identification (Dashed line), and with *Blind* identification (Solid line). The 90% confidence intervals are constructed based on 1,000 bootstrap replications (Grey shaded area).

B Monetary policy shock with quarterly series

The model follows a well known model on monetary policy, (Stock and Watson, 2001). The aim is to identify policy shocks with a simple model. This framework conveys to show how with quarterly series and a small finite sample, *Blind* identification is not accurate. Therefore, it could hardly be helpful for identification purpose because of lack tail events in the sample.

We include three variables in the VAR model: inflation rate and unemployment rate, representing the non-policy block and the real interest rate, representing the policy block. Although most of the literature considers a larger sets of variables, (Leeper et al., 1996; Bernanke and Mihov, 1998; Christiano et al., 1999), there are few existing papers that use the same small system of equations, (Rotemberg and Woodford, 1997; Cogley and Sargent, 2005, 2001; Stock and Watson, 2001). Here, the choice is mostly for simplicity.

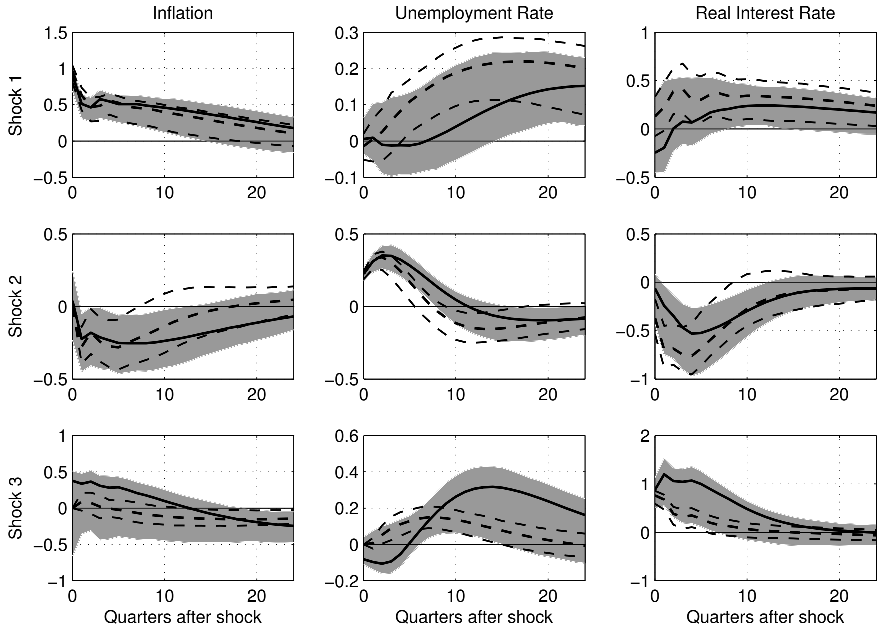
The quarterly sample runs from 1960Q1 to 2000Q4, following Stock and Watson (2001). Four lags are used for the estimation. The identification method of the *monetary* shock used, for comparison, relies on the recursiveness assumption, (Christiano et al., 1999). The main reason for adopting this scheme is its simplicity, making it a natural benchmark reference, while *Blind* identification is such that the shocks are independent.

The IRFs are summarized in Figure 7. The dashed line is the *economic* IRF, while the solid line and the shaded grey area are, respectively, the point estimate and 90% confidence intervals for the *statistics* IRF. We obtain the confidence bands using 1,000 bootstrap replications. Similar to the Section 4, we do not directly label shocks a priori. The focus is on "shock 3" that corresponds to monetary policy shocks in the literature.

In response to the "shock 3", the real interest rate increases at 1 point basis and decreases to zero after 20 quarters. In particular, the shock raises the unemployment rate up to 3 point basis at 12-14 quarters, and over time it reduces the inflation rate. The "shock 3" could be interpreted as a non-systematic monetary policy that captures policy mistakes and interest movements that are responses to exogenous variables. We identify *monetary policy* shock as a measure of non-systematic policy actions.

Clearly, the analysis is limited because of the large confidence bands. The length of the "period" is potentially relevant. These large confidence bands are due to the small sample implying not enough non-Gaussianity. In particular, the "shock 3" to inflation where the confidence bands are extremely large.

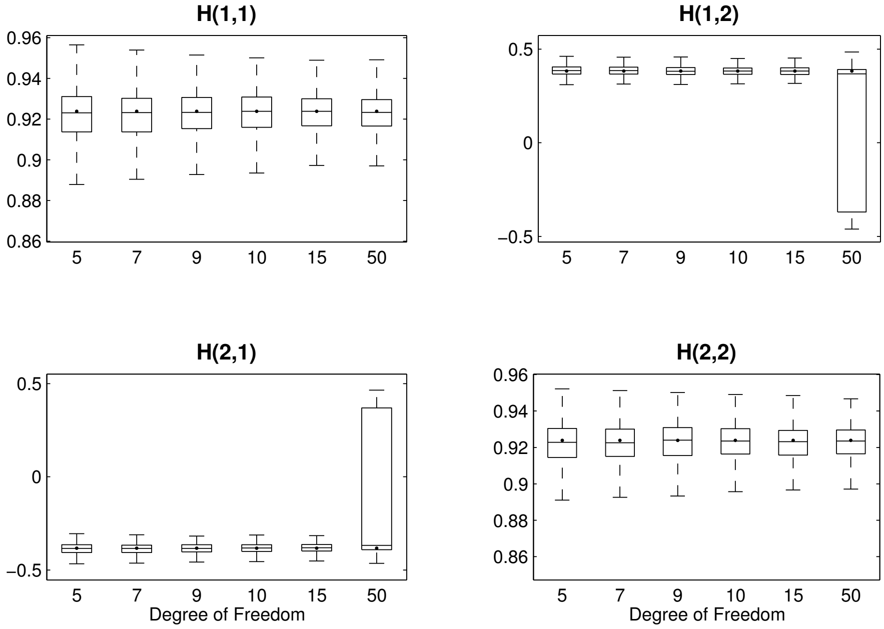
Figure 7: Impulse Response Function: *Monetary policy* shock



The Figure contains the impulse response function for a horizon of up to 25 quarters after the shock. The IRFs are estimated both with *economic* identification (Dashed line), and with independent method (Solid line). The 90% confidence intervals for the independent methods are constructed based on 1,000 bootstrap replications (Grey shaded area).

C Additional Tables and Figures

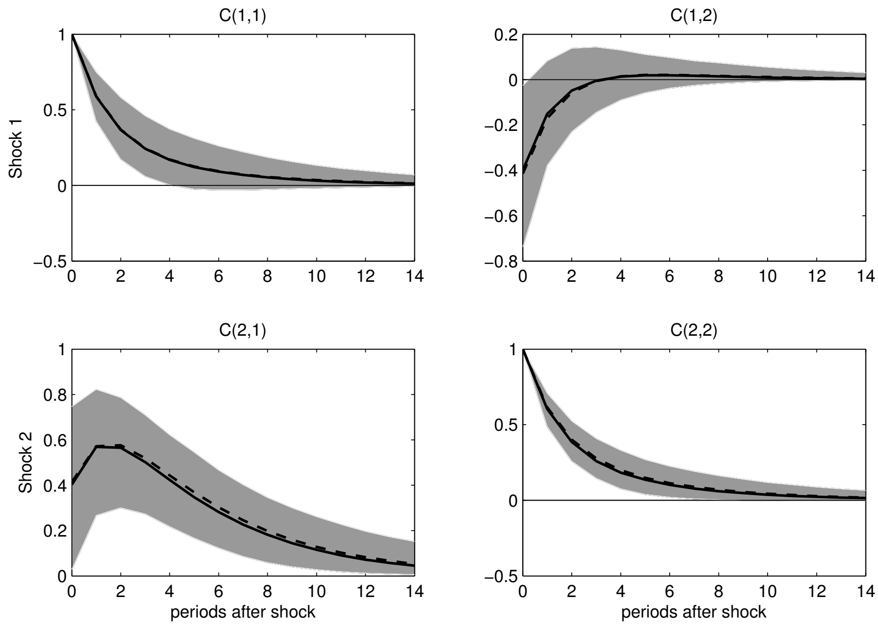
Figure 8: BOXPLOT OF THE MATRIX **H**: T=250



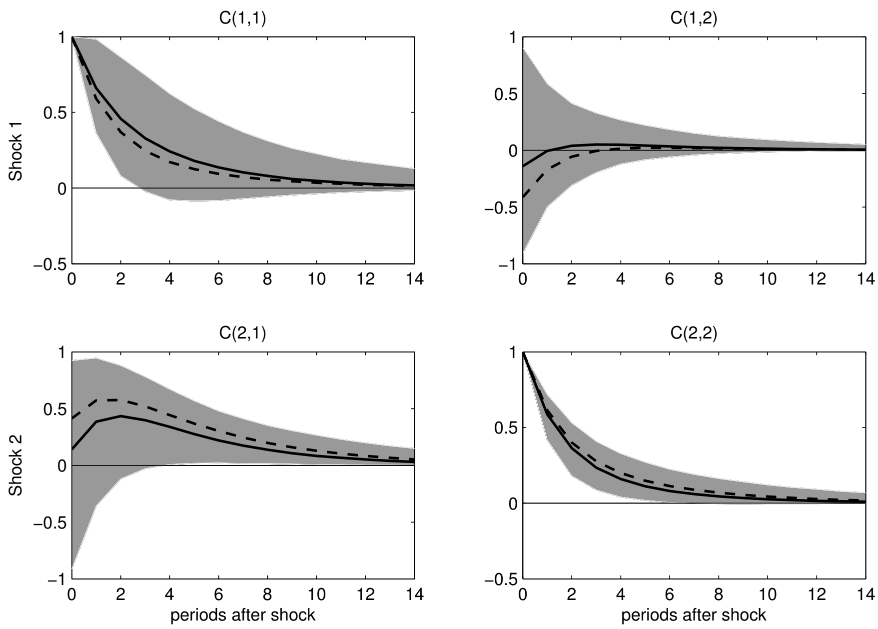
This Figure contains the boxplots of the estimation of the elements $\mathbf{H}$. On the x-axis are represented the degrees of freedom, and on the y-axis the coefficients of $\mathbf{H}(i,j)$. Results are shown for a sample size of 250 observations and 1000 draws.

Figure 9: Impulse response function Simulated: T=250

(a) Bivariate Independent Student-t with 5 degree of freedom

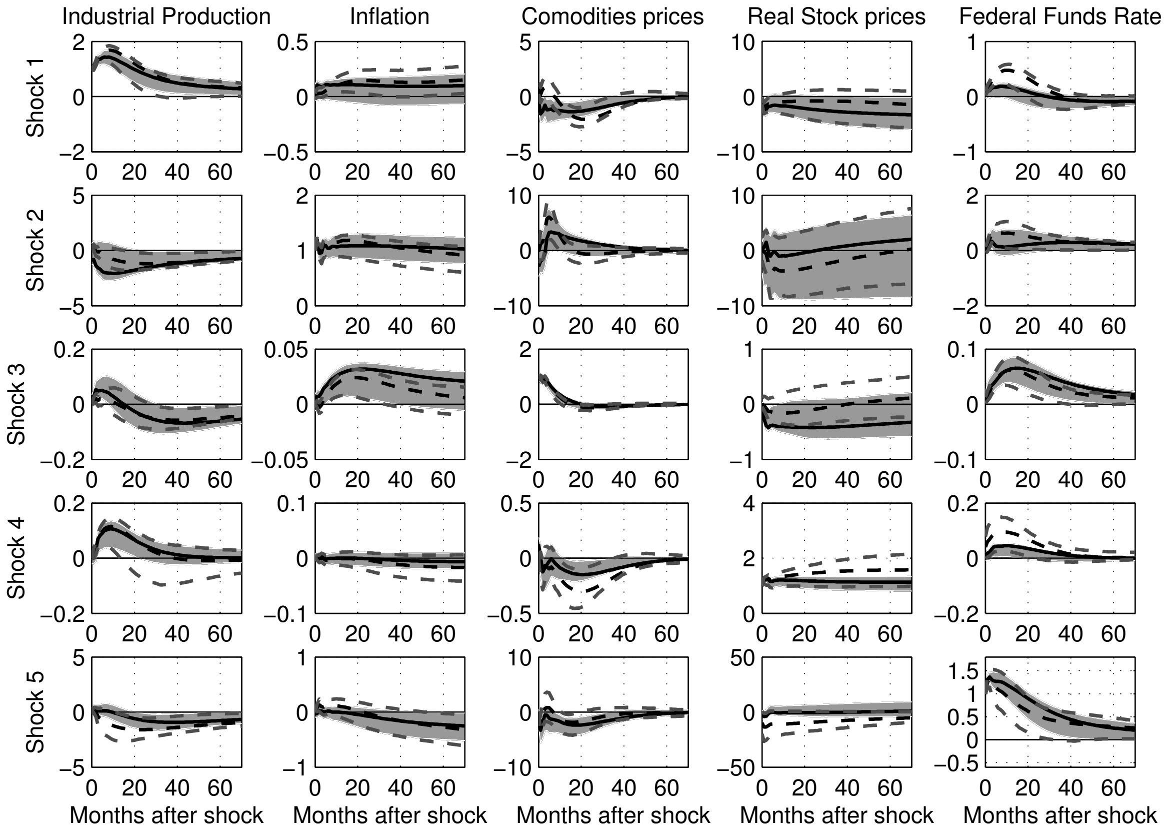


(b) Bivariate Independent Student-t with 50 degree of freedom



This Figure contains the median estimated IRF (Solid line) together with 2.5% and 97.5% quantiles (Shaded area), as well as the true IRF (Dashed line). Results are shown for a sample size of 250 observations, and for 5, and 50, degrees of freedom.

Figure 10: Impulse Response Function (All Shocks): *Stock market*



The Figure contains all the impulse response functions for a horizon of up to 70 months after the shock. The IRFs are obtained with the two different identification schemes: the solid line and the shaded grey area are, respectively, the point estimate and 68% confidence intervals (1,000 replications) for *Blind* identification, while the black dashed line and the grey dashed lines are, respectively, the point estimate and confidence intervals for the *economic* identification.