Structural VAR identification in asset markets using short-run market inefficiencies*

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Abstract

We impose a structure on the short-run market inefficiencies in the asset markets and use this structure to identify a structural vector autoregressive model. This novel identification method is based on more reasonable assumptions than the standard approaches and also gives estimates for inefficiency measures in the markets, which are important on their own. Applying our method on the major European stock markets, we find that while the UK shocks were dominant in Europe until 1999, German innovations have been more important since 1999. We also find that the pattern of inefficiencies are consistent with the rational inattention model of Sims (2003).

Keywords: Structural VAR; Overreaction and Underreaction; Stock Market

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1 Introduction

Although structural vector autoregressive (SVAR) models are frequently used for asset markets, not enough attention has been paid on the identification methods in these models. For identification, most of the studies on asset markets use contemporaneous restrictions due to Sims (1980), which restrict the responses of variables to shocks on other variables contemporaneously (e.g., Eun and Shim, 1989; Karolyi, 1995; Chen et al., 2002; Hsiao et al., 2003; Knif and Pynnonen, 1999). However, as Sarno and Thornton (2004) note asset prices respond to news rapidly, and these contemporaneous restrictions are not appropriate. Long-run restrictions in the sense that one variable is neutral to the shocks in another variable is another approach for identifying SVARs (Shapiro and Watson, 1988; Blanchard and Quah, 1989), but this approach is not appropriate for asset markets either since there is usually no reasonable long-run restriction in the asset markets.

We believe that in order to identify a SVAR model in asset markets, a customized identification approach, which is based on the properties of asset markets, should be used.[1] In this paper we present such a customized approach.

In asset markets, under perfect efficiency, news is processed immediately and completely resulting zero serial correlation in asset returns. However, since Lo and MacKinlay's (1988) finding of significant serial correlation in stock returns, similar findings have been documented by various studies, and return predictability was registered as part of the 'new facts in finance'

[1]Recently, several studies used such customized identification approaches to identify the effects of a monetary policy shock. For example, in an interesting study Faust et al. (2004) impose restrictions on the dynamics of the impulse responses by assuming that responses of the fed funds rate to policy shocks match the impulse responses estimated in the futures market.

(Cochrane, 1999).[2]

We use these documented deviations from efficiency in asset markets to link the contemporaneous responses of the variables to their long-run responses. More specifically, we assume that contemporaneous reactions to news deviate from long-run reactions because of two obstacles. One obstacle is related with the domestic market and the other one is related with the foreign market that the news originates from. Using these two obstacles, we formulate the degree of immediate utilization of j-th market news in i-th market and then use it as a constraint on the model parameters to identify the structural VAR model parameters along with the degree of inefficiency measures by employing a constrained maximum likelihood (ML) estimation. While this approach identifies the column vectors of the variance decomposition matrix, it does not identify the locations of these column vectors in the matrix. This is analogous to the indeterminacy of column locations of a matrix C whose columns are eigenvectors of a matrix A, i.e. $C\Lambda C^{-1} = A$ where Λ is a diagonal matrix that holds the eigenvalues of A. In order to identify the locations of the columns, we assume that idiosyncratic market shocks explain their own asset markets' variations at least as much as they explain other markets' variations.

Using this novel approach, we identify a SVAR model and study the changes in the transmission of shocks among the largest four European stock markets since the commencement of the Economic and Monetary Union (EMU) in the financial markets on January 1, 1999. We find that while

[2]The literature has pointed out various reasons for possible sources of autocorrelation in the stock returns. For example, some studies note the importance of psychological biases which result in overreaction/underreaction to news (e.g., Barberis et al., 1998), some other studies highlight the information processing constraints due to Sims (2003), (e.g., Hong et al., 2003).

the UK shocks were dominant before 1999, German innovations have been playing a very important role since 1999.

We also study the characteristics of the inefficiency measures by checking whether the estimated inefficiency measures are consistent with the implications of the rational inattention model of Sims (2003). If agents tend to pay more attention to the more important news sources and tend to ignore the less important ones, then we expect to find a negative relation between the measure of inefficiency with respect to a particular news source and the relative importance of that news source. We find a significant negative relation between these two elements consistent with the rational inattention explanation.

In the next section we present a framework to model the informational efficiencies in the stock markets using a structural VAR model. Section 3 discusses the implications of the rational inattention model. Section 4 presents the results and the last section concludes.

2 A novel structural VAR model

2.1 Short-run asset market inefficiencies

Suppose that returns in n assets are stacked in the vector $r_t = (r_{1t}, ..., r_{nt})'$ which is covariance stationary with a Wold representation

$$r_t = \Phi(L)\varepsilon_t \tag{1}$$

where $\Phi(L) = \phi_0 + \phi_1 L + \phi_2 L^2 + ...$ and $\phi_0 = I$, ε_t is serially uncorrelated and $E[\varepsilon_t \varepsilon_t'] = \Omega$ for all t. Assuming that $\Phi(L)$ is invertible, r_t has a reduced form VAR representation

$$\Psi(L) r_t = \varepsilon_t \tag{2}$$

where $\Psi(L) = \Phi(L)^{-1}$ and $\Psi_0 = I$.

Suppose that u_t represents the idiosyncratic asset specific shocks $u_t = A^{-1}\varepsilon_t$ with $E(u_t u_t') = I$ so that[3]

$$AA' = \Omega. \tag{3}$$

From equation (1) we get

$$r_t = \Phi(L)Au_t. \tag{4}$$

Under efficient market hypothesis a shock should cause immediate adjustment of the asset prices. That is, the full impact of an idiosyncratic shock $\Phi(1)A$ should be reflected in the prices immediately after u_t is observed so that $\Phi(1)A = \Phi(0)A$. But since we have $\phi_0 = I$, the initial utilization of news is represented by A and our perfect efficiency condition becomes $\Phi(1)A = A$. In other words, if r_t is an efficient market variable and the agents efficiently incorporate all the information in their decisions, the vector moving average coefficient matrices $\phi_i,\ i \geq 1$, should be zero. Based on this, one can construct a measure for the immediate utilization of the j-th market news in the i-th market as

$$\theta_{0,ij} \equiv \frac{e_i' A e_j}{e_i' \left(\Phi(1)A\right) e_j} \tag{5}$$

where e_i denote i-th column of the identity matrix. In equatioin (5) the numerator represents the immediate utilization of news and the denominator represents the full impact of news. When $\theta_{0,ij} = 1$, the asset prices in the i-th market are efficiently formed with respect to the information in the j-th market; when $\theta_{0,ij} < 1$, agents initially under react to news from the j-th

[3]In this study, we assume that the commonalties among the asset markets are driven mainly by transmission of uncorrelated idiosyncratic asset market shocks across the markets. If it is assumed that market shocks are correlated with each other, then generalized VAR models due to (Koop et al., 1996; Pesaran and Shin, 1998) can be used to study the transmission of shocks.

market; and when $\theta_{0,ij} > 1$ agents initially over react to the news from the j-th market.

In order to identify the SVAR we impose a structure on the inefficiency measure $\theta_{0,ij}$. To model the $\theta_{0,ij}$, we consider two obstacles that cause deviations from efficiency: One related with the asset market that is of interest and one related with the market the shock originates from. There can be various interpretations of these obstacles. For example, if r_t denotes the vector of stock market returns in n countries, the first source of inefficiency may be related with the sentiment of a typical investor in one country or it may be related with the institutions in that country. Similarly, the second source of inefficiency may be related with a typical investor's utilization of news from a specific country or it may be related with the country's institutions that may affect the announcement and interpretation of news. Briefly, the first obstacle affects how a particular stock market investor utilizes a typical information and the second obstacle affects how a particular news source is utilized by a typical investor.

The reaction coefficient of the agents in market i is denoted k_i. The reaction coefficient of agents to market j news is denoted d_j. If $k_i > (<)1$ we say that the agents in market i typically overreact (underreact) to news. If $d_j > (<)1$ we say that agents typically overreact (underreact) to the j-th market news. When market j is shocked, the total reaction in market i is measured as $k_i d_j$. Then optimum value of the $k_i d_j$ is 1 and any deviation of $k_i d_j$ from 1 is considered as a mis-reaction to news. As before, if $k_i d_j > (<)1$, we say that agents in market i over (under) react to the news originating from market j. From equation (5), substituting $\theta_{0,ij} = k_i d_j$, we get a relation between the initial reaction to news and the final impact of it[4]

$$A_{ij} = k_i d_j \left(e_i' \Phi(1) A e_j\right) \tag{6}$$

or in matrix notation

$$A = K\Phi(1)AD \tag{7}$$

where K and D are diagonal matrices $K = diag(k_i, i = 1 \dots n)$ and $D = diag(d_j, j = 1 \dots n)$. The initial utilization of news in the whole system can be represented by $n \times n$ matrix

$$\Theta_0 = \{\theta_{0,ij}, i, j = 1 \dots n\} = K\mathbf{1}D$$

where $\mathbf{1}$ is a $n \times n$ matrix of ones so that $[\Theta_0]_{ij} = k_i d_j$.

To estimate the model parameters including the n^2 elements of matrix A, one can maximize the likelihood function subject to the constraints given in equation (7). Formally, one can solve the problem

$$\begin{aligned} \max_{A_{ij},k_i,d_j} \quad & -\log(|AA'|) - \text{trace}[(AA')^{-1}\hat{\Omega}] \\ s.t. \quad & A_{ij} = k_i d_j e_i' \left[\Phi(1)A\right] e_j, \qquad i, j = 1, \dots, n. \end{aligned} \tag{8}$$

where $\hat{\Omega}$ denotes the $n \times n$ estimated variance covariance matrix.

2.2 Identification

If there are matrices A^*, K^* and D^* that satisfy equations (3) and (7) then they also solve the maximization problem given in (8). So the basic idea behind our identification method is that while we introduce $2n$ unknowns via K and D matrices, we also introduce n^2 equations in the system through

[4] In section 2.3 we propose a flexible estimation method to relax this structure and check for the robustness of the results.

equation (7), which, we hope, are sufficient for identifying the system for a suitable n. In order to satisfy both equations, the order condition is given by $n \geq 3$ since the number of unknowns is $n^2 + 2n$ and the number of equations is $(3n^2 + n)/2$. However, even if $n \geq 3$, the parameter estimates still cannot be determined uniquely. To see this rewrite equation (7) as

$$AD^{-1}A^{-1} = K\Phi(1). \tag{9}$$

Suppose K^* is a solution for K in equation (9), then A and D can be calculated using Jordan decomposition such that D contains the reciprocals of the eigenvalues of $K^*\Phi(1)$ and A contains the corresponding eigenvectors. But since the order of the eigenvalues in matrix D can be selected arbitrarily, i.e. which eigenvalue will be the first, second, and so on, the corresponding columns of matrix A can be selected arbitrarily as well. Moreover, the same arbitrary selection of columns is true for the second condition $AA' = \Omega$, which is implied by the maximum likelihood estimation too. Since $AA' = \sum_i a_i a_i'$ where a_i is column i of A, switching the locations of two columns does not change the value of AA' but only the order of $a_i a_i'$ in the summation. All of these imply that while we can detect the column vectors in matrix A, we cannot identify the location of the columns in the matrix. Fortunately, a refinement process can be applied without imposing any strong assumptions and the position of the columns can also be identified.[5]

For elimination of unreasonable matrix formations of the matrix A, we assume that, in terms of explained share in the steady-state variance decompositions, the idiosyncratic market shocks have the largest impact on the own-markets. Note that this assumption does not rule out the case that, for

[5] The identification is a problem for individual K and D matrices too. But this is not a major problem since $k_i d_j$, i.e. the elements of Θ_0, which are of great interest, are uniquely identified.

example, German shocks explain, say, 60 percent of the variation in French stock market while French shocks explain less than 10 percent of French stock market variation. Such a case is totally consistent with our assumption. But in this case the assumption suggests that German shocks should explain more than 60 percent of German stock market variations and French shocks should not account for more than 10 percent of another country's stock market variations. So if i-th market's explained share of variation by the j-th market's shocks is represented by $(i, j)^{th}$ element of matrix V, then our assumption is equivalent to arranging the columns of the steady-state variance decompositions such that in each column the largest number locates on the diagonal of the matrix V. But it is not the same as arranging the columns of the matrix such that in each row the largest number locates on the diagonal.

2.3 Constrained ML estimation and penalty function

Since the constraints imply n^2 restrictions on the parameters, a maximization algorithm that can handle large number of constraints can be used to solve the problem given in (8).[6] Note that the problem given in equation (8) can be represented in a more general form by constructing the penalty function problem

$$\min_{A,K,D} \quad p_l \left[L_u - L(A) \right] + p_c \left(\sum_{ij} \left[A - K\Phi(1)AD \right]_{ij}^2 \right) \tag{10}$$

where $L(A) = -\frac{T}{2}(\log(|AA'|) + \text{trace}[(AA')^{-1}\hat{\Omega}])$, L_u is a predetermined value of the likelihood function such as the unconstrained maximized value of the relevant part of the likelihood function, e.g., $L_u = L_u^* \equiv -\frac{T}{2}(\log(|\hat{\Omega}|) + n)$.

[6]For example, Interactive Matrix language package of SAS (SAS/IML) has two nonlinear optimization functions "nlpmns" and "nlpqn" that can be used.

The penalty function (10) is quite general and any constrained and unconstrained maximization problem can be expressed as a special case of this minimization problem by changing the penalty coefficients p_l and p_c. For example the problem given in (8) is the case when $p_c \to \infty$ and $p_l > 0$. Similarly, the unconstrained maximization of the likelihood function is the special case when $p_c = 0$ and $p_l > 0$.

Now consider the case in (8) so that $p_l > 0$ and $p_c \to \infty$. In this case the restrictions given in equation (7) will be fully satisfied at the expense of possibly large deviations from zero in the first part of the minimization problem. In this case, the maximized value of likelihood function could be very low compared to the unconstrained maximized likelihood value, the overidentifying restrictions could be rejected, and the estimates would not be valid since the model information provided in the variance covariance matrix of the system would be largely destroyed by the imposed constraints.

An alternative approach would be *relaxing* the restrictions imposed by equation (7). For example, instead of assuming that $A_{ij} = k_i d_j e_i' \left[\Phi(1)A\right] e_j$ is a deterministic process and exactly satisfied, we can let some small perturbations v_{ij} so that

$$A_{ij} = k_i d_j e_i' \left[\Phi(1)A\right] e_j + v_{ij}$$

and minimize the sum of squares of the elements of $A - K\Phi(1)AD$ as given in (10). For example, when $p_l \to \infty$ and $p_c > 0$, the likelihood function will reach its unconstrained maximum value and the elements of the matrix $|A - K\Phi(1)AD|$ will be minimized. This way, while the model information summarized in $\hat{\Omega}$ will not be disturbed at all, the information imposed by the constraints will be utilized in the best possible way. This is an interesting way for identification since the constraints are used to *filter out* a large set of unreasonable solutions $\tilde{A}$ whose likelihood functions give the same value as L^*, i.e. $L(\tilde{A}) = L^*$, but do not fit with the assumptions behind the constraints.

One can estimate the model with several different values of p_l and p_c to check for the robustness of the estimates. If the estimates are very sensitive to the values of p_l and p_c, then it would mean that the constraints are not suitable for the model. To check for the robustness of our results we solve the minimization problem given in (10) for three different cases:

i. when the likelihood function is maximized so that it reaches its unconstrained value and the constraints are utilized as well ($p_l \to \infty$ and $p_c > 0$); and,

ii. when $p_l >> 0$ and $p_c > 0$ is selected such that the estimated LR statistic is less than $LR^* = 3$ (an arbitrary selection to perturb the model a little such that LR test does not reject the null hypothesis at 5 percent significance level even when the degrees of freedom is one).[7]

iii. when the constraints are fully satisfied at the expense of the information in the variance-covariance matrix of the system (i.e., $p_c \to \infty$ and $p_l > 0$);

As we show later, while the results change somewhat in numerical values for these three cases, the pattern of the variance decompositions generally does not change and, more importantly, the conclusions of this study hold for all three cases.

[7]Note that this case can be estimated by setting $L_u = L_u^* - \frac{LR^*}{2}$ and $p_l \to \infty$, $p_c > 0$.

3 Implications of rational inattention

Rational inattention model of Sims (2003) implies that agents have limited information-processing capacity, which causes inefficient usage of information. Implications of such a model on stock markets is presented by Peng and Xiong (2002). They assume that investors have only limited total capacity and allocate their limited capacity on the most important factors and, ignore some of the less relevant factors. Under this model we expect that the degree of inefficiency in utilization of country j news in country i stock market prices should be inversely proportional to the share of explained steady-state variance of country i stock market prices by country j shocks.[8]

We can construct a measure of inefficiency using $\theta_{0,ij} - 1$ which gives the degree of overreaction to j-th country's news in i-th country's stock market. Alternatively, for measuring the degree of inefficiency, it will be useful to ignore the direction of the reaction and just concentrate on the deviations from perfect efficiency. If we take the absolute value of the deviations from perfect reaction, we get such a measure

$$\pi_{ij} = |\theta_{ij} - 1| \tag{11}$$

which is monotonic with respect to the absolute deviations from efficiency.

The share of how much of the variation in stock prices in the i-th variable is accounted for by the j-th variable at the steady-state can be computed as:

$$w_{ij} = \frac{(e_i'\Phi(1)Ae_j)^2}{e_i'\Phi(1)AA'\Phi(1)'e_i} \tag{12}$$

where the denominator gives the total variation in the i-th stock price and the numerator gives the explained variance by the j-th innovation.

[8] Such a model is somewhat trivial and is available from the author.

The rational inattention model implies that if $\pi_{ij} = f(w_{ij})$ where $f(w_{ij}) \geq 0$ for all w_{ij}, then we should have $f' < 0$. The validity of this conjecture is checked when we discuss the empirical results.

4 Empirical results

4.1 The data and a preliminary analysis

We use daily stock index returns for the largest four countries of Europe: Germany, the UK , France and Italy. The stock indices used are the Frankfurt DAX 30 (Germany), the FTSE 100 Share Index (the UK), the CAC 40 Composite Stock Index (France) and the MIBTEL Index (Italy). The data are downloaded from finance.yahoo.com. The data range from Jan. 1994 to Dec. 2003. We pick this sample period on purpose so that Jan-1999, the start of final stage of the Economic and Monetary Union (EMU) is at the center of the sample period.

Table 1 presents the correlations for the daily stock returns over 1994-1998 and 1999-2003 periods. As it is seen from the table, the correlations seem to be quite high and tend to increase even more after 1999. For example, the correlation between German and French stock returns were 0.69 during 1994-1998 period, but it increased to 0.93 during 1999-2003 period. This pattern can be seen for the other countries too.

Trading hours of these stock exchanges is an important determinant of the identification method. If, for example, the trading hours did not overlap between these markets, then identification using Cholesky decomposition would be reasonable. However, there are significant overlaps in trading hours of these markets although they usually do not have exactly the same hours. Moreover, in recent years several European stock exchanges made arrangements among themselves for synchronous trading.

One may wonder the impact of using Cholesky decomposition for identification in SVAR model. In order to demonstrate the importance of the ordering of the variables in the Cholesky decomposition, we estimate a VAR(2) model on daily stock returns over 1994-1998 and 1999-2003 and use Cholesky decomposition for identification. We employ two different orderings: i) Germany, the UK, France, Italy; ii) the UK, Germany, France, Italy. The steady-state variance decompositions are presented in Table 2. A look at the first two rows will be sufficient to understand the impact of ordering. When Germany is the first country in the ordering (top panel in the table), the UK shocks have almost no effect on German stock prices (1.9 and 0.0 percent in the pre-EMU and post-EMU periods respectively) and German shocks have a very large impact on the UK stock prices (42.5 and 56.9 percent). But when the UK is the leading country in the VAR (bottom panel), we get exactly the opposite results. In this case, German shocks have almost no effect on the UK stock prices (2.3 and 0.2 percent) but the UK shocks have a quite significant impact on German stock prices (50.0 and 46.0 percent). These results suggest that it is not possible to draw a conclusion about the transmission of shocks between the stock exchanges using Cholesky decomposition.

4.2 Identification of SVAR: An example

As noted earlier, by solving the constrained maximization problem we can identify the column vectors uniquely but we cannot identify the positions of these column vectors in the A matrix. This means that with different initial conditions numerical maximization problem yields the very same vectors but the position of the vectors in the matrix change. The same is true for $\Phi(1)A$

and for the steady-state variance decompositions calculated using (12) too. In order to identify the locations of the columns in the matrix, we will use our identifying restriction on the steady-state variance decompositions.

To understand the identification problem and our solution, we present an example in Table 3. Table presents both the initial estimate of the steady-state variance decomposition estimates and the final version of them after we use our assumption to identify the location of the vectors. In the left part of the table we present the initial estimates of vectors with titles, Vec1, Vec2, Vec3 and Vec4. Note that, the locations of these column vectors are arbitrarily selected. If we had used different initial conditions, we could have found exactly the same vectors but they could be ordered, say, Vec2, Vec3, Vec4 and Vec1. Our aim is to relate these vectors with country innovations.

The explained share of variation by each country is shown in the columns of the table. The largest number in each column is shown in bold. If vector 1 were consistent with our assumption then the largest number in the first column should be located in the first row, that is, for Germany. But at its current position, the largest explained variation is for France (i.e., 33 percent). So this column should be in the third place to represent the innovations to France. Similarly, the largest number in the third column is located in the first row (42 percent) and so this column should locate in the first column. After this reshuffling of columns, we can now name the columns with the corresponding country names, which is given on the right side of the table.

In the previous example there was one bold number in each row. If we have more than one bold numbers in a row, we can have several alternatives for identification. First, a mechanical solution for identification would be to design a method that penalizes the degree of deviations from our assumption. It is also possible to use any additional *a priori* information on the structure of the matrix other than the assumption we made. For example, it may be necessary to pick one dominant country among two countries as the leader. Notice that such an assumption is much weaker than imposing restrictions on matrix A (i.e., with Cholesky ordering), as it is usually done. If there are no reasonable assumptions to refine the results, then it may be a good idea to accept that there is more than one matrix formation that can explain the system. In this case, as long as the possible explanations are not too many, we can still get valuable information from this approach.

4.3 SVAR results

We estimate the model in two steps. In the first step, we estimate a VAR(2) model where disturbances are assumed to follow a GARCH(1,1) process.[9] We construct the 4×4 variance covariance matrix using the residuals. In the second step we maximize the likelihood function under the constraints given in equation (7) for all three cases: i) $p_l \to \infty$ and $p_c > 0$; ii) $p_l >> 0$ and $p_c > 0$ s.t. $LR \leq 3$; iii) $p_c \to \infty$ and $p_l > 0$. Remember that in our first case, the maximized value of the likelihood function is the same as the unconstrained maximized value. So this case can be thought as an unconstrained maximum likelihood estimation along with some structure on the estimated A matrix that is consistent with our assumptions on the form of inefficiency. The second case is estimated in such a way that any positive deviation from $LR - 3$ is penalized with $p_l \to \infty$. The third case satisfies the constraints but the maximized value of the likelihood function is usually

[9]Number of lags are assigned using AIC.

much lower than the maximum value of it causing quite large LR statistics and rejecting the null hypothesis of overidentifying restrictions at 5 percent significance.

Estimated steady-state variance decompositions are presented in Table 4. In the table left panel gives the steady-state variance decompositions for 1994-1998 period and the right panel presents the results for 1999-2003 period. The top panel in the table presents the results for the first case ($p_l \to \infty$ and $p_c > 0$), the middle panel presents the results for the second case ($p_l >> 0$ and $p_c > 0$ s.t. $LR \leq 3$) and the bottom panel gives the results for the last case ($p_c \to \infty$ and $p_l > 0$).

First note that, among all six models one of the models, the first case for 1994-1998, do not fit our assumptions exactly pointing an identification problem between the France and Italy columns. In the top panel for 1994-1998 period, we see that the diagonal element in the third column is slightly lower than the fourth row value (52.2 percent vs. 53.5 percent), which suggests that the third column should be actually in the fourth place. However, in this case the third column would have larger deviations from the assumption (17.9 vs. 20.4). So the current selection of columns deviates less from our assumption. Moreover, our perturbed results in the the second case do not point a problem in the current selection of columns.

The results show a clear difference in the variance decompositions between the two periods especially in the weights of Germany and the UK. For example, while, during the pre-1999 period, all three cases consistently show that the share of German shocks account for 42 percent (41.9, 41.6 and 42.3 percent in three cases respectively) of the variation in German stock market index, in the post-1999 period German shocks dominate German stock market variations by accounting for more than 90 percent (97.5, 97.7 and 93.6 percent respectively) of the variation in German stock market variations.

As for the UK case, the situation is exactly the opposite. While during the pre-1999 period, the UK shocks explain more than 90 percent of the variation in the UK stock market index (96.3, 95.5 and 93.3 percent respectively), during the post-1999 period explained share by domestic shocks decreases substantially (30.8, 24.1 and 16.3 percent respectively).

The decrease in the importance of the UK shocks and the increase in the importance of German shocks can be also seen for Italian and French stock markets too. For example, in the second case, we find that the contribution of the UK shocks decreases from 27.3 percent to 0.4 percent for Italy. Similarly, the contribution of the UK shocks drop significantly from 29.4 to 0.5 percent for France. Briefly, we find that in the post-1999 period, while the importance of German shocks increased for all the countries, the importance of the UK shocks decreased substantially.

Finally we study the relation between the degree of inefficiency and the share of explained variance and we present the results in Figure 1 and Figure 2. In the vertical axis we give the degree of inefficiency as calculated by absolute deviations from efficiency $|\theta_{ij} - 1|$. In the horizontal axis we present the explained share of the variance w_{ij} as calculated from equation (12). First note that the measures of inefficiencies in the 1994-1998 period are larger than those in the 1999-2003 period. While the deviations from efficiency are estimated as large as 0.7 in the pre-EMU period, in the post-EMU period the largest deviation is found 0.29. Second, in both of the figures we observe significant negative relation between the measure of inefficiency with respect to a news source and the importance of that news source, which implies that the pattern of inefficiencies are consistent with the rational inattention model.[10]

5 Conclusions

In this study we propose a new approach for identification of structural VAR models in asset markets. We impose a structure on the deviations from efficiency by assuming that there are market specific and news source specific obstacles, which cause overreaction or underreaction to a particular news source in a particular market. We use this structure as constraints in the maximum likelihood estimation and employ a constrained maximum likelihood estimation. In order to check for the robustness of our results, we generalize our estimation method by introducing a flexible penalty function representation of the problem. We allow small deviations from the constraints and reach the unconstrained maximized value of the likelihood function as if there were no constraints. This approach is interesting because the information summarized in the variance covariance matrix of the system is not damaged by the constraints at all and the constraints are utilized as well.

Applying our method to identify a SVAR model on four major stock markets in Europe, we find that there has been a significant change in the transmission of shock structure among the European stock markets since 1999. While the UK shocks were dominant before 1999, German shocks have become dominant since 1999. We also observe that deviations from efficiency have decreased since 1999 and are consistent with the rational inattention model of Sims (2003).

[10]For brevity, we only present the results for the third case. The other two cases give similar results. All three cases show significant negative relation between the inefficiency measure and the importance of news.

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Table 1: Correlations of daily stock market returns

	1994-1998				**1999-2003**			
	Germany	UK	France	Italy	Germany	UK	France	Italy
Germany	1				1			
UK	0.66	1			0.73	1		
France	0.69	0.73	1		0.83	0.83	1	
Italy	0.57	0.6	0.61	1	0.74	0.71	0.81	1

Table 2: Impact of ordering: Steady-state variance decompositions using Cholesky Decompositions (%)

Order of variables: Germany - UK - France - Italy

Market	Innovations 1994-1998				Innovations 1999-2003			
	Germany	UK	France	Italy	Germany	UK	France	Italy
Germany	95.4	1.9	2.5	0.2	100.0	0.0	0.0	0.0
UK	42.5	57.2	0.1	0.2	56.9	43.1	0.0	0.0
France	37.1	10.2	52.6	0.1	76.6	7.2	16.1	0.0
Italy	22.9	6.6	8.6	61.9	59.6	5.0	5.3	30.1

Order of variables: UK - Germany - France - Italy

Market	Innovations 1994-1998				Innovations 1999-2003			
	Germany	UK	France	Italy	Germany	UK	France	Italy
Germany	49.8	50.0	0.1	0.1	54.0	46.0	0.0	0.0
UK	2.3	91.2	5.9	0.7	0.2	99.8	0.0	0.1
France	6.3	41.8	51.8	0.1	16.5	67.2	16.3	0.0
Italy	3.2	26.0	9.0	61.8	13.6	50.8	5.3	30.3

Table 3: Initial and final estimates of variance decompositions (%)

	Initial Estimate				**Final Estimate**			
Market	Vec1	Vec2	Vec3	Vec4	Germany	UK	France	Italy
Germany	7	41	**42**	10	**42**	41	7	10
UK	6	**93**	0	0	0	**93**	6	0
France	**33**	22	1	44	1	22	**33**	44
Italy	13	13	2	**72**	2	13	13	**72**

Notes: Vec1, Vec2, etc., denotes Vector1, Vector2, etc. The largest values in the columns are shown in bold.

Table 4: Steady-state variance decomposition estimates (%)

$p_l \to \infty$ and $p_c > 0$

Market	Innovations 1994-1998 Germany	UK	France	Italy	1999-2003 Germany	UK	France	Italy
Germany	41.9	41.5	12.7	4.0	97.5	0.0	0.0	2.5
UK	0.7	96.3	0.6	2.4	56.0	30.8	10.3	2.8
France	1.1	28.8	52.2	17.9	74.7	0.0	24.1	1.2
Italy	2.3	23.7	53.5	20.4	73.6	1.8	7.9	16.8

$p_l >> 0$ and $p_c > 0$ s.t. $LR \leq 3$

Market	Innovations 1994-1998 Germany	UK	France	Italy	1999-2003 Germany	UK	France	Italy
Germany	41.6	41.8	12.5	4.0	97.7	0.0	0.9	1.4
UK	0.6	95.5	0.3	3.7	58.1	24.1	15.0	2.9
France	1.1	29.4	51.7	17.8	73.4	0.5	24.3	1.8
Italy	2.5	27.3	49.5	20.8	72.4	0.4	0.5	26.7

$p_l > 0$ and $p_c \to \infty$

Market	Innovations 1994-1998 Germany	UK	France	Italy	1999-2003 Germany	UK	France	Italy
Germany	42.3	40.6	7.0	10.0	93.6	5.1	0.2	1.2
UK	0.5	93.3	6.1	0.1	80.2	16.3	2.1	1.3
France	1.0	21.9	32.7	44.4	42.8	14.5	42.5	0.2
Italy	2.4	12.8	13.1	71.7	34.1	13.7	18.5	33.7

Notes: See the section (2.3) for the details of the estimation process.

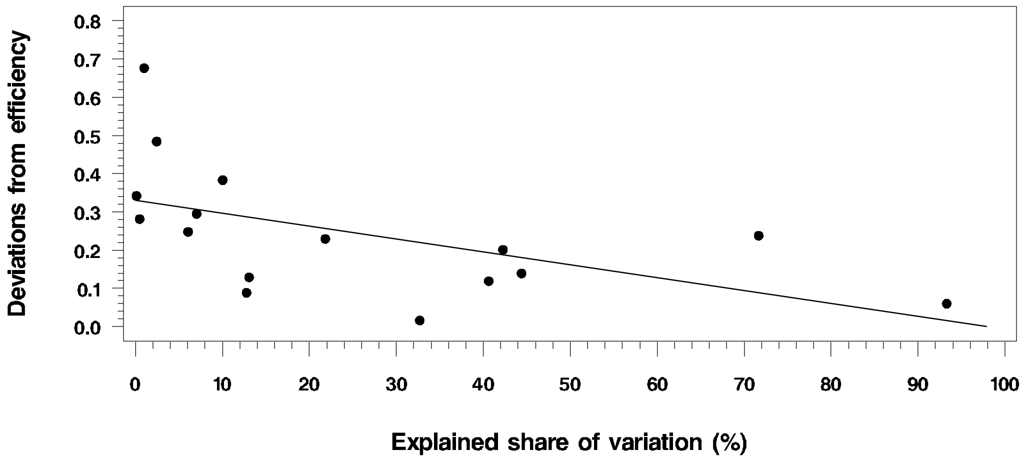

Figure 1: Absolute deviations from efficiency ($|1-\theta_{ij}|$) versus explained share of variance (w_{ij}), 1994 - 1998, ($p_l > 0$ and $p_c \rightarrow \infty$)

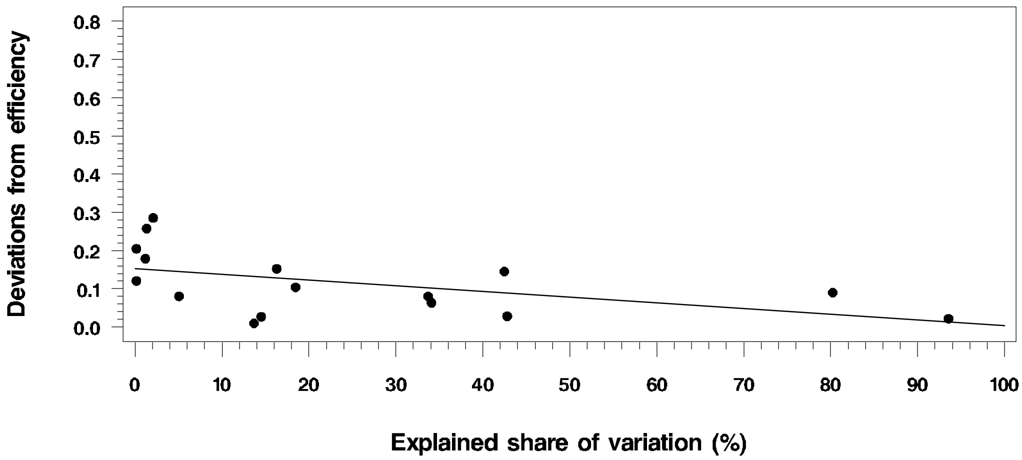

Figure 2: Absolute deviations from efficiency ($|1-\theta_{ij}|$) versus explained share of variance (w_{ij}), 1999 - 2003, ($p_l > 0$ and $p_c \rightarrow \infty$)