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Research article

On the importance of testing structural identification schemes and the potential consequences of incorrectly identified models

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Abstract: Identification schemes are of essential importance in structural analysis. This paper focuses on testing a commonly used long-run structural parameter identification scheme claiming to identify fundamental and non-fundamental shocks to stock prices. Five related widely used structural models on assessing stock price determinants are considered. All models are either specified in vector error correction (VEC) or in vector autoregressive (VAR) form. A Markov switching in heteroskedasticity model is used to test the identifying restrictions. It is found that for two of the models considered, the long-run identification scheme appropriately classifies shocks as being either fundamental or non-fundamental. A small empirical exercise finds that the models with properly identified structural shocks deliver realistic conclusions, similar as in some of the literature. On the other hand, models with identification schemes not supported by the data yield dubious conclusions on the importance of fundamentals for real stock prices. This is because their structural shocks are not properly identified, making any shock labelling ambiguous. Hence, in order to ensure that economic shocks of interest are properly captured, it is important to test the structural identification scheme.

Keywords: markov switching model; vector autoregression; vector error correction; heteroskedasticity; stock prices
JEL classification numbers: C22

1. Introduction

An important issue in the economics and finance literature is whether stock prices reflect some underlying fundamentals or whether they are merely driven by speculation. For instance, Fama (1990), Schwert (1990), Canova and De Nicolo (1995), Lee (1998), Cheung and Ng (1998), Nasseh and Strauss (2000) and Velinov and Chen (2015), among others find that fundamentals are important in explaining stock prices. On the other hand, studies such as Shiller (1981), Summers (1986), Binswanger (2000, 2004b, c), Allen and Yang (2004) and Laopodis (2009, 2011) tend to find that stock prices are not fully driven by fundamentals.

Naturally, to answer this question, one would have to determine what stock price fundamentals are. Although the studies cited above use varying methodologies, one way of identifying such fundamentals is by means of a structural vector autoregressive (SVAR) model with appropriate parameter restrictions. Of course, if there happen to be cointegrating relationships among some of the variables then a structural vector error correction (SVEC) model can be used instead. Such multivariate time series models are quite popular in this line of literature and are the main focus of this paper.

In particular, we consider simple systems consisting of three variables that claim to be able to capture fundamental shocks to stock prices. Such trivariate models are popularly used, as shown in Table 1. All these models are similar in the sense of using a different proxy of real economic activity for the first variable, while the other two variables usually remain the same. They have the advantage of being relatively straightforward to implement and to work with. Further, due to their low dimensionality, they do not require too many restrictions so as to identify the structural shocks. For example, in case of a SVAR model only three restrictions are enough to exactly identify the shocks.

Structural identification restrictions however, need to be well founded and should be convincingly justified since they are usually not testable (Erceg et al, 2005). In fact, all of the studies cited in Table 1 use exactly identified structural models, hence none of the restrictions can be tested in a conventional setting. This is problematic since stock price fundamentals are identified through some assumptions by the researcher and any subsequent conclusions are based on these non-testable assumptions. It could be a reason why the papers in Table 1 reach different conclusions concerning the drivers of stock prices. Hence, for instance, Rigobon (2003) and Gospodinov (2010) advocate the need for statistical information to help verify the structural shocks.

Table 1. Popular models used in the literature.

Model	**Used by**
$y_t = [Y_t, r_t, s_t]'$	Lee (1995a), Rapach (2001)*, Binswanger (2004a), Jean and Eldomiaty (2010) Lanne and Lütkepohl (2010)
$y_t = [IP_t, r_t, s_t]'$	Binswanger (2004a), Laopodis (2009)*, Jean and Eldomiaty (2010)
$y_t = [D_t, r_t, s_t]'$	Lee (1995a), Allen and Yang (2004), Jean and Eldomiaty (2010)
$y_t = [E_t, r_t, s_t]'$	Binswanger (2004a), Jean and Eldomiaty (2010), Hatipoglu et al. (2014)
$y_t = [E_t, D_t, s_t]'$	Lee (1998), Chung and Lee (1998), Allen and Yang (2001), Binswanger (2004a), Jean and Eldomiaty (2010)

The variables used are real GDP (Y_t), the index of industrial production (IP_t), real dividends (D_t), real earnings (E_t), real interest rates (r_t) and real stock prices (s_t).

* These variables are a subset of the variables used in the original model.

This paper tests the identification schemes used by the studies in Table 1. In particular, we use the novel approach developed in Lanne et al. (2010) and Herwartz and Lütkepohl (2014) to test whether the structural identification schemes are supported by the data. This could determine whether fundamental shocks have been correctly identified and hence reduce any conflicting conclusions arising form similar types of analyses. As far as we are aware, this is the first paper to test the identification assumptions of different models in this line of literature.

Structural restrictions are tested by extending the basic linear model to allow for a regime dependent covariance matrix. While, potentially other parameters can also switch, a switching covariance matrix is what we need to test the restrictions and hence, this specification will be used. The regimes switch according to a first order discrete Markov process. This allows for heteroskedastic error terms across states. By means of this methodology there are enough reduced form parameters to identify the structural parameters. Hence, any (identifying) restrictions become over-identifying and can be tested.

We conclude with a small empirical exercise investigating the practical implications of accepting/rejecting the identification scheme. We find that the models with properly identified structural shocks deliver plausible and similar conclusions as some existing studies. On the other hand, models with identification schemes not supported by the data yield unrealistic conclusions on the importance of fundamentals for real stock prices - either explaining everything or nothing. This is because their structural shocks are not properly identified, making any shock labelling ambiguous. Hence, in order to ensure that economic shocks of interest are properly captured, it is important to test the structural identification scheme.

The basic theory and methodology used in this paper is outlined in Section 2. Section 3 presents the identification test results along with relevant details on the model selection procedure. Section 4 deals with model robustness issues. Section 5 presents the practical implications of accepting/rejecting the identification scheme through an empirical exercise. Finally, Section 6 summarizes the main conclusions.

2. The models

This section briefly introduces the basic multivariate structural models used in Table 1 and the regime switching extension needed for testing the structural restrictions.

2.1. The basic structural models

The conventional vector autoregressive model with p lags, VAR(p) can be written as

$$y_t = \nu + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t, \tag{1}$$

where y_t is a $(K \times 1)$ vector of stationary endogenous variables, ν is a $(K \times 1)$ vector of constants and $A_i, i = 1, \ldots, p$ are $(K \times K)$ autoregressive parameter matrices. The $(K \times 1)$ vector of reduced form error terms, u_t is assumed to have an expected value of 0 and a positive definite covariance matrix Σ_u. Hence, $u_t \sim (0, \Sigma_u)$.

In case of cointegration, the following reduced form vector error correction model (VEC(p-1)) is used

$$\Delta y_t = \nu_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t, \tag{2}$$

where y_t may include variables with unit roots. Here ν_t is a K dimensional deterministic component that can include an intercept and a trend term, hence $\nu_t = \nu_0 + \nu_1 t$. Further, $\Gamma_i, i = 1, \ldots, p-1$ are $(K \times K)$ parameter matrices and the residual terms, u_t are assumed to have the same properties as before. Here Δ is the first difference operator (so that $\Delta y_t = y_t - y_{t-1} = (1 - L) y_t$, where L is the lag operator). This means that Δy_t is assumed to be $I(0)$, such that Πy_{t-1} also needs to be stationary. The $(K \times K)$

matrix Π is of rank r, (where $0 < r < K$) and captures the cointegrating relations of the model. More specifically, since Π is singular, it can be decomposed into the product of two $(K \times r)$ matrices of full column rank, α, β so that $\Pi = -\alpha\beta'$. Here β is referred to as the cointegrating matrix and contains the r linearly independent cointegrating relations, so that $\beta' y_{t-1}$ is stationary, and α is known as the loading matrix.

In line with the literature, structural shocks are defined as $u_t = B\varepsilon_t$, where ε_t is a K dimensional vector of structural residuals such that $\varepsilon_t \sim (0, \Sigma_\varepsilon)$, where Σ_ε is usually assumed to be I_K, the identity matrix. Here B is a $(K \times K)$ matrix depicting contemporaneous effects. According to these assumptions $\Sigma_u = BB'$. The structural parameters can be derived from the reduced form parameters. However, since Σ_u is symmetric, this only leaves $K(K+1)/2$ reduced form parameters to identify the K^2 structural parameters of the B matrix. Hence, $K^2 - K(K+1)/2 = K(K-1)/2$ restrictions need to be imposed. This is done in different ways for the SVAR and SVEC model and is discussed in the following.

2.1.1. Restrictions on the VAR model

The papers considered in Table 1 all make use of long-run identifying restrictions, as in Blanchard and Quah (1989). Hence, it is briefly explained here how such restrictions are implemented. Rewriting equation (1) in lag polynomial form gives

$$A(L)y_t = \nu + u_t, \tag{3}$$

where $A(L) = I_K - A_1 L - A_2 L^2 - \cdots - A_p L^p$. Provided that $A(L)^{-1}$ exists, the Wold moving average (MA) representation for the stationary y_t process is

$$y_t = \mu + \sum_{s=0}^{\infty} \Phi_s u_{t-s} = \mu + \Phi(L)u_t, \tag{4}$$

where $\mu = (I_K - A_1 - A_2 - \cdots - A_p)^{-1}\nu = A(1)^{-1}\nu$, $\Phi(L) \equiv A(L)^{-1}$ and $\Phi_0 = I_K$. Having defined the structural shocks as $\varepsilon_t = B^{-1}u_t$, the structural representation of (4) is

$$y_t = \mu + \sum_{s=0}^{\infty} \Psi_s \varepsilon_{t-s} = \mu + \Psi(L)\varepsilon_t, \tag{5}$$

here $\Psi_i \equiv \Phi_i B$, for $i = 0, 1, 2, \ldots$. The accumulated long-run effects of the structural shocks over all time periods are given by the long-run impact matrix, $\Psi \equiv \Phi B$, where $\Phi \equiv \sum_{s=0}^{\infty} \Phi_s = A(1)^{-1}$. It is on the Ψ matrix that Blanchard and Quah (1989) suggest imposing identifying restrictions, usually in the form of zeros. This is interpreted as some shocks having permanent effects and others only having transitory effects.

Most studies reported in Table 1 make use of the following lower triangular Ψ matrix

$$\Psi = \begin{bmatrix} \star & 0 & 0 \\ \star & \star & 0 \\ \star & \star & \star \end{bmatrix}, \tag{6}$$

where $\star$ denotes an unrestricted element. The studies claim that this identification scheme distinguishes between fundamental and non-fundamental shocks (see for eg. Zhong et al. (2003)).

The non-fundamental shock is assumed not to have any permanent effect on any of the variables except the last one (last column of (6)). The other two shocks are assumed to be of a fundamental nature; in that one of them (first column of (6) influences all variables in the long-run, while the other (second column of (6) only leaves a permanent impact on the last two model variables.* The identification scheme in (6) is used for testing restrictions on SVAR models throughout this paper.

2.1.2. Restrictions on the VEC model

From Granger's representation theorem, the VEC counterpart of Φ is given as

$$\Xi = \beta_\perp \left[\alpha'_\perp \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha'_\perp,$$

where $\perp$ stands for the orthogonal complement of a given matrix. For instance, the orthogonal complement of an $(m \times n)$ matrix, A, is given by the $(m \times (m - n))$ matrix, $A_\perp$. The Ξ matrix is computed from the estimates of the reduced form parameters.

The long-run impact matrix is ΞB, this is the VEC equivalent to the Ψ matrix above. The number of restrictions on the ΞB matrix necessary to achieve exact identification of the structural parameters depends on the number of cointegrating relations, r. Note that Ξ is a singular matrix, in particular, the rank of Ξ is $K - r$ and according to King et al. (1991) there can be at most r transitory shocks, i.e. r columns of ΞB can be 0 and each column of zeros stands for only $K - r$ restrictions. In addition, there need to be $r(r - 1)/2$ restrictions on the B matrix to identify the non-permanent shocks. The remaining restrictions needed to exactly identify the model can be placed on the non-zero elements of ΞB or B.

As will be seen in Section 3.11, all the VEC models considered in this paper have a cointegrating rank of one. Hence, long-run restrictions on SVEC models are placed as follows

$$\Xi B = \begin{bmatrix} \bigstar & 0 & 0 \\ \bigstar & \bigstar & 0 \\ \bigstar & \bigstar & 0 \end{bmatrix}. \tag{7}$$

Here again $\bigstar$ denotes unrestricted elements. This seemingly lower triangular identification scheme potentially also distinguishes between fundamental and non-fundamental shocks. In particular, a non-fundamental shock is assumed not to have permanent effects on any of the variables, i.e. the last column of (7) contains only zeros. Note that such an assumption cannot be made for the SVAR model restrictions since Ψ in (6) cannot be a singular matrix. Indeed, it may be more realistic to assume that shocks labeled as non-fundamental do not have a permanent impact on any of the model variables. Note that the column of zeros provides two independent restrictions and hence, there needs to be one more restriction on the second column of ΞB to exactly identify the model. Further, since $r = 1$ (see Section 3.1.1) there do not need to be any restrictions on B.

2.2. The Markov switching SVAR and SVEC models

In order to test identification schemes such as in (6) or in (7), Lanne et al. (2010) and Herwartz and Lütkepohl (2014) expand the standard structural models discussed above to allow for regime dependent

*The zero restriction in the second column of Ψ in (6) is left out in Lee (1995) and Laopodis (2009). The shocks are still labeled as fundamental and non-fundamental, even though the model itself is under-identified. Further, the models used in Jean and Eldomiaty (2010) are initially identified according to the Swanson and Granger (1997) identification scheme, however, in a section on model robustness, they note that a lower triangular long-run impact matrix as in (6) performs equally well.

covariance matrices. In addition, for estimation convenience they also assume that the residuals are normally distributed, hence,

$$u_t \sim \mathrm{NID}(0, \Sigma_u(S_t)). \tag{8}$$

The normality assumption still leads to a very general class of unconditional distributions and is hence, not restrictive. S_t is assumed to follow a first-order discrete valued Markov process with transition probabilities given by

$$p_{ij} = P(S_t = j | S_{t-1} = i),$$

which can be grouped in an $(M \times M)$ matrix of transition probabilities, P such that the rows add up to 1 and where M are the number of different states.

Note that it is also possible to allow for switches in the intercept term, ν in the SVAR case and ν_0 in the SVEC case. Indeed, this may be a reasonable assumption given the data and will be further investigated in Section 4 on robustness. In principle, all the parameters could be subject to regime switches, however such assumptions need to be justified in the sense of there being structural breaks in the data or some reasonable economic explanation as to why a certain parameter could be switching. In this analysis it is crucial for the covariance matrices to be switching and all other parameters are assumed to be stable. We therefore, only consider models with a switching covariance matrix.[†]

2.3. Estimation and testing procedure

This section concludes with a brief examination of parameter estimation and restrictions testing procedures used in this paper.

The VAR parameters are estimated by means of OLS. Further, since only long-run restrictions are imposed, estimation of the structural parameters is straightforward. After a simple substitution it follows that $\Phi\Sigma_u\Phi' = \Psi\Psi'$. The left hand side of this equation is known, hence for a fully identified model, Ψ is easy to derive. The contemporaneous matrix is then easily obtained as $B = \Phi^{-1}\Psi$.

The VEC parameters are estimated by the method of reduced rank regression discussed in Johansen (1995). Since the cointegrating matrix, β, is not unique it can be identified by a simple normalization such that the first r rows contain an $(r \times r)$ identity matrix, as is shown in (Lütkepohl, 2005). The structural parameters are estimated by an iterative algorithm proposed by Amisano and Giannini (1997) subject to identifying restrictions placed as in Vlaar (2004).

The MS models parameters are estimated using the iterative expectation maximization (EM) algorithm following Velinov and Chen (2015). This algorithm was initially popularized by Hamilton (1994) for univariate processes and later extended to multivariate processes by Krolzig (1997). Since the β matrix in the VEC models symbolizes long-run relationships, it is not re-estimated at each maximization step of the EM algorithm.[‡]

In order to test the identifying restrictions it is necessary to decompose the covariance matrices in the following way

$$\Sigma_u(1) = BB', \quad \Sigma_u(2) = B\Lambda_2 B', \quad \ldots \quad \Sigma_u(M) = B\Lambda_M B', \tag{9}$$

[†]Note that the Markov switching (MS) model is a convenient way of dealing with data subject to structural breaks. In the relevant literature changes in structural relationships are documented in Lee (1998), Chung and Lee (1998), Binswanger (2000,2004b, c) and Laopodis (2009) among others. However, this is not the purpose of the present analysis.

[‡]It is trivial to change this so that a reduced rank regression is performed in each maximization step. However, this leads to increased computational time without influencing the overall results since they are robust to this specification.

where the $\Lambda_i, i = 2, \ldots, M$ matrices are diagonal with positive elements, $\lambda_{ij}, i = 2, \ldots, M, j = 1, \ldots, K$ and can be interpreted as relative variance matrices. The underlying assumption is that the contemporaneous effects matrix, B stays the same across states. This assumption is testable for models with more than two Markov states. The corresponding test statistic has an asymptotic χ^2 distribution with $(1/2)MK(K+1) - K^2 - (M-1)K$ degrees of freedom.

In order for the B matrix in (9) to be unique up to changes in sign and column ordering, it is necessary for all pairwise diagonal elements in at least one of the $\Lambda_i, i = 2, \ldots, M$ matrices to be distinct. For example, for a 3-state model it is required that $\lambda_{ij} \neq \lambda_{il}, i = 2$ and/or 3, $j, l = 1, \ldots, K, j \neq l$. In other words, even if these elements are equal in one state, they should not be equal in the other state. For a more detailed explanation of the uniqueness of the B matrix the reader is referred to Proposition 1 in the appendix of Lanne et al. (2010). If this distinction requirement is fulfilled, then B is said to be identified through heteroskedasticity.

In this paper Wald tests[§] are used to determine whether the $\lambda_{ij}, i = 2, \ldots, M, j = 1, \ldots, K$ parameters are distinct. In order to implement such tests standard errors of the parameter estimates are obtained from the inverse of the negative of the Hessian matrix evaluated at the optimum.

Finally, provided that the B matrix is identified through heteroskedasticity, any restrictions (short or long-run) are over-identifying and can therefore be tested. This is done by means of an LR test, which has an asymptotically χ^2 distributed test statistic with degrees of freedom equal to the number of restrictions being tested.

3. Testing results

This section first discusses model specification and selection and then presents the results of testing the long-run identification schemes.

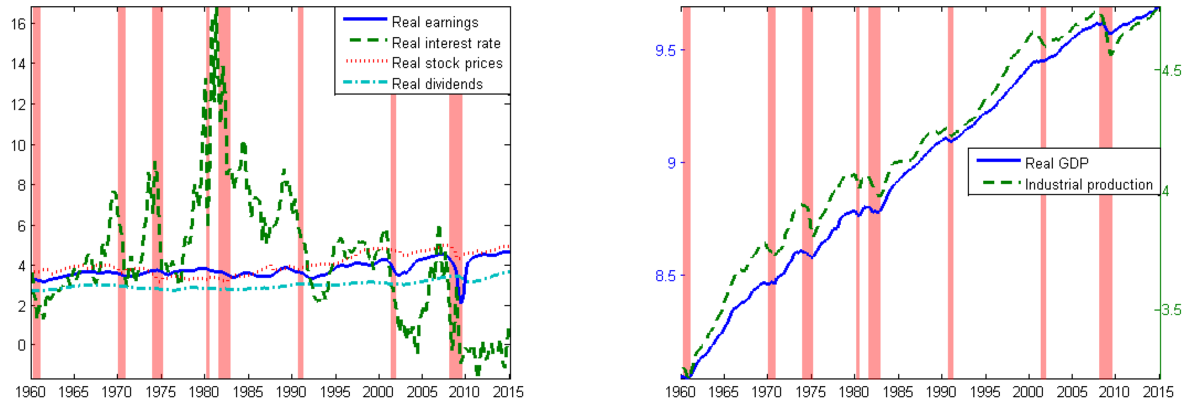
3.1. The data and model specification

All data used in this paper are for the US. Data on dividends (D) and earnings (E) are from Robert Schiller's webpage.[¶] All other data on GDP (Y), industrial production (IP) the federal funds rate (r) and the stock price (s) are from the St. Louis Federal Reserve Economic Database (FRED). The data is quarterly ranging from 1960:I - 2015:I (the last available date of the stock price series in the FRED database). All variables are in real terms. The interest rate is transformed to real terms by subtracting the CPI growth rate and all other variables are transformed to real terms by dividing by the percent level of the CPI. Further, all series are in logs, except for the interest rate series. Figure 1 plots the data used along with recession periods according to NBER dating indicated by the shaded bars.

Standard unit root tests indicate that all variables are $I(1)$. The null hypothesis of a unit root for the real interest rate series is only weakly accepted at the 10% level according to the ADF test. Hence, as is customary in the economics and finance literature (for eg. Rigobon (2003)), the real interest rate

[§]One could potentially use likelihood ratio (LR) tests for this purpose as well. However, such tests are not reliable with these types of models since the restricted model usually converges to the same optimum regardless of where the restrictions are placed. For instance, the LR test proceeds by restricting two diagonal elements of $\Lambda_i, i = 2, \ldots, M$ to be equal and then comparing the log-likelihoods of the restricted and unrestricted models. This is done until all pairwise combinations of elements are exhausted. However, in some cases the same parameter estimates and therefore log-likelihood value is reached for different restricted models. This leads to multiple LR tests having the same values.

[¶]Found at http://www.econ.yale.edu/ shiller/data.htm.



(a) E, r, s, D

(b) Y, IP

Figure 1. Data used with recession dates indicated by the bars.

series is kept in levels throughout the analysis.

The Johansen (1995) and the Saikkonen and Lütkepohl (2000) cointegration tests indicate that two of the models in Table 1 show signs of cointegration and have a cointegrating rank, r of 1. These are models IV with $y_t = [E_t, r_t, s_t]'$ and V with $y_t = [E_t, D_t, s_t]'$. Evidence of cointegration in these models is quite plausible since company earnings, dividends and stock prices would tend to be driven by a common stochastic trend. This is further documented in Lee (1996) who finds evidence of cointegration among earnings, dividends and stock prices.

3.1.1. MS model specification

The number of volatility states is chosen based on the Akaike Information Criterion (AIC) and the Schwartz Criterion (SC) developed by Psaradakis and Spagnolo (2006).

Table 2 shows results of the information criteria along with values of the log-likelihoods, $\ln(L)$ for all unrestricted[‖] i.e. VAR/VEC models. Note that models I, II and III are in VAR form and models IV and V are in VEC form. Minimum values of the information criteria are in bold. The maximum number of states considered is three. This is due to a preference for parsimony as well as for several practical considerations: Firstly, there is no state with very few observations (only with outliers), which could cause algorithm convergence and estimation problems. Secondly, estimation of such parsimonious specifications is usually robust to starting values (see Section 2.3). Finally, computational time is greatly reduced when having to estimate models with fewer states.

According to these criteria we choose three states for models III, IV and V. Further, for identification purposes, (see Section 2.3) we also choose three states for model II. Finally, 2 states are chosen for model I since a model with three states tends to have a state with very few observations, rendering the accuracy of parameter estimates questionable. Finally, it is worth noting that models with one state, or simply linear VAR and VEC models, are not favoured by any criterion. Although, the purpose of this paper is to test the commonly used restrictions, and not to find the most appropriate model for the data,

[‖]Here unrestricted refers to no (short or) long-run restrictions on the state invariant B matrix (see (6) and (7)).

these results do suggest that a Markov switching model may be more appropriate than a conventional linear model.[**]

Model lag orders are chosen based on the (parsimonious) Schwartz Criterion (SC) of the conventional linear VAR model. Therefore, one lag order is used for models II, III and IV, two lags for model V and three lag orders for model I. Note that the number of lags is indicated by p in equations (1) and (2) for the VAR and VEC models respectively.[††]

Table 2. Information criteria of unrestricted models.

Model	States	AIC	SC	ln(L)
	1	-1412.265	-1280.449	745.123
I: $y_t = [Y_t, r_t, s_t]'$	2	-1584.211	**-1435.495**	836.105
	3	**-1594.245**	-1421.870	848.122
	1	-1221.763	-1150.593	631.882
II: $y_t = [IP_t, r_t, s_t]'$	2	-1410.299	**-1322.183**	731.150
	3	**-1427.885**	-1316.046	746.943
	1	-1203.022	-1131.851	622.511
III: $y_t = [D_t, r_t, s_t]'$	2	-1384.012	-1295.896	718.006
	3	**-1408.420**	**-1296.580**	737.210
	1	-317.230	-218.947	187.615
IV: $y_t = [E_t, r_t, s_t]'$	2	-838.750	-730.300	451.375
	3	**-926.363**	**-794.190**	502.182
	1	-2472.602	-2343.991	1274.301
V: $y_t = [E_t, D_t, s_t]'$	2	-2917.483	-2748.488	1508.741
	3	**-2966.398**	**-2803.942**	1531.199

The AIC is calculated as -2(log-likelihood $-n$) and the SC is calculated as -2log-likelihood + log(T)n, where T is the sample size and n is the number of free parameters, ln(L) is the log-likelihood.

Table 3. Summary of the Markov switching specifications of the models in Table 1.

Specifications	Model	
Model I	$y_t = [Y_t, r_t, s_t]'$	MS(2)-VAR(3)
Model II	$y_t = [IP_t, r_t, s_t]'$	MS(3)-VAR(1)
Model III	$y_t = [D_t, r_t, s_t]'$	MS(3)-VAR(1)
Model IV	$y_t = [E_t, r_t, s_t]'$	MS(3)-VEC(1), $r = 1$
Model V	$y_t = [E_t, D_t, s_t]'$	MS(3)-VEC(2), $r = 1$

MS(M) stands for Markov switching with M states, r is the cointegration rank of the VEC models.

Table 3 summarizes the Markov switching (MS) vector model specifications introduced in Table 1.

[**]Further, although not shown here, the log-likelihoods of models with a fully unrestricted state varying B matrix are only slightly higher than those with a state invariant B matrix (see (9)); and the AIC and SC values are lower for such models. This means that the assumption of a state invariant B matrix in (9) has support from the data, although this is formally tested in the following subsection (see Table 4).

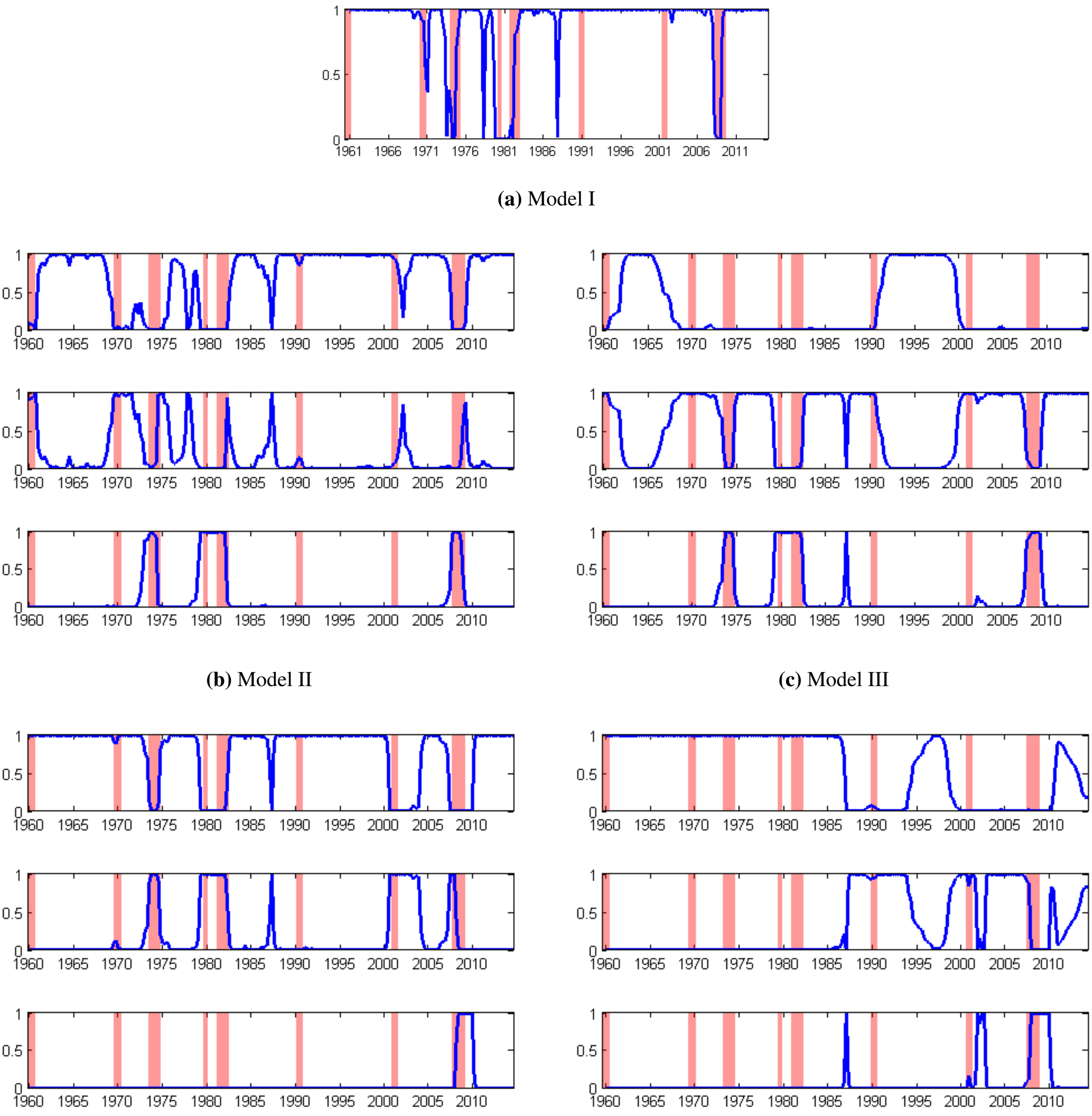
[††]More precisely, for the VEC models a one lag model is $\Delta y_t = \nu_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + u_t$ a two lag model is $\Delta y_t = \nu_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + u_t$, etc..

Table 4. Parameter estimates with standard errors, σ and covariance matrices for all MS unrestricted models. Tests for a state-invariant B matrix below.

Model	I: $y_t = [GDP_t, r_t, s_t]'$			II: $y_t = [IP_t, r_t, s_t]'$			III: $y_t = [D_t, r_t, s_t]'$			IV: $y_t = [E_t, r_t, s_t]'$			V: $y_t = [E_t, D_t, s_t]'$		
Parameter	estimate	σ		estimate	σ		estimate	σ		estimate	σ		estimate	σ	
λ_{21}	2.971	1.022		5.040	1.584		4.512	1.104		6.545	1.795		5.364	1.260	
λ_{22}	20.367	7.801		1.173	0.538		1.671	0.387		12.073	3.172		1.313	0.300	
λ_{23}	7.456	2.394		4.464	1.627		3.068	0.059		3.264	0.911		0.398	0.106	
λ_{31}	-	-		2.153	0.808		59.385	21.638		633.736	333.348		519.031	190.872	
λ_{32}	-	-		21.993	7.240		9.364	3.438		0.166	0.098		1.940	0.983	
λ_{33}	-	-		7.788	2.856		6.274	1.379		8.301	4.351		6.022	2.392	
p_{11}	0.963	0.017		0.945	0.031		0.957	0.226		0.967	0.094		0.977	0.015	
p_{22}	0.719	0.117		0.742	0.144		0.948	0.021		0.857	0.060		0.930	0.010	
p_{33}	-	-		0.869	0.186		0.841	0.175		0.871	0.360		0.769	0.120	
	0.033	–	–	0.056	–	–	0.041	–	–	0.408	–	–	0.242	–	–
$\Sigma(1) * 10^3$	0.859	471.516	–	1.206	480.476	–	0.836	172.743	–	4.126	581.401	–	0.053	0.077	–
	0.026	0.484	2.304	−0.003	−0.719	1.705	0.002	−3.472	1.467	−0.011	−5.835	2.027	−0.081	0.068	3.162
	0.190	–	–	0.259	–	–	0.120	–	–	2.732	–	–	1.083	–	–
$\Sigma(2) * 10^3$	−2.681	8693.817	–	0.945	565.336	–	2.295	706.641	–	38.041	5831.314	–	0.054	0.097	–
	0.809	−21.871	12.652	−0.088	−2.410	7.880	0.097	−1.473	2.638	0.598	66.516	8.483	0.215	0.146	1.503
	–	–	–	0.273	–	–	0.266	–	–	245.368	–	–	100.003	–	–
$\Sigma(3) * 10^3$	–	–	–	28.737	10560.292	–	9.584	8786.071	–	400.215	1814.073	–	−1.309	0.175	–
	–	–	–	0.722	−9.680	10.644	−0.159	18.964	13.790	26.812	−83.563	18.204	16.167	−0.379	21.023
							H_0: state invariant B as in (9)*								
p-value	0.091**			0.260			0.545			0.222			0.167		

[*] This test has an asymptotic χ^2 distribution with 3 degrees of freedom

[**] This is the p-value of a three state model.



(a) Model I

(b) Model II

(c) Model III

(d) Model IV

(e) Model V

Figure 2. Smoothed probabilities of state 1 (top), state 2 (middle) and state 3 (bottom) along with recession dates (shaded bars). For Model I only the smoothed probabilities of state 1 are shown.

3.2. Estimation results

The parameter estimates of interest along with their standard deviations and the covariance matrices for all unrestricted models, are shown in Table 4.

The covaraince matrices give information on the volatility of the different states. In particular, the variances (the diagonal elements of the covariance matrices) usually tend to increase with each state. Hence, the states can be classified as increasing in volatility.

This can further be observed in the model smoothed probabilities given in Figure 2. These probabilities depict the degree of certainty the model attributes to being in a particular state at a given time period. Shaded bars in the figure represent recession dates according to NBER dating. It is usually the case that most severe recessions are present in state 2 and (except for model I) state 3, which, as the covariance matrices suggest are the more volatile states. In particular, severe recessions, such as the great recession of the late 2000s are always present in state 3 (state 2 for model I), the most volatile state. In fact, for model IV, state 3 is only present during the great recession period. This however, does not pose an estimation problem as is discussed in section 4. Finally, note that since model I only has two states, the first state is depicted in Figure 2, the second state is naturally the mirror image of the first.

Further, transition probabilities, $p_{ii}, i = 1, 2, 3$ in Table 4, show that state 1 is most persistent.[‡‡] This is to be expected given the labelling of the states — crisis periods tend to be more transitory than economically stable periods. In this case the duration of the most volatile state (state 2 for model I and state 3 for all other models) is roughly between 4 and 7 quarters, depending on the model used. This is a reasonable severe recession duration estimate given the data range considered. Hence, there is substantial credence to the state labelling.

Finally, the bottom part of Table 4 displays p-values of the null hypothesis of a state invariant B matrix as given in (9). The alternative hypothesis is a fully unrestricted state varying B matrix.[‡]

Table 5. Null hypotheses and p-values of Wald tests.

Model	H_0 : $\lambda_{21} = \lambda_{22}, \lambda_{31} = \lambda_{32}$	$\lambda_{21} = \lambda_{23}, \lambda_{31} = \lambda_{33}$	$\lambda_{22} = \lambda_{23}, \lambda_{32} = \lambda_{33}$
I: $[GDP_t, r_t, s_t]'*$	0.028	0.080	0.106
II: $[IP_t, r_t, s_t]'$	0.001	0.120	0.016
III: $[D_t, r_t, s_t]'$	0.038	0.049	0.052
IV: $[E_t, r_t, s_t]'$	0.042	0.058	0.004
V: $[E_t, D_t, s_t]'$	0.001	0.000	0.003

* Since this is a two state model the null hypothesis only involves elements of Λ_2, i.e. $\lambda_{2i},\ i = 1, 2, 3$

3.2.1. Determining whether the B matrix is identified

The B matrix is identified through heteroskedasticity on the condition that all pairwise diagonal $\lambda_{ij}, i = 2, \ldots, M, j = 1, \ldots, K$ elements are distinct over any $\Lambda_i, i = 2, \ldots, M$ matrix (see section

[‡‡]State persistence is calculated as $1/(1\text{-}p_{ii}), i = 1, 2, 3$.

[‡]As noted in section 2.3, the test statistic under the null is asymptotically χ^2 with $(1/2)MK(K + 1) - K^2 - (M - 1)K$ degrees of freedom, which is 3 for all three state models.

2.3). This condition is tested by means of a Wald test. The test statistic follows a χ^2 distribution with degrees of freedom equal to the number of joint hypotheses being examined. The exact hypotheses and corresponding p-values are given in Table 5.

The hypotheses are largely rejected at a 10% critical level meaning that the B matrix is identified through heteroskedasticity and hence, any restrictions on it become over-identifying and are thus testable. Although, there are some instances of higher p-values for models I and II, Likelihood Ratio (LR) tests (not reported here) reject the nulls at values of around or below 5%. Further, when model I is modelled in three states the nulls are all rejected even at a 5% critical value. This issue is further addressed in Section 4 where the conclusion of distinct λ elements tends to be fairly robust.

3.2.2. Testing the identification restrictions

We now turn to testing the lower triangular long-run identification schemes in (6) and (7) using LR tests. The distribution of the test statistic is asymptotically χ^2 with 3 degrees of freedom since all restricted models have 3 restrictions so that they are just-identified in the traditional sense. The alternative hypothesis is the model without any restrictions on the state invariant B matrix.

Table 6 presents the test results. These indicate that the restrictions are either fairly well supported or are strongly rejected, depending on the model used. We therefore conclude that only models I and II have support from the data for the lower triangular long-run identification scheme. Such restrictions could indeed categorize shocks as fundamental and non-fundamental. With other models these restrictions do not seem to be warranted by the data, meaning that the identified shocks can probably not be interpreted as fundamental and non-fundamental. We will investigate this issue in more detail in Section 5.

Table 6. p-values for LR tests of the long-run restrictions. The alternative hypothesis is a state invariant, unrestricted B matrix.

model	H_0	LR test	p-value
I: $[Y_t, r_t, s_t]'$	(6)	3.608	0.307
II: $[IP_t, r_t, s_t]'$	(6)	2.657	0.448
III: $[D_t, r_t, s_t]'$	(6)	21.050	1.028×10^{-4}
IV: $[E_t, r_t, s_t]'$	(7)	58.884	3.171×10^{-11}
V: $[E_t, D_t, s_t]'$	(7)	43.238	2.191×10^{-9}

4. Robustness analysis

This section investigates whether the results obtained thus far rely to some extent on the exact model specifications used. In general the number of states do not influence the results. They only matter for identifying the B matrix in (9) by heteroskedasticity, up to changes in sign and column ordering. The number of lags, as well, do not drive the results, although models with different lag orders may have residual autocorrelation as indicated by Portmanteau tests.

To more thoroughly investigate the robustness of the results we conduct the following tests. Firstly, we relax the Markov switching (MS) specification so as to allow for a switching intercept term in addition to the switching covariance matrix. This may even better fit our data.* For instance, stock prices tend to rise (fall) in periods of low (high) volatility. This specification within the VAR framework (1) would look as follows

$$y_t = \nu(S_t) + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + u_t, \tag{10}$$

where S_t follows a discrete valued first order Markov process as before and u_t still has the same distributional assumption as in (8). The reduced form VEC model is similar to (10) with the switching intercept being $\nu_0(S_t)$.

Secondly, we use a reduced sample, excluding all observations from the financial crisis onwards i.e. our reduced sample ends on 2007:I. This crisis marks a very volatile period, as indicated by all models. For instance, the smoothed probabilities of model IV in panel (d) of Figure 2 show that only the financial crisis is present in the most volatile third state. Removing the financial crisis would reduce the amount of volatility in the data.

Thirdly, we use the S&P 500 index as the third variable in all models. Although, the above used total share prices for all shares series is very general, it is not an official index such as the S&P 500. We therefore, investigate whether the results would be robust to the proxy of the real stock price.

In conducting the robustness analysis we use the same VAR/VEC specifications as before. Cointegration tests further confirm evidence of cointegration at reasonable levels in the robustness configurations. Hence, models IV and V are still of the VEC form, with a cointegrating rank of 1, while models I - III are still of the VAR form. This would also allow the results of the robustness checks to be easily compared with the original ones.

As in the original analysis, it is first necessary to confirm whether the assumption of a state invariant B matrix is justified. Recall, that this can be tested for models with three Markov states. This indeed turns out to be the case whenever a three state model is employed.

Table 7. p-values for LR tests of the long-run restrictions for different robustness specifications. The alternative hypothesis is a state invariant, unrestricted B matrix.

model	H_0	Intercept	Until 2007:I	S&P 500	Original
I: $[Y_t, r_t, s_t]'$	(6)	0.378^{*}	0.008	0.287^{*}	0.307^{*}
II: $[IP_t, r_t, s_t]'$	(6)	$0.673^{\dagger\,*}$	$0.052^{\dagger}$	$0.653^{\dagger\,*}$	0.448^{*}
III: $[D_t, r_t, s_t]'$	(6)	$2.465\times10^{-5\dagger\,*}$	$5.751\times10^{-7\dagger\,*}$	$7.845\times10^{-5*}$	$1.028\times10^{-4*}$
IV: $[E_t, r_t, s_t]'$	(7)	$1.545\times10^{-10*}$	$1.471\times10^{-8*}$	$1.160\times10^{-9*}$	$3.171\times10^{-11*}$
V: $[E_t, D_t, s_t]'$	(7)	$4.872\times10^{-8*}$	$0.758^{\dagger}$	1.384×10^{-9}	$2.191\times10^{-9*}$

* The B matrix is identified through heteroskedasticity.

† A two state model is used (originally three states).

Table 7 presents the results of all three robustness checks along with the original findings, in terms of LR tests of the structural restrictions. Starting with the first specification of a switching intercept, we

*We need to stress here that the purpose of the MS model is to test the identifying restrictions and not to best model the data. In that respect, we do not allow the autoregressive parameters to switch since this would be harder to justify and interpret. Further, this may cause estimation issues since the number of parameters to be estimated increases by $K^2 p$ for every additional state.

see that the original conclusions have not changed. In case of models II and III, two Markov states are used as indicated by the information criteria (see Section 3.1.1).[†] Thus, the findings are robust to the MS model specification used. Since the purpose of the MS model is to test the identifying restrictions, it is sufficient to use a MS in heteroskedasticity specification.

Moving on to the shorter sample range, we see that the results are again robust whenever the B matrix is identified (through heteroskedasticity). For models I, II and V this matrix is not identified. Hence, for instance, even though the restrictions on model II are again accepted at the 5% level, this finding is not reliable. Usually the p-values of the hypotheses tested in Table 5 are well above 20%, in some instances above 50%. Since this shorter sample excludes 32 observations and a volatile part of the data, it may not be sufficient for the purpose of restrictions testing for models I, II and V. Indeed, for example, GDP and industrial production may not have been very volatile before the financial crisis. The absence of the very volatile crisis period is also the reason why two states are used for all models, except for model IV. Three volatility states would appear to be unnecessary according to the information criteria. It is worth noting that the results for model IV are robust to the exclusion of the financial crisis, which only occurs in state 3 of the original specification (see Figure 2d).

Finally, using the S&P 500 as a proxy for the real stock price, leaves the original results unchanged. Only in case of model V is the B matrix not identified. However, given the low p-value (similar to the original one) this is unlikely to be a problem. Hence, the model results are robust to this specification.

In summary, these robustness tests indicate that the original findings are reliable and not merely subject to some favourable conditions.

5. Practical implications

Now we go back to the initial issue of our investigation; whether stock prices reflect some underlying fundamentals. To see whether the testing methodology implemented thus far has any practical implications, we use all the popular models (Table 1) and investigate whether their conclusions differ. Following the literature, we only use linear conventional VAR/VEC specifications.[*] Hence, we keep the model form and lag lengths as described in Table 3, however we do not consider any regime switches.

A popular means of determining the significance of fundamentals in stock prices is by means of a forecast error variance decomposition (FEVD) (for example Lee (1995b), Binswanger (2004b), Pan (2007) and Velinov and Chen (2015)). This allows us to investigate the fractions of the error variance in forecasting a particular variable that are attributable to the various system shocks. In particular, the h period ahead FEVD is given as

$$\mathrm{FEVD}_{kj,h} = \frac{\Psi^2_{kj,0} + \Psi^2_{kj,1} + \cdots + \Psi^2_{kj,h-1}}{\sum_{i=0}^{h-1} \sum_{j=1}^{K} \Psi^2_{kj,i}}, \tag{11}$$

where the Ψs are the moving average coefficients of the structural model (see (5)). The decomposition in (11) is interpreted as the contribution of innovations in variable j to the forecast error variance of

[†]As noted before, this does not influence the test results, however it could help identify the B matrix through heteroskedasticity (see Table 5).

[*]Recall, the Markov switching specifications were used in effect only to test the identifying restrictions and not for the purpose of data modelling.

the h-step forecast of variable k (see Lütkepohl, 2005). This formula is identical for both SVAR and SVEC models.

Table 8. Forecast error variance decompositions of the real stock price for all models. Values are in percent

	Percentage of variance attributable to:				Percentage of variance attributable to:		
Quarters ahead	Fundamental shock 1	Fundamental shock 2	Non fundamental shock	Quarters ahead	Fundamental shock 1	fundamental shock 2	Non fundamental shock
		model I: $y_t = [Y_t, r_t, s_t]'$				model II: $y_t = [IP_t, r_t, s_t]'$	
1	25.94	13.63	60.42	1	27.27	13.57	59.16
2	30.47	11.50	58.03	2	26.29	12.18	61.52
3	30.32	11.56	58.12	3	25.98	12.31	61.71
4	30.87	11.46	57.68	4	25.89	12.63	61.48
5	30.89	11.49	57.52	5	25.84	12.83	61.33
10	30.86	11.54	57.60	10	25.79	13.01	61.20
20	30.86	11.56	57.58	20	25.79	13.05	61.16
50	30.85	11.57	57.58	50	25.79	13.06	61.15
		model III: $y_t = [D_t, r_t, s_t]'$				model IV: $y_t = [E_t, r_t, s_t]'$	
1	0.03	0.58	99.39	1	90.73	9.08	0.19
2	0.02	0.53	99.44	2	82.83	17.01	0.16
3	0.04	0.62	99.35	3	80.38	19.53	0.10
4	0.05	0.73	99.22	4	78.98	20.94	0.08
5	0.08	0.83	99.09	5	78.11	21.79	0.10
10	0.18	1.11	98.70	10	76.64	23.26	0.10
20	0.28	1.27	98.45	20	76.34	23.61	0.05
50	0.32	1.31	98.37	50	76.13	23.85	0.02
		model V: $y_t = [E_t, D_t, s_t]'$					
1	18.12	76.11	5.77				
2	17.74	77.24	5.01				
3	17.89	77.97	4.15				
4	18.04	78.52	3.43				
5	18.19	78.92	2.89				
10	18.69	79.75	1.56				
20	18.83	80.38	0.79				
50	18.69	80.99	0.32				

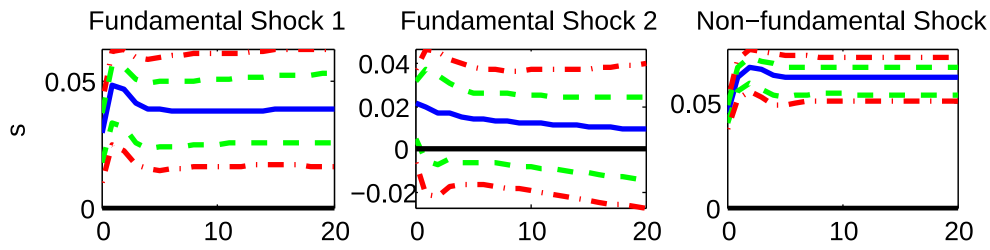
Since the identification schemes in (6) and (7) claim to identify fundamental shocks, we label the first shock as the fundamental one. In what follows we could also consider the second shock as a type of fundamental shock (see Pan (2007)) since it has a long-run impact on real interest rates (dividends in case of model V). Finally, the third model shock is labelled as a non-fundamental shock. Hence, the structural shocks are

$$\varepsilon_t = \left[\varepsilon_{1t}^{F1} \;\; \varepsilon_{2t}^{F2} \;\; \varepsilon_{3t}^{NF}\right]' \tag{12}$$

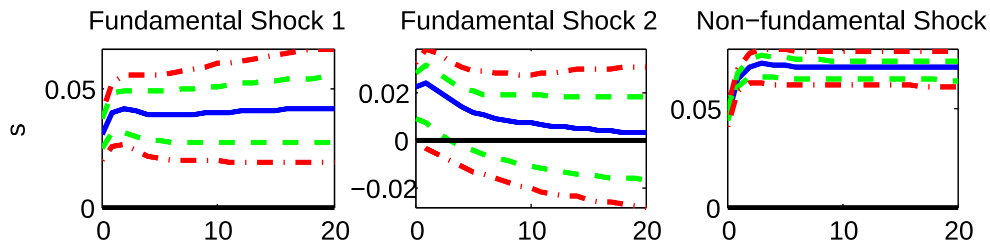
where F stands for fundamental and NF for non-fundamental.

Table 8 displays the FEVDs of the real stock price for all models. For models I and II, the first fundamental shock explains roughly 30% of the forecast error variance of real stock prices. Both fundamental shocks combined would account for around 40% of the forecast error variance. This finding is similar to that in the literature (for example Binswanger (2004b), Jean and Eldomiaty (2010), Velinov and Chen (2015)).

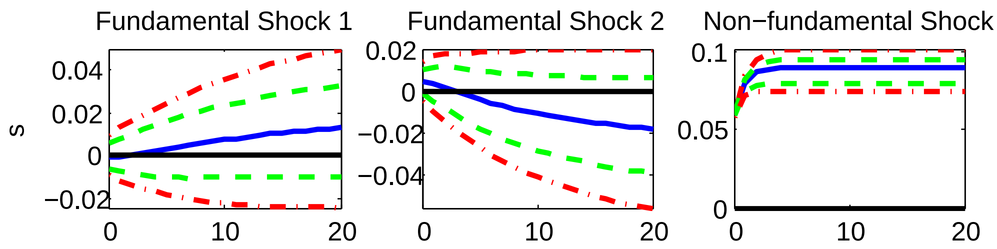
On the other hand, results differ greatly for models III to V — the ones for which the long-run identification scheme is not supported by the data. For instance, model III indicates that fundamental shocks explain almost none of the forecast error variance of real stock prices, barely more than 1%. Models IV and V however, deliver the opposite conclusion, namely that fundamental shocks explain almost all of the forecast error volatility of real stock prices, more than 99%. Moreover, the first fundamental shock is by far the most important in model IV while it is far less dominant in model V, even though real earning are still ordered first. Clearly, these extreme conclusions are unrealistic.



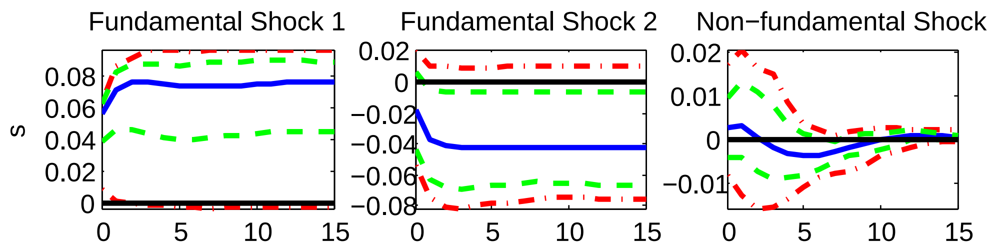
(a) Model I



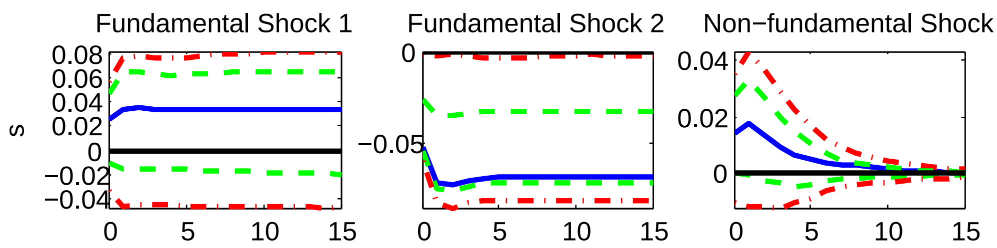
(b) Model II



(c) Model III



(d) Model IV



(e) Model V

Figure 3. Impulse responses (accumulated for models I to III) to real stock prices. Dashed (dash-dot) lines depict 68 (90) percentile Efron confidence intervals generated with 2000 fixed design wild bootstrap replications using the likelihood preserving normalization method.

To investigate this issue further, we conduct an impulse response (IR) analysis. As evidenced in the Markov switching models above, the data seem to show signs of heteroskedasticiy. So as to take this into account we use the wild bootstrap technique as suggested by Podskawski and Velinov (2016) to formulate the confidence bands of the IRs. For example, using the VAR specification, the series are bootstrapped as

$$\Delta y_t^\star = \widehat{\nu} + \widehat{A}_1 \Delta y_{t-1}^\star + \widehat{A}_2 \Delta y_{t-2}^\star + \cdots + \widehat{A}_p \Delta y_{t-p}^\star + u_t^\star, \tag{13}$$

where $u_t^\star = \varphi_t \widehat{u}_t$ and where φ_t is a random variable, independent of y_t following a Rademacher distribution. In other words, φ_t is either 1 or -1 with a 50% probability. The hat denotes estimated parameters. This procedure is analogous for the VEC models.

Further, so as to avoid the problem of very wide confidence bands, due in part to arbitrary normalization methods, we employ the likelihood preserving (LP) normalization as suggested by Waggoner and Zha (2003). Note that this would bias the analysis in favour of narrower confidence bands since the LP normalization is not commonly used in this literature. However, any insignificant impulse responses would, in this case, be stronger emphasised.

Figure 3 displays the responses of the real stock price to the various structural shocks for each model. So as to make the SVAR and SVEC models comparable, the accumulated effects are displayed in the figure for all SVAR models (I to III). Our main shock of interest is the first fundamental shock, which is usually considered the most important in the literature (Lee (1995a), Laopodis (2009)).

For models I and II (the correctly identified models) the first fundamental shock to real stock prices is significant throughout the whole forecast horizon. The second fundamental shock would also be significant for model II upon impact at the 68% band.

Models III to V on the other hand find all fundamental shocks insignificant. Only model IV finds any significance for the fundamental shocks, however, only at the 68% level.[†] The second fundamental shock for model V is barely significant at the 90% level, even though it is the most dominant one in the FEVDs. The findings from these incorrectly identified models do cast doubts about whether the structural shocks they generate can truly be labelled as fundamental.

Finally, we note that, compared with conventional normalization methods[‡] the LP normalization does not significantly influence the size and shape of the confidence bands for the SVAR models, i.e. it does not change any of the conclusions above. For the SVEC models on the other hand, without this normalization, both fundamental shocks would have insignificant impulse responses at both the 90% and 68% levels. This casts further doubt on their shock labelling.

This small empirical exercise illustrates the importance of being able to test structural restrictions. Any empirical analysis using the incorrectly identified models III to V would give distorted conclusions on the importance of fundamentals for real stock prices.

6. Conclusions

This analysis focuses on testing a commonly used structural parameter identification scheme claiming to identify fundamental and non-fundamental shocks to stock prices. In particular, five related structural models, which are widely used in the literature on assessing stock price determinants are considered. Each of these models consist of three variables. The first variable

[†] Note that the non-fundamental shock in the SVEC models is set to have a cumulative long-run impact of 0 by construction (see (7)).

[‡] Such as multiplying by -1 the columns of the B matrix whose diagonal elements are negative.

represents different proxies of economic activity such as real GDP, the industrial production index, real dividends and real earnings; each proxy being a different model. All models are either specified in vector error correction (VEC) or in vector autoregressive (VAR) form. Restrictions are placed on the long-run effects matrix as in Blanchard and Quah (1989), making it lower triangular. All models are hence just-identified in the traditional sense.

A Markov switching in heteroskedasticity model as in Lanne et al. (2010) and Herwartz and Lütkepohl (2014) is used to test whether the long-run restrictions are supported by the data. It is found that for two of the models considered, the long-run identification scheme appropriately classifies shocks as being either fundamental or non-fundamental.

A small empirical exercise is conducted to investigate the practical implications of accepting/rejecting the identification scheme. This finds that the models with properly identified structural shocks deliver plausible and similar conclusions as some existing studies. On the other hand, models with identification schemes not supported by the data yield unrealistic conclusions on the importance of fundamentals for real stock prices. This is because their structural shocks are not properly identified, making any shock labelling ambiguous. Hence, in order to ensure that economic shocks of interest are properly captured, it is important to test the structural identification scheme.

Conflict of Interest

The authors declare no conflict of interest.

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