European
University
Institute

Department of Economics

EUI Working Papers

ECO 2008/29

Stock Prices and Economic Fluctuations: A Markov Switching Structural Vector Autoregressive Analysis

Markku Lanne and Helmut Lütkepohl

EUROPEAN UNIVERSITY INSTITUTE
DEPARTMENT OF ECONOMICS

Stock Prices and Economic Fluctuations: A Markov Switching Structural Vector Autoregressive Analysis

MARKKU LANNE AND HELMUT LÜTKEPOHL

EUI Working Paper **ECO** 2008/29

ISSN 1725-6704

Printed in Italy
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy

http://www.eui.eu/
http://cadmus.eui.eu/

August 9, 2008

Stock Prices and Economic Fluctuations: A Markov Switching Structural Vector Autoregressive Analysis[1]

Markku Lanne
Department of Economics
P.O. Box 17 (Arkadiankatu 7)
FI-00014 University of Helsinki, FINLAND
email: markku.lanne@helsinki.fi

Helmut Lütkepohl
Department of Economics, European University Institute
Via della Piazzola 43, I-50133 Firenze, ITALY
email: helmut.luetkepohl@eui.eu

Abstract. The role of expectations for economic fluctuations has received considerable attention in recent business cycle analysis. We exploit Markov regime switching models to identify shocks in cointegrated structural vector autoregressions and investigate different identification schemes for bivariate systems comprising U.S. stock prices and total factor productivity. The former variable is viewed as reflecting expectations of economic agents about future productivity. It is found that some previously used identification schemes can be rejected in our model setup. The results crucially depend on the measure used for total factor productivity.

Key Words: Cointegration, Markov regime switching model, vector error correction model, structural vector autoregression, mixed normal distribution

JEL classification: C32

[1]We thank Pentti Saikkonen for helpful discussions about the model setup and the associated inference procedures. The research of the first author was supported by the Academy of Finland and the Yrjö Jahnsson Foundation.

1 Introduction

The role of expectations about future developments in productivity for business cycle fluctuations is a topic of considerable interest in the recent literature. For example, Beaudry and Portier (2005, 2006), Jaimovich and Rebelo (2006, 2007), Lorenzoni (2006) and Haertel and Lucke (2008) found that news on technology are an important force for business cycle movements. They use theoretical models and present empirical results for different countries to underpin their arguments.

Our point of departure is the study by Beaudry and Portier (2006) (henceforth BP). They argue that news on future productivity is reflected in stock prices which thereby affect economic fluctuations. They find evidence for their view in U.S. data. Their analysis is based on cointegrated structural vector autoregressions to investigate the relation between U.S. stock prices (SP) and total factor productivity (TFP). The former variable is chosen because it reflects expectations of market participants. Thus, if expectations are an important driving force of economic fluctuations as, for example, captured by TFP, then the same should be true for stock prices. BP fitted vector error correction models (VECMs), that is, cointegrated vector autoregressions (VARs) and used two alternative schemes for just-identifying structural shocks. They found that the resulting technology innovations from the two alternative schemes are quite similar and so are the implied impulse responses. They present an innovation diffusion model which is in line with these results.

Their approach has one important drawback, however. Specifying a structural VAR (SVAR) model with just-identifying restrictions for the shocks ensures that no unnecessary and possibly false restrictions are imposed. On the other hand, statistical information cannot be used to check the validity of just-identifying restrictions. It may easily go unnoticed that the just-identifying restrictions deliver shocks or innovations which are not informative about what actually happens in the underlying economic system. In other words, it is conceivable that the shocks are not what they are meant to be. In SVAR practice a model identification scheme is often checked by considering the plausibility of the resulting impulse responses. In that situation it is not uncommon that alternative identification schemes are proposed which have a justification based on theoretical arguments and lead to essentially different conclusions about some features of the phenomenon under consideration. For example, in monetary economics a range of alternative models coexist which are meant to explain the transmission mechanism of monetary policy (see, e.g., Christiano, Eichenbaum and Evans (1999) for an overview).

In BP's framework where two alternative just-identified models are compared, a model could, of course, be set up which merges the two identification schemes and thereby incorporates over-identifying restrictions which can be tested against the data. BP perform such tests and find that the over-identifying restriction cannot be rejected (see BP, footnotes 4, 6 and 7). Such tests are conditional on one set of just-identifying assumptions being correct, however. More generally, in such tests it may go unnoticed that none of the just-identifying restrictions may be appropriate. Which set of restrictions is eventually used is a matter of taste or beliefs rather than of testable facts.

In this study we will therefore use a different approach and draw on data properties to obtain identifying information so that restrictions such as BP's become over-identifying constraints and can thus be tested. Specifically we use BP's reduced form model and exploit the fact that the residuals are not normally distributed. If such nonnormality is due to business cycle fluctuations which generate different statistical properties in expansions and recessions, a Markov regime switching (MS) mechanism may capture them. Such models have been used extensively in business cycle analysis ever since they were first introduced into econometrics by Hamilton (1989). Therefore it is plausible to consider them in the present context. These models generalize the mixed normal models used by Lanne and Lütkepohl (2008) to identify shocks in SVAR analyses.

Using the MS-SVAR model we find that it is not at all clear that BP's identifying restrictions can actually stand up against the data. In fact, it depends on the measure of TFP whether their restrictions can or cannot be rejected. Using the TFP measure which appears to be favored by BP, their restrictions are clearly rejected in our model setup.

Our study makes two main contributions. First, it presents an MS-SVAR model which gives rise to identifying restrictions simply by assuming orthogonality of the structural shocks across the different regimes. Secondly, these models are applied to check BP's identifying restrictions using different TFP measures. The result is that the acceptability of BP's identifying restrictions crucially depends on the TFP measure used.

The paper is structured as follows. In the next section our model setup is presented and the associated estimation strategy is sketched. In Section 3 the empirical analysis is discussed and conclusions are provided in Section 4.

2 The Model

2.1 General Setup

We consider a K-dimensional reduced form VAR(p) model of the type

$$y_t = Dd_t + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{2.1}$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a K-dimensional vector of observable time series variables, d_t is a deterministic term with coefficient matrix D, the A_j's ($j = 1, \ldots, p$) are $(K \times K)$ coefficient matrices and u_t is a K-dimensional white noise error term with mean zero and positive definite covariance matrix Σ_u, that is, $u_t \sim (0, \Sigma_u)$. If some of the variables are cointegrated, the VECM form may be more convenient,

$$\Delta y_t = D^* d_t^* + \alpha\beta' y_{t-1}^* + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t, \tag{2.2}$$

where Δ denotes the differencing operator, defined such that $\Delta y_t = y_t - y_{t-1}$, $\Gamma_j = -(A_{j+1} + \cdots + A_p)$ ($j = 1, \ldots, p-1$) are $(K \times K)$ coefficient matrices, α is a $(K \times r)$ loading matrix of rank r, β is the $(K^* \times r)$ cointegration matrix which may include parameters associated with deterministic terms and y_{t-1}^* is y_{t-1} augmented by deterministic terms in the cointegration relations. The rank r is the cointegration rank of the system. The term d_t^* represents unrestricted deterministic components and its parameter matrix is denoted by D^*.

In the standard SVAR approach a transformation of the reduced form residuals u_t is used to obtain the structural shocks, say ε_t. A transformation matrix B is chosen such that $\varepsilon_t = B^{-1} u_t \sim (0, I_K)$ has identity covariance matrix, that is, the structural shocks are assumed to be orthogonal and typically their variances are normalized to one. Hence, $\Sigma_u = BB'$. To obtain identified, unique structural shocks, some restrictions have to be imposed on B. For example, BP use a zero restriction on one element of B and thereby preclude an instantaneous effect of one of the shocks on TFP. In another scheme they identify the shocks by enforcing that only one of them has a long-run effect on TFP.

Notice that although normality of the u_t's is often assumed for convenience, such an assumption is usually not backed by theoretical considerations nor is it necessarily required for asymptotic inference. Moreover, VAR residuals are often found to be nonnormal in applied work. In the following we will specify a Markov switching structure on the residuals which implies a more general distribution class for the u_t's and we will discuss how that can be used for the identification of shocks.

2.2 Markov Regime Switching Residuals

We assume that the distribution of the error term u_t depends on a Markov process s_t. More precisely, it is assumed that s_t ($t = 0, \pm1, \pm2, \dots$) is a discrete Markov process with two different regimes, 0 and 1. We focus on a two regime case here for convenience to simplify the following notation and discussion. The case of two regimes only is also considered in the application in Section 3. The *transition probabilities* are

$$p_{ij} = \Pr(s_t = j | s_{t-1} = i), \quad i, j = 0, 1.$$

The *conditional* distribution of u_t given s_t is assumed to be normal,

$$u_t | s_t \sim \mathcal{N}(0, \Sigma_{s_t}). \tag{2.3}$$

Although here the conditional normality assumption is made for convenience only, it should be clear that it opens up a much wider class of distributions than just the unconditional normal. We will discuss this issue further below. The distributional assumption will be used for setting up the likelihood function. If normality does not hold the estimators will only be pseudo maximum likelihood (ML) estimators.

Note that the transition probabilities are the same in all periods. They can be conveniently summarized in the (2×2) *transition matrix*

$$P = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix}.$$

This matrix contains all necessary conditional probabilities to reconstruct the distributions of the stochastic process s_t. For example, the unconditional distribution of s_t can be derived from the conditional probabilities in P (see, e.g., Hamilton (1994, Chapter 22)).

For later reference we note that $p_{10} = 1 - p_{00}$ and $p_{01} = 1 - p_{11}$. If $p_{00} = p_{01}$ and $p_{11} = p_{10}$ the conditional distributions of the states are independent of the previous state,

$$\Pr(s_t = j) = \Pr(s_t = j | s_{t-1} = 0) = \Pr(s_t = j | s_{t-1} = 1), \quad j = 0, 1.$$

Hence, the MS model reduces to a model with mixed normal (MN) errors,

$$u_t \sim \begin{cases} \mathcal{N}(0, \Sigma_0) \text{ with probability } \gamma = p_{00}, \\ \mathcal{N}(0, \Sigma_1) \text{ with probability } 1 - \gamma = p_{11}. \end{cases}$$

In that case the transition matrix has the form

$$P = \begin{bmatrix} \gamma & \gamma \\ 1-\gamma & 1-\gamma \end{bmatrix}.$$

Given that mixed normal distributions constitute a very large and flexible class of distributions, this shows that assuming a conditionally normal distribution in (2.3) results in a very rich distribution class for the error terms. The case of mixed normal errors in the context of SVAR analysis was considered by Lanne and Lütkepohl (2008).

To discuss the identification of shocks in the context of the MS model we note that a well-known result of matrix algebra establishes that there exists a $(K \times K)$ matrix B such that $\Sigma_0 = BB'$ and $\Sigma_1 = B\Lambda B'$, where $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_K)$ is a diagonal matrix (e.g., Lütkepohl (1996, Section 6.1.2)). Lanne and Lütkepohl (2008, Appendix) show that the matrix B is unique up to changes in sign if all diagonal elements of Λ are distinct and ordered in some prespecified way. For example, they may be ordered from smallest to largest or largest to smallest. The important point to note here is that this setup delivers shocks $\varepsilon_t = B^{-1}u_t$ which are orthogonal in both regimes. Since B is unique (up to sign changes), the model is in fact identified by the assumption that the shocks have to be orthogonal across regimes. Thus, any restrictions imposed on B in a conventional SVAR framework become over-identifying in our setup and, hence, can be tested against the data.

The nonuniqueness of B with respect to sign is no problem for our purposes. The precise condition from Proposition A of Lanne and Lütkepohl (2008) is that all signs in any of the columns of B can be reversed. This corresponds to considering negative shocks instead of positive ones or vice versa. Usually it will not be a problem for the analyst to decide on whether positive or negative shocks are of interest. Also, from the point of view of asymptotic inference, local identification of this kind is sufficient for the usual results to hold.

In our setup MS is confined to the error covariance matrix only and no MS is assumed in other parameters because we wish to extend BP's framework as little as possible. MS in the other parameters would have implied different impulse responses in different regimes which would be a major change in the model. Allowing for MS in the residuals only means that we basically remain within BP's model. We are just more specific about the properties of the residuals. Nonnormal residuals generated by a MS mechanism do not seem to be excluded by BP.

2.3 Estimation

An analysis of Gaussian ML estimation in a univariate model of the type (2.3) (that is, the process is white noise conditional on a given state of the Markov chain) was provided by Francq and Roussignol (1997). Very general asymptotic estimation results for stationary processes are also available in

Douc, Moulines and Rydén (2004). The case of cointegrated VARs seems less well explored. We use a two-step estimation procedure. In the first step the cointegration relation is estimated by Johansen's reduced rank regression. Then a Gaussian ML estimation conditional on the first-step cointegration relation is performed. Although there is no apparent reason why this procedure should not result in estimators with standard asymptotic properties, we admit that we don't know of a formal proof and strictly speaking our results are conditional on knowing the true cointegrating vector. It will be seen, however, that the general MS-VAR model may not be needed anyway in our application but can be reduced to a mixed normal model for which inference is discussed in Lanne and Lütkepohl (2008). Therefore, exploring the asymptotic properties of more general MS-VECMs is left for future research.

3 Empirical Analysis

3.1 The Data

As mentioned earlier, we are interested in the relation between U.S. stock prices (SP) and total factor productivity (TFP). The question of interest here is whether expectations reflected in stock price movements are an important driving force of economic fluctuations as, for example, captured by TFP. Our data set was previously analyzed by BP. It consists of quarterly observations from 1948Q1 - 2000Q4. Thus, we have a sample size of $T = 212$. The stock prices are measured by the deflated Standard & Poors 500 Composite Stock Price Index. BP use two different measures of TFP. The first one is computed as

$$TFP_t = \log(Q_t / H_t^{\bar{s}_h} KS_t^{1-\bar{s}_h}),$$

where Q_t is output, H_t is hours worked, KS_t measures capital services and $\bar{s}_h$ is the average level of the labor share over the sample period. Further details are given in BP's article. We use their data which are available from the *American Economic Review* website.[2] The second measure controls for variable rates of factor utilization. Their adjusted measure is defined as

$$TFP_t^A = \log(Q_t / H_t^{\bar{s}_h} (CU_t KS_t)^{1-\bar{s}_h}),$$

where CU_t measures capacity utilization. BP have constructed a quarterly series for this measure. The adjusted TFP measure is plausible in the present context because technological innovations may change the relative factor productivity. We use only the quarterly series, while BP also consider annual

[2]See http://www.e-aer.org/data/sept06/20030282_data.zip.

data. We focus on quarterly data because our model setup is more general and, hence, requires larger sample sizes.

3.2 The Empirical Models

For quarterly data BP fitted a VECM with cointegration rank $r = 1$ and five lags of differenced variables ($p - 1 = 5$ in model (2.2)). They used two alternative schemes for identifying structural shocks. The first one restricts one of the shocks to have no instantaneous effect on productivity, that is, a zero restriction is imposed on B in our notation. The rational is that a technological innovation may not have an instantaneous effect on productivity but only with some delay when production technologies have been adjusted. Thus, the shock defined in this way is thought of as a technology shock. The second identification scheme imposes a zero restriction on the long-run effects of one of the shocks. More precisely, one of the shocks is assumed to have no long-run impact on TFP. Such a shock could, for instance, be a money shock. It should be understood, however, that this restriction implies that there is at least one other zero element in the matrix of long-run effects because the matrix has rank 1 when the cointegration rank is 1.

While both of these schemes are based on a plausible reasoning and BP present an innovation diffusion model which backs them, it is desirable to apply statistical procedures to check whether the assumptions are supported by the data. We will do so by fitting VECMs as in BP, augmented by Markov switching in the residual covariance. In other words, we fit a two-regime MS-SVECM with five lagged differences and cointegration rank one. We also include an intercept term in the cointegration relation and in the model, i.e., we use $y_t^* = (y_t', 1)'$ and specify $d_t = 1$ in (2.2). Unfortunately, BP are silent about the deterministic terms they included in their models. Therefore we decided to include the minimal set of deterministic terms that can capture the data properties. Apart from possible differences in the deterministic terms and the MS feature in the residual covariance structure, our models are the same as those of BP. Because our models are slightly more general than those of BP in that they allow for different residual regimes, they should be good representations of the data generation mechanism if BP's models satisfy this condition. Although our generalizations of BP's models are minimal, they are sufficient to ensure identification of shocks without imposing BP's identification schemes and, hence, we can test their identification schemes as over-identifying restrictions against the data.

In the context of this application, considering an MS model makes sense for a number of reasons. First of all, the residuals of a standard VECM of the type used here are clearly nonnormal. As discussed in Section 2, the

MS model for the error term may just be seen as a generalization of the distribution class considered for the residuals. We have checked normality by performing different variants of Jarque-Bera tests (see Lütkepohl (2005, Sec. 4.5)) and obtained clear rejections at a 1% significance level. Second, the model can be seen as an attempt to account for changing volatility throughout the sampling period. There are different plausible mechanisms which could bring about changing volatility. The basic question concerns the impact of stock prices and news on business cycle fluctuations and MS models have been used traditionally to accommodate differences in the phases of the business cycle. Thus, the model may capture changing volatility across the business cycle. Alternatively, in financial market series conditional heteroskedasticity is often diagnosed. It is well-known that MS in the variances can generate conditional heteroskedasticity (e.g., Krolzig (1997)). If we fit an MS model we usually do not know a priori what the regimes will represent. Looking at the estimated regime probabilities may suggest some plausible interpretation of the regimes, however. In the present case, it is important to note that the MS model is a plausible extension of the original model used by BP.

3.3 Results

We use the estimation strategy outlined in Section 2.3. In other words, we first estimate the cointegration vector by reduced rank regression and then all the other parameters are estimated by (pseudo) Gaussian ML conditionally on the cointegration vector estimated in the first step. We first use the unadjusted TFP measure. Estimation results for four different models are given in Table 1. In the first model no restriction is imposed on the B matrix ("unrestricted"), in the second model a zero restriction is placed on the upper right-hand corner element of B ($B_{12} = 0$) ("short-run restr."), in the third model a long-run restriction is imposed ("long-run restr.") and in the final model both a short-run and a long-run restriction are imposed ("both restr."). The restrictions imposed on the second and third models are those used by BP to identify the structural shocks.

In our model setup the B matrix is unique (up to sign) if $\lambda_1 \neq \lambda_2$. Clearly the estimates of these two quantities and their standard errors in the unrestricted model indicate that this condition is likely to be satisfied. The point estimates are in fact of a different order of magnitude, $\hat{\lambda}_1 = 0.0108$ and $\hat{\lambda}_2 = 2.0181$, and two-standard error intervals around these estimates do not overlap. Thus, provided our minimal extension of the BP model is a good description of the data, there is strong evidence that our identification assumption is satisfied. Note also that it is an advantage of our setup that

Table 1: Estimates of structural parameters of MS model for (SP, TFP) with standard errors in parentheses

Parameter	unrestricted	short-run restr.	long-run restr.	both restr.
B_{11}	0.0118 (0.0007)	0.0118 (0.0007)	0.0118 (0.0007)	0.0118 (0.0007)
B_{12}	-0.0001 (0.0001)	.	0.0000 (0.0001)	.
B_{21}	0.0124 (0.0043)	0.0112 (0.0042)	0.0112 (0.0043)	0.0111 (0.0042)
B_{22}	0.0453 (0.0028)	0.0453 (0.0028)	0.0454 (0.0028)	0.0454 (0.0028)
λ_1	0.0108 (0.0022)	0.0117 (0.0024)	0.0105 (0.0023)	0.0105 (0.0023)
λ_2	2.0181 (0.4456)	2.0242 (0.4503)	2.0467 (0.4565)	2.0479 (0.4554)
p_{00}	0.2153 (0.1225)	0.2085 (0.1417)	0.2585 (0.1270)	0.2576 (0.1260)
p_{11}	0.7367 (0.1617)	0.7404 (0.1661)	0.7664 (0.1700)	0.7660 (0.1701)
log likelihood	1085.65	1085.12	1085.56	1084.56

Table 2: LR tests of models for (SP, TFP)

H_0	H_1	LR statistic	p-value
MS with short-run restriction	unrestricted MS	1.06	0.30
MS with long-run restriction	unrestricted MS	2.18	0.14
MS with both restrictions	unrestricted MS	2.18	0.37
unrestricted MN	unrestricted MS	0.05	0.81
MN with short-run restriction	unrestricted MN	1.04	0.31
MN with long-run restriction	unrestricted MN	2.14	0.14
MN with both restrictions	unrestricted MN	2.14	0.34

the data are actually informative about our identification assumption and we do not have to rely entirely on non-statistical information. The only additional identification assumption we need to make and which cannot be checked by statistical tests is the orthogonality of the shocks in both regimes. This assumption, of course, is standard in the SVAR literature and it was also made by BP. Accepting this assumption makes it possible to test the restrictions imposed by BP. A test of their restrictions may be based on (pseudo) likelihood ratio (LR) tests.

Test results are given in the upper part of Table 2 where the p-values are based on χ^2-distributions with as many degrees of freedom as there are restrictions. Clearly, at conventional significance levels, none of the restrictions can be rejected. More precisely, all p-values are larger than 10%. Hence, rejection of the null hypotheses at significance levels of 10% or smaller is not possible. Thus, this first examination suggests that the two models used by

Table 3: Estimates of structural parameters of mixed normal model for (SP, TFP) with standard errors in parentheses

Parameter	unrestricted	short-run restr.	long-run restr.	both restr.
B_{11}	0.0118 (0.0007)	0.0118 (0.0007)	0.0118 (0.0007)	0.0118 (0.0007)
B_{12}	-0.0001 (0.0001)	.	0.0000 (0.0001)	.
B_{21}	0.0124 (0.0043)	0.0112 (0.0042)	0.0111 (0.0043)	0.0111 (0.0042)
B_{22}	0.0453 (0.0028)	0.0453 (0.0028)	0.0454 (0.0028)	0.0454 (0.0028)
λ_1	0.0108 (0.0022)	0.0116 (0.0026)	0.0105 (0.0023)	0.0105 (0.0023)
λ_2	2.0161 (0.4453)	2.0258 (0.4530)	2.0483 (0.4558)	2.0493 (0.4570)
γ	0.7651 (0.0963)	0.7671 (0.1005)	0.7502 (0.0982)	0.7506 (0.0979)
log likelihood	1085.62	1085.10	1084.55	1084.55

BP are both acceptable in our framework.

Looking at the transition probabilities in Table 1 it is seen, however, that the estimates almost add up to one. As mentioned in Section 2, this is just the condition for the MS model to collapse to a mixed normal (MN) model. To check whether a mixed normal model may be sufficient in the present case, we have actually tested it against the MS model using again a (pseudo) LR test with one degree of freedom. The result is also shown in Table 2. The related p-value of 0.81 is strong evidence in favor of the MN model. Therefore we have also estimated MN models with the BP restrictions. The estimation results for the structural parameters for all four models are presented in Table 3 and the related LR tests are reported in the lower part of Table 2.

Notice that also in the MN models the λ_i's are clearly distinct. In fact, they are very close to those obtained for the MS models. Moreover, they are clearly different from one which suggests that the covariance matrices in the two mixing models are different. Of course, this may be regarded as another confirmation that the residual distribution is nonnormal.

The LR tests for the MN models in Table 2 all have p-values substantially above 10%. Hence, also in this more restrictive framework BP's restrictions cannot be rejected.

Because BP argue that the adjusted TFP measure may be more appropriate, we have also estimated all our models with TFP_t replaced by TFP_t^A. The results for the MS models are given in Table 4. Although they are different from the ones in Table 1, there are also important similarities. In particular, the identification condition $\lambda_1 \neq \lambda_2$ appears to hold. Thus, we can again perform our tests for BP's restrictions. The results are given in the upper part of Table 5. Now both restrictions are clearly rejected as all p-values are very small and in particular substantially smaller than 1%.

Table 4: Estimates of structural parameters of MS model for (SP, TFP^A) with standard errors in parentheses

Parameter	unrestricted	short-run restr.	long-run restr.	both restr.
B_{11}	0.0075 (0.0007)	0.0095 (0.0006)	0.0076 (0.0007)	0.0104 (0.0006)
B_{12}	-0.0057 (0.0004)	.	-0.0057 (0.0004)	.
B_{21}	0.0576 (0.0046)	0.0173 (0.0041)	0.0580 (0.0047)	0.0189 (0.0052)
B_{22}	0.0323 (0.0022)	0.0455 (0.0028)	0.0328 (0.0022)	0.0539 (0.0034)
λ_1	0.0056 (0.0013)	0.0118 (0.0023)	0.0072 (0.0015)	0.0099 (0.0020)
λ_2	0.3070 (0.0712)	1.6703 (0.3768)	0.2998 (0.0670)	0.6222 (0.1441)
p_{00}	0.2724 (0.1474)	0.2045 (0.1070)	0.2520 (0.1395)	0.2443 (0.1135)
p_{11}	0.7849 (0.1850)	0.7411 (0.1782)	0.7210 (0.1827)	0.8319 (0.1406)
log likelihood	1148.73	1129.30	1142.52	1125.30

Table 5: LR tests of models for (SP, TFP^A)

H_0	H_1	LR statistic	p-value
MS with short-run restriction	unrestricted MS	38.86	4.5e-10
MS with long-run restriction	unrestricted MS	12.42	0.0004
MS with both restrictions	unrestricted MS	46.86	3.6e-9
unrestricted MN	unrestricted MS	0.04	0.84
MN with short-run restriction	unrestricted MN	38.88	4.5e-10
MN with long-run restriction	unrestricted MN	13.90	0.0002
MN with both restrictions	unrestricted MN	46.98	6.3e-11

Table 6: Estimates of structural parameters of mixed normal model for (SP, TFP^A) with standard errors in parentheses

Parameter	unrestricted	short-run restr.	long-run restr.	both restr.
B_{11}	0.0075 (0.0007)	0.0095 (0.0006)	0.0076 (0.0007)	0.0104 (0.0006)
B_{12}	-0.0057 (0.0004)	.	-0.0057 (0.0004)	.
B_{21}	0.0576 (0.0046)	0.0173 (0.0041)	0.0578 (0.0046)	0.0189 (0.0052)
B_{22}	0.0324 (0.0022)	0.0455 (0.0029)	0.0327 (0.0022)	0.0539 (0.0034)
λ_1	0.0057 (0.0012)	0.0118 (0.0023)	0.0068 (0.0014)	0.0099 (0.0019)
λ_2	0.0012 (0.0702)	1.6629 (0.3777)	0.3135 (0.0699)	0.6220 (0.1410)
γ	0.7482 (0.1142)	0.7789 (0.0916)	0.7377 (0.1110)	0.7797 (0.0914)
log likelihood	1148.71	1129.27	1141.76	1125.22

Since the estimated transition probabilities p_{00} and p_{11} again almost sum to one, we have also tested the MS model against the simpler MN model. The p-value given in Table 5 is 0.84 and thus the MN model is strongly favored. Hence, we have also examined the MN models corresponding to all the MS models and show some estimation results in Table 6. Again the identification condition appears to be satisfied. The corresponding LR tests of the restrictions are given in the lower part of Table 5. Like for the MS models they are very small and, hence, the restrictions are rejected.

We emphasize that our rejection of BP's identifying restrictions is not due to a more restrictive framework but is obtained although we use a slightly more general model setup. Also, we are using an identification assumption (namely the orthogonality of the shocks) which was also used by BP in addition to their short-run and long-run restrictions. Thus, it cannot be argued that we are actually testing some other restriction at the same time which may be incompatible with BP's identification schemes.

The overall conclusion from our empirical results is that it depends on the TFP measure used whether BP's models are rejected or not. Using the TFP measure which controls for variable rates of factor utilization, BP's models are rejected. Clearly, variable rates of factor utilization are plausible if technological innovations occur. Thus, they are plausible in the present context and were preferred by BP. If indeed the adjusted TFP measure is the relevant variable in the present context, our results shed doubt on the conclusions drawn from BP's analysis.

4 Conclusions

This note contributes to the literature which investigates the role of expectations regarding developments in productivity for business cycle fluctuations. We have augmented VECM models by Markov switching to obtain identified shocks simply by assuming orthogonality of the shocks across regimes. Expectations on technological developments are assumed to be reflected in stock prices. Hence, we have investigated the relation between stock prices and TFP. We have used quarterly U.S. data from BP and we used their models as a basis to study the relation between stock prices and TFP. Augmenting the models by Markov switching allows us to test BP's identifying assumptions for news shocks. It turns out that it crucially depends on the measure used for TFP whether their identification assumption conforms with the data. If a TFP measure is used which allows for variable rates of factor utilization, BP's identifying restrictions are clearly rejected in the augmented model.

References

Beaudry, P. and Portier, F. (2005). The 'news' view of economic fluctuations: Evidence from aggregate Japanese data and sectoral US data, *Journal of Japanese International Economies* **19**: 635–652.

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations, *American Economic Review* **96**: 1293–1307.

Christiano, L. J., Eichenbaum, M. and Evans, C. (1999). Monetary policy shocks: What have we learned and to what end?, *in* J. B. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*, Vol. 1A, Elsevier, Amsterdam, pp. 65–148.

Douc, R., Moulines, E. and Rydén, T. (2004). Asymptotic properties of the maximum likelihood estimator in autoregressive models with Markov regime, *Annals of Statistics* **32**: 2254–2304.

Francq, C. and Roussignol, M. (1997). On white noise driven by hidden Markov chains, *Journal of Time Series Analysis* **18**: 553–578.

Haertel, T. and Lucke, B. (2008). Do news shocks drive business cycles? Evidence from German data, *Economics* **2**: 0–21.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica* **57**: 357–384.

Hamilton, J. D. (1994). *Time Series Analysis*, Princeton University Press, Princeton, New Jersey.

Jaimovich, N. and Rebelo, S. (2006). Can news about the future drive the business cycle?, *Working Paper 12537*, NBER.

Jaimovich, N. and Rebelo, S. (2007). News and business cycles in open economies, *Working Paper 13444*, NBER.

Krolzig, H.-M. (1997). *Markov-Switching Vector Autoregressions: Modelling, Statistical Inference, and Application to Business Cycle Analysis*, Springer-Verlag, Berlin.

Lanne, M. and Lütkepohl, H. (2008). Structural vector autoregressions with non-normal residuals, *Journal of Business & Economic Statistics*, forthcoming.

Lorenzoni, G. (2006). A theory of demand shocks, *Working Paper 12477*, NBER.

Lütkepohl, H. (1996). *Handbook of Matrices*, John Wiley & Sons, Chichester.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*, Springer-Verlag, Berlin.