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The Relation between Monetary Policy and the Stock Market in Europe

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The Relation between Monetary Policy and the Stock Market in Europe

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Abstract. We use a cointegrated structural vector autoregressive model to investigate the relation between euro area monetary policy and the stock market. Since there may be an instantaneous causal relation we consider long-run identifying restrictions for the structural shocks and also use (conditional) heteroskedasticity in the residuals for identification purposes. Heteroskedasticity is modelled by a Markov-switching mechanism. We find a plausible identification scheme for stock market and monetary policy shocks which is consistent with the second order moment structure of the variables. The model indicates that contractionary monetary policy shocks lead to a long-lasting down-turn of real stock prices.

Key Words: Cointegrated vector autoregression, heteroskedasticity, Markov-switching model, monetary policy analysis

JEL classification: C32

[1]The views and opinions expressed in this paper are those of the authors and do not represent an official position of Eesti Pank or the Eurosystem. Financial support from the Estonian Research Council grant MOBTP11 is gratefully acknowledged.

1 Introduction

The interaction of monetary policy and the stock market has been studied extensively with structural vector autoregressive (VAR) models. A central problem is the identification of the structural shocks. Nowadays a range of different tools is available for identifying structural VARs (see Kilian and Lütkepohl (2017)). Therefore different types of identifying restrictions for the monetary policy and stock market shocks have been used. For example, Bjørnland and Leitemo (2009) consider a structural VAR model for the US, where long-run and short-run restrictions are combined to identify structural shocks. Such models were also used in the context of identification by heteroskedasticity (e.g., Lütkepohl and Netšunajev (2017a, 2017b), Bertsche and Braun (2018)). All these studies investigate the relation between monetary policy and the stock market in the US but ignore any possible cointegration relations of the variables involved. In the present study we consider the relation between monetary policy and the stock market in Europe and explicitly account for cointegration.

European monetary policy is, of course, a central topic of empirical macroeconomics (e.g., Peersman and Smets (2001)). There are also studies investigating explicitly the impact of monetary policy in Europe on the stock market. Cassola and Morana (2004) find that price stabilizing monetary policy contributes to the stability of the stock market in the euro area. Bredin, Hyde, Nitzsche and O'Reilly (2009) perform an event study and find a negative relation between UK monetary policy and stock returns but not between German monetary policy and stock returns. Kholodilin, Montagnoli, Napolitano and Siliverstovs (2009) use the approach of Rigobon and Sack (2004) and find heterogeneous relations of monetary policy and stock prices for different sectors, but the effect of an increase in the policy rate of the European Central Bank (ECB) on an aggregate stock index is reported to be negative. Haitsma, Unalmis and de Haan (2016) identify the ECB monetary policy shocks using an event-study approach and via heteroskedasticity following Rigobon and Sack (2004). Both identification methods yield a negative relationship between unexpected changes in policy rates and stock returns. Alessi and Kerssenfischer (2016) estimate a structural factor model using euro area data and argue that the responses of stock returns to monetary policy is larger and quicker than in a conventional small-scale structural VAR. In a more recent study, Fausch and Sigonius (2018) use different techniques to investigate the relation between ECB monetary policy and German stock returns including an event study, a VAR analysis, where monetary policy surprises are captured by a proxi variable and a threshold VAR model. They find a negative relation between the ECB monetary policy and stock returns in the pre-crisis period.

In this study we use a structural vector error correction model (VECM) identified through heteroskedasticity to investigate the relation between monetary policy and the stock market. The cointegration framework developed by Johansen and Juselius (see Johansen and Juselius (1990), Johansen (1991, 1995), Juselius (2006)) opens up a convenient way to impose restrictions on the long-run effects of structural shocks in structural VAR analysis, as shown by King, Plosser, Stock and Watson (1991). They use the Granger-Johansen representation of a VAR model (Johansen (1995)) to determine the long-run effects of their shocks and the framework is easy to combine with identifying information obtained from the second moment structure of the model (see Lütkepohl and Velinov (2016) or Kilian and Lütkepohl (2017, Chapter 14)). We use this framework in our empirical investigation.

We model the conditional heteroskedasticity in the data by a Markov-switching (MS) mechanism and find a cointegrated structural VAR model for which conventional identifying restrictions are in line with the second moment structure of the data. The impulse responses are plausible and, in particular, production and price level go down after a contractionary monetary policy shock. Although the long-run impact of a monetary policy shock on stock prices is restricted to zero, such a shock is found to have a rather long-lasting negative impact on the stock market.

The structure of this study is as follows. In the next section the basic structural VECM is presented and the model for the second moments is discussed in Section 3. The empirical analysis is discussed in Section 4 and conclusions are presented in Section 5. The appendix provides details on the data sources.

2 Structural Vector Error Correction Models

The time series variables of interest are collected in the $(K \times 1)$ vector y_t. The components of y_t may be integrated and cointegrated variables. We assume that all variables are stationary ($I(0)$) or integrated of order one ($I(1)$). Assuming a cointegration rank r, $0 \leq r \leq K$, our point of departure is the VECM form of a VAR model,

$$\Delta y_t = \nu + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t, \tag{1}$$

where Δ is the differencing operator such that $\Delta y_t = y_t - y_{t-1}$, ν is a $(K \times 1)$ constant term, α is a $(K \times r)$ loading matrix of rank r, β is a $(K \times r)$ cointegration matrix of rank r and $\Gamma_1, \ldots, \Gamma_{p-1}$ are $(K \times K)$ coefficient matrices (see also Johansen (1995)).

The reduced-form residuals u_t are white noise, that is, u_t is serially uncorrelated with mean zero but may have time-varying second moments. In other words, u_t may be heteroskedastic or conditionally heteroskedastic. The structural shocks, denoted by ε_t, are obtained from the reduced form residuals by a linear transformation $\varepsilon_t = B^{-1}u_t$ or $B\varepsilon_t = u_t$. The $(K \times K)$ transformation matrix B is assumed to be such that the structural shocks are instantaneously uncorrelated. Hence, $\mathbb{E}(\varepsilon_t \varepsilon_t') = \Sigma_{\varepsilon_t}$ is a diagonal matrix.

Substituting $B\varepsilon_t$ for u_t in (1), the matrix B is easily recognized as the matrix of impact effects of the structural shocks. Thus, imposing restrictions directly on the impact effects means putting restrictions on the elements of B. Typically, zero restrictions are imposed on B which imply that certain variables do not respond instantaneously to a shock.

The long-run effects of the shocks are easily obtained through the Granger-Johansen representation (see Johansen (1995, Theorem 4.2)) of y_t corresponding to (1),

$$y_t = \Xi \sum_{i=1}^{t} u_i + \Xi^*(L)u_t + \delta_t + y_0^*, \tag{2}$$

where

$$\Xi = \beta_\perp \left[\alpha'_\perp \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha'_\perp, \tag{3}$$

$\Xi^*(L)u_t$ is a stationary process, δ_t contains deterministic terms and y_0^* represents initial conditions. In (3), $\beta_\perp$ and $\alpha_\perp$ are $(K \times (K-r))$ dimensional orthogonal complements of the $(K \times r)$ dimensional matrices β and α, respectively. If the cointegration rank r is zero, the orthogonal complement matrices are replaced by $(K \times K)$ identity matrices so that the long-run effects matrix becomes

$$\Xi = \left(I_K - \sum_{i=1}^{p-1} \Gamma_i \right)^{-1}. \tag{4}$$

The corresponding long-run effects of the structural shocks are given by ΞB. Since α and β have rank r, their orthogonal complements have rank $K-r$ implying that Ξ also has rank $K-r$ and the same holds for ΞB because B is an invertible matrix of full rank K. For a given reduced-form matrix Ξ, restrictions on ΞB imply restrictions for B and, hence, can help identifying the structural shocks. The reduced rank of the long-run effects matrix implies that there can be at most r shocks without any long-run effects, corresponding to r columns of zeros of ΞB. In other words, only r shocks can be purely transitory. Another side-effect of the reduced rank of ΞB is, however, that simply counting zero restrictions is not enough to assess identification of the structural matrix B, as we will see in our empirical application in Section 4.

This setup for identifying structural shocks in VAR models was proposed by King et al. (1991). Introductory treatments are given by Lütkepohl (2005, Chapter 9) and Kilian and Lütkepohl (2017, Chapter 10). There are a number of situations of special interest.

For $r = 0$ the matrix of long-run effects ΞB is of full rank K and, hence, cannot have zero columns. Thus, for $r = 0$, all K structural shocks have some long-run effects. If the cointegrating rank is zero, the VECM (1) reduces to a VAR model in first differences,

$$\Delta y_t = \nu + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + u_t,$$

for which the accumulated long-run effects on the Δy_t are known to be

$$\left(I_K - \sum_{i=1}^{p-1} \Gamma_i\right)^{-1} B.$$

The accumulated effects on the first differences are just the long-run effects on the levels y_t, of course. This case was considered by Blanchard and Quah (1989) and the estimation of the structural parameters, i.e., the B matrix, is particularly easy for this case (e.g., Lütkepohl (2005, Chapter 9)).

If some of the components of y_t are $I(0)$, the long-run effects matrix Ξ and, hence, also ΞB has corresponding rows of zero elements because a stationary variable is not affected permanently by a shock. Formally that can be seen by dividing up the vector

$$y_t = \begin{bmatrix} y_t^n \\ y_t^s \end{bmatrix},$$

where all components of the $(K_n \times 1)$ vector y_t^n are $I(1)$ and all components of the $(K_s \times 1)$ vector y_t^s are $I(0)$. In this case there exists a cointegration matrix of the form

$$\beta = \begin{bmatrix} \beta_{(11)} & 0_{K_n \times K_s} \\ 0_{K_s \times (r-K_s)} & I_{K_s} \end{bmatrix},$$

where $\beta_{(11)}$ is a $(K_n \times (r - K_s))$ matrix. Thus, there exists an orthogonal complement of β such that

$$\beta_\perp = \begin{bmatrix} \beta_\perp^{(1)} \\ 0_{K_s \times (K-r)} \end{bmatrix}.$$

Hence, the last K_s rows of Ξ are rows of zeros.

There are alternative proposals for imposing long-run restrictions for identifying structural shocks in VARs. Examples are proposals by Gonzalo and Ng (2001), Fisher, Huh and Summers (2000), and Pagan and Pesaran (2008). Fisher and Huh (2014) review the literature and discuss the relations between alternative approaches.

3 Structural VAR Models with Changes in Volatility

If the reduced-form residuals u_t are heteroskedastic or conditionally heteroskedastic, this property can be used for identification purposes. We use the approach of Lanne, Lütkepohl and Maciejowska (2010) and Herwartz and Lütkepohl (2014) who propose a Markov-switching (MS) mechanism for modelling volatility changes in this context. They assume that the distribution of the error term u_t depends on a discrete Markov process s_t such that

$$u_t | s_t \sim (0, \Sigma_u(s_t)). \tag{5}$$

The Markov process s_t has states $1, \dots, M$, and transition probabilities

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

Note that only the residual covariance matrices depend on the state s_t, whereas the VAR slope parameters are not state dependent. The model captures conditional heteroskedasticity of a quite general form.

The second moment structure can be used for structural identification if the covariance matrices can be decomposed such that

$$\Sigma_u(1) = BB', \quad \Sigma_u(m) = B\Lambda_m B', \quad m = 2, \dots, M, \tag{6}$$

where the Λ_m are $(K \times K)$ diagonal matrices. In that case the matrix B can be used to obtain the structural shocks from the reduced-form residuals and B is identified if the following condition holds, where λ_{jk} denotes the k^{th} diagonal element of Λ_j:

$$\forall k, l \in \{1, \dots, K\} \quad \exists j \in \{2, \dots, M\} \quad \text{such that } \lambda_{jk} \neq \lambda_{jl}. \tag{7}$$

If $M = 2$ the condition means that the diagonal elements of Λ_2 must all be distinct. Generally, the condition requires that there is sufficient heterogeneity in the volatility changes across the shocks. If this condition is satisfied, B is unique up to column sign changes and column permutations. In other words, using this B matrix for computing the structural shocks from the reduced-form residuals, only the sign and positioning of the shocks remain undetermined.

Assuming a normal conditional distribution for $u_t | s_t$, the model can be estimated by Gaussian maximum likelihood (ML) using the algorithm described by Herwartz and Lütkepohl (2014). It may be useful to estimate the cointegration matrix β in a first step and keep it fixed in the subsequent optimization of the log-likelihood with respect to the remaining parameters including the transition probabilities. Computing the Gaussian ML estimates can be a challenge for larger models with many variables, autoregressive lags or volatility states.

The fact that the model assigns the volatility regimes endogenously is appealing. Hence, the researcher can estimate the volatility states rather than having to know or assume them. We use the model in our empirical application which is discussed in the next section.

4 Monetary Policy and the Stock Market in Europe

A five-dimensional VAR model for the euro area with variables $y_t = (q_t, p_t, c_t, s_t, r_t)'$ is considered, where q_t is the log of an industrial production index, p_t denotes the log of the harmonized index of consumer prices (HICP), c_t is a log non-energy commodity price index, s_t is the log of the real Euro Stoxx 50 stock price index and r_t denotes the 3month Euribor. The set of variables corresponds to the system used by Bjørnland and Leitemo (2009) for analysing the relation between monetary policy and the stock market in the US. We use monthly data for the period 1999M1 - 2014M12 and, hence, avoid the period of quantitative easing in the euro zone. Further details on the variables and data sources are given in the appendix and the time series are plotted in Figure 1.

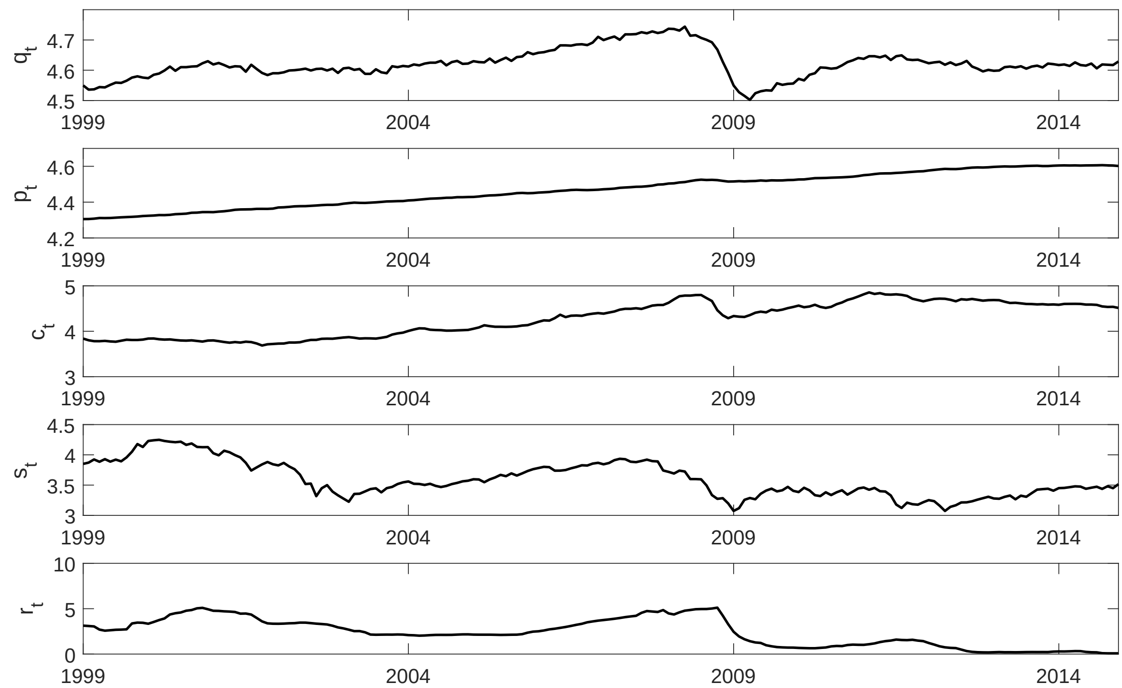

Figure 1: Time series used in the empirical study for sample period 1999M1-2014M12.

Based on ADF tests all five variables are classified as $I(1)$ variables. Johansen's (1995) cointegration tests suggest a cointegration rank of $r = 2$. Thus, we consider a VECM(1) with one lag of the differenced variables (i.e., $p - 1 = 1$) and cointegration rank $r = 2$ for our structural analysis. The lag order is suggested by the Akaike Information Criterion (AIC) (see Lütkepohl (2005, Section 4.3.2)). The residuals show apparent changes in volatility. Clearly this is not surprising, given that we have a stock price index in our set of variables. Thus, we fit a volatility model of the type discussed in Section 3 with 2 states of the Markov process. The model is referred to as a VECM(1)-MS(2) in the following. Given our small sample size, considering more volatility states is unreasonable.[1] The AIC, HQ and SC values shown in Table 1 clearly signal that allowing for conditional heteroskedasticity improves the model fit. The values of all three model selection criteria are substantially smaller than the corresponding values for the model without heteroskedasticity. In other words, the second moment structure may well provide useful identifying

[1]We also tried a Markov process with $M = 3$ volatility states but failed to get reasonable Gaussian ML estimates.

information for the structural shocks.

Table 1: Comparison of Models for $y_t = (q_t, p_t, c_t, s_t, r_t)'$.

Model	**Log** L	**AIC**	**SC**	**HQ**
VECM(1)	2505.139	−4888.278	−4690.210	−4966.639
VECM(1)-MS(2)	2595.154	−5034.308	−4781.040	−5134.507

Note: L – Gaussian likelihood, AIC $= -2\log L + 2\times$ number of free parameters, SC $= -2\log L + \log T\times$ number of free parameters, HQ $= -2\log L + 2\log(\log T)\times$ number of free parameters.

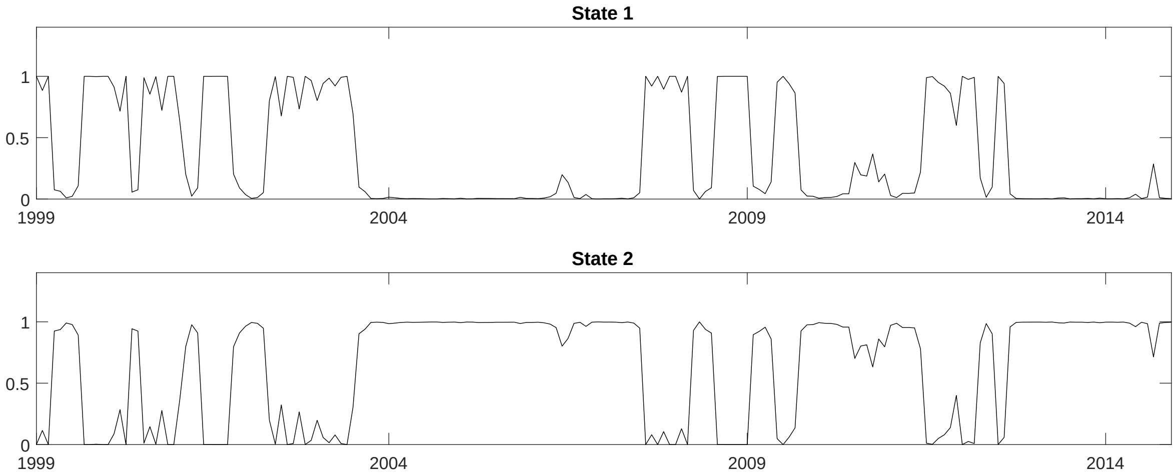

Figure 2: Smoothed state probabilities of VECM(1)-MS(2) model.

In Figure 2 the smoothed state probabilities of the VECM(1)-MS(2) model are presented. They show that the two volatility regimes change frequently throughout the sample period so that guessing the change points reliably would be difficult for a researcher. Hence, using a model which allows for endogenously assigned volatility changes is clearly an advantage over a model where the volatility states have to be prespecified by the researcher.

To explore the identification issue we have to consider the diagonal elements of Λ_2, as explained in Section 3. They are displayed in Table 2 together with estimated standard errors. The estimated diagonal elements are all distinct, but the estimation uncertainty reflected in the standard errors is rather high. This uncertainty in the estimates is not surprising given the relatively small sample size. However, some of the standard errors are quite small compared to the corresponding estimates of the relative variances, so it is reasonable to think that at least some of the diagonal elements of Λ_2 are distinct. Thus, there is at least some identifying information in the second moments.

We are primarily interested in a monetary policy shock and a stock market shock. Therefore we place these shocks in the last two positions of ε_t, that is, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_t^{sm}, \varepsilon_t^{mp})'$.

Table 2: Estimated Relative Variances of VECM(1)-MS(2) Model for $y_t = (q_t, p_t, c_t, s_t, r_t)'$.

Relative variance	**Estimate**	**Estimated standard error**
λ_{21}	1.557	0.587
λ_{22}	0.765	0.294
λ_{23}	0.479	0.186
λ_{24}	0.024	0.007
λ_{25}	0.202	0.075

In other words, the stock market shock, ε_t^{sm}, is the fourth shock and the monetary policy shock, ε_t^{mp}, is last. The other components of ε_t are left unspecified and represent other shocks in the economy.

We consider the two alternative identification schemes in Table 3. Since we have a cointegration rank $r = 2$, there can be two columns of zeros in the long-run effects matrix ΞB. The first identification scheme in Table 3 assumes that both the stock market shock and the monetary policy shock are purely transitory and, hence, do not have any long-run effects on any of the variables. The two shocks are distinguished by the assumption that ε_t^{sm} does not affect the commodity price index instantaneously but only with some delay. Hence, there is a corresponding zero in the third row of B. The long-run restrictions may be justified by the notion that the effects of monetary policy and stock market shocks should be transitory. In a conventional VAR analysis effects of these shocks on the macroeconomic variables vanish over time (see Christiano, Eichenbaum and Evans (1999), Bjørnland and Leitemo (2009)). The restriction on the short-run effect is needed to distinguish the two shocks which are both neutral in the long run and it is part of identification schemes used by Christiano et al. (1999), Bjørnland and Leitemo (2009) and others for US data. Note also that no restrictions are imposed on the first three columns of B and ΞB so that the first three shocks are identified purely by the volatility changes. Since we are not interested in them, we do not ensure that they have economic interpretations.

The second identification scheme is due to Bjørnland and Leitemo (2009) who use it for US data. They are also primarily interested in the last two shocks and arbitrarily identify the first three shocks by the three zero restrictions on the first three columns of B. Again the last shock is specified as monetary policy shock. It is assumed to have no long-run impact on stock prices and this distinguishes the shock from the stock market shock. Both shocks are assumed to have no impact effects on industrial production, the price level and the commodity price index. This assumption reflects the belief that these variables move slowly in response to ε_t^{sm} and ε_t^{mp}. There are no further long-run restrictions.

The two identification schemes differ not only in the way they identify the shocks of in-

Table 3: Identification Schemes for $y_t = (q_t, p_t, c_t, s_t, r_t)'$.

Scheme	B	ΞB
(1)	$\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & 0 & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}$	$\begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \end{bmatrix}$
(2)	$\begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}$	$\begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}$

terest. While the first scheme relies primarily on long-run restrictions, the second scheme imposes most restrictions on the impact effects. Without heteroskedasticity, scheme (1) is under-identified and the second scheme is just-identified. Thus, in the absence of heteroskedasticity they cannot be compared with statistical tests without further assumptions. However, assuming that the shocks are already identified by the second moment structure, the zero restrictions on B and ΞB are over-identifying and can be tested by standard likelihood ratio (LR) tests.

Table 4: Tests of Identification Schemes

$\mathbb{H}_0$	**LR statistic**	**Degrees of freedom**	p**-value**
Scheme (1)	62.494	7	4.787e−11
Scheme (2)	18.807	10	0.043

The results of such tests are presented in Table 4, where the alternative is a model that is purely identified by heteroskedasticity and has no zero restrictions on B or ΞB. In addition to the value of the LR statistic, the assumed degrees of freedom of the χ^2 limiting distributions are presented on which the p-values are based. For both tests the number of degrees of freedom is determined under the assumption that the structural matrix B is fully identified by heteroskedasticity. The number of degrees of freedom for testing scheme (1) is seven because, for $r = 2$, the long-run effects matrix ΞB has rank $K - r = 3$ and, hence, each column of zeros counts for three independent restrictions only. The corresponding p-value is less than 1% so that scheme (1) is rejected at any conventional significance level. This also indicates that there must be identifying information in the second moment structure because the $\mathbb{H}_0$ model is not identified by the zero restrictions alone. Thus, the heteroskedastic structure has identifying power.

In contrast, the second identification scheme cannot be rejected at a 1% level although its p-value is slightly below 5%. This outcome is interesting because in a related study based on identification through heteroskedasticity, Lütkepohl and Netšunajev (2017a) find strong evidence against the restrictions for the US. Admittedly this evidence is based on a quite different sample period. Moreover, Bertsche and Braun (2018) do not confirm this result with a different volatility model. However, Lütkepohl and Netšunajev (2017b) also find an implausible reaction of the inflation rate to a monetary policy shock for the US. Thus, it is instructive to see the responses of the variables to the two shocks of interest for our European model when identification scheme (2) is used.

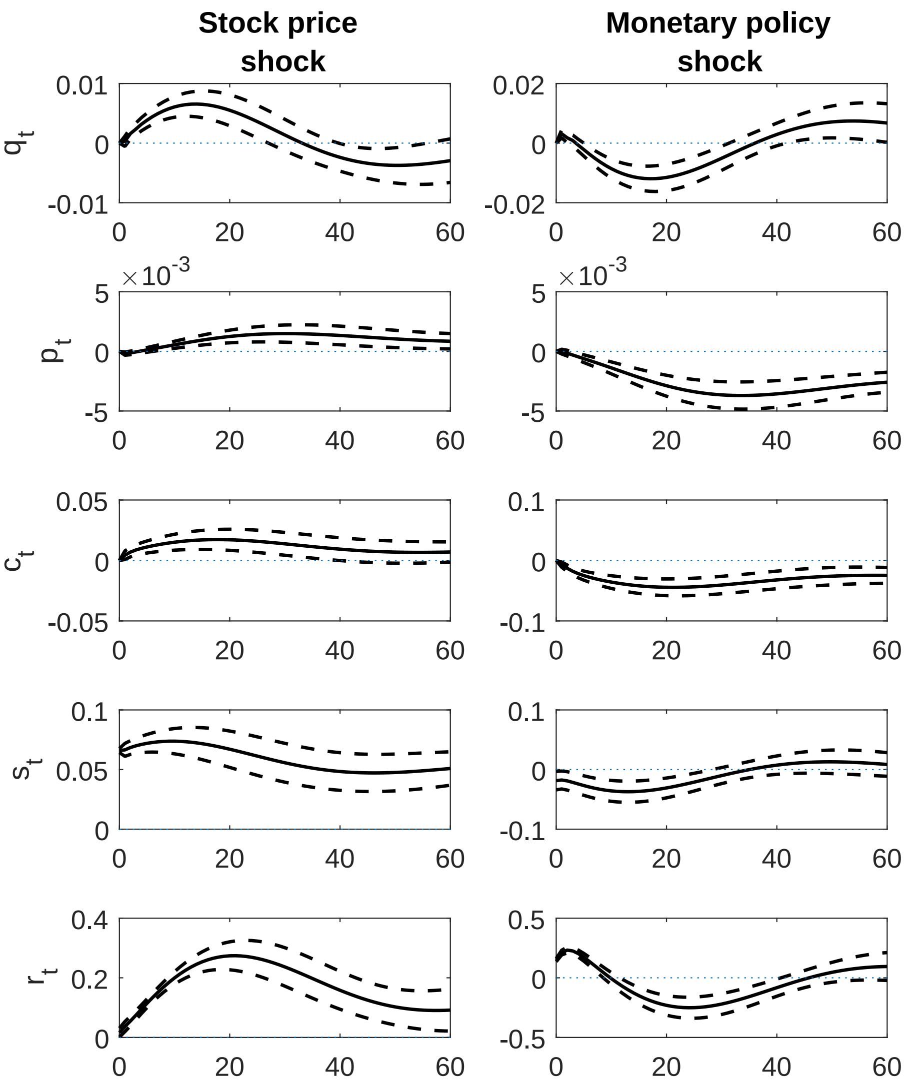

Figure 3: Responses to stock market and monetary policy shocks with ± one-standard error confidence intervals for identification scheme (2).

The estimated impulse responses with ± one-standard error bootstrap confidence intervals are shown in Figure 3. The confidence intervals have a 68% level in a Gaussian environment. The standard errors are estimated with a fixed-design wild bootstrap conditioning on the transition probabilities, as proposed in Herwartz and Lütkepohl (2014) and also used in Lütkepohl and Netšunajev (2017a).

The responses of the variables to both shocks are quite plausible. A stock market shock is followed by increases in all other variables although these upswings occur with some delay. This is in line with the studies by Bjørnland and Leitemo (2009) and Li, Iscan and Xu (2010) for the US. The increase in output and inflation is consistent with the view that a rise in stock prices increases consumption (Beaudry and Portier (2006)) through a wealth effect and investment through a Tobin Q effect, thus inducing aggregate demand to increase. Due to nominal rigidities, prices react slowly and inflation as well as commodity prices rise in the intermediate run. The response of the interest rate may be explained by the behaviour of an inflation-targeting central bank which is increasing interest rates to combat the inflationary pressure of a high aggregate demand.

A contractionary monetary policy shock, induced by an increase in the interest rate, reduces industrial production, the price level and commodity prices with some delay. Similar to Peersman and Smets (2001) and Ehrmann, Gambacorta, MartinezPags, Sevestre and Worms (2003) we do not find any price puzzle and observe long-run effects on prices. The shock leads to a long-lasting downturn of the stock index after a monetary policy tightening. This is in line with results of Bjørnland and Leitemo (2009) for the US but the effect for the euro area is not as pronounced as in their study. Even though there is mixed evidence regarding the influence of monetary policy on industry- or country-level stock returns in Europe, most of the studies agree on a negative relation between ECB monetary policy and aggregate stock returns in the euro area (Kholodilin et al. (2009), Alessi and Kerssenfischer (2016), Fausch and Sigonius (2018)). Clearly, our results support those previous findings which show that the policy of the ECB has a substantial impact on the stock market in Europe.

5 Conclusions

We have constructed a five-dimensional cointegrated structural VAR model for monthly euro area variables for the period 1999M1 - 2014M12 to study the relation between monetary policy and the stock market. The period of quantitative easing is explicitly excluded because it may be regarded as a new monetary policy regime. We allow for conditional heteroskedasticity in the data and model volatility changes by a Markov-switching mechanism. Heteroskedasticity is used to disentangle a stock market and a monetary policy shock. Conventional identification restrictions on the impact and long-run effects of the structural shocks that have been used for a similar model for the US, are found to be roughly consistent with the second moment structure of the variables for our sample period, while an alternative identification scheme is strongly rejected.

The impulse responses for the maintained identification scheme are economically plausible and, in particular, production and price level go down after a contractionary monetary policy shock. Although the long-run impact of a monetary policy shock on stock prices is restricted to be neutral, such a shock is found to have a rather long-lasting negative impact on the stock market.

Appendix. Variables and Data Sources

The industrial production index is seasonally adjusted and obtained from the ECB Statistical Data Warehouse. The harmonized index of consumer prices (HICP) is also seasonally adjusted and obtained from Eurostat. The non-energy commodity price index is obtained from the World Bank. The Euro Stoxx 50 stock price series is obtained from www.stoxx.com and deflated by the consumer price index to measure real stock prices. Finally, the 3month Euribor is obtained from the ECB Statistical Data Warehouse.

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