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Simultaneity and Asymmetry of Returns and Volatilities: The Emerging Baltic States' Stock Exchanges*

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Abstract

The paper suggests a nonlinear and multivariate time series model framework that enables the study of simultaneity in returns and in volatilities, as well as asymmetric effects arising from shocks and exogenous variables. The model is employed to study the three closely related Baltic States' stock exchanges and the influence exerted by the Russian stock exchange. Using daily data, we find recursive structures with returns in Riga directly depending on returns in Tallinn and Vilnius, and Tallinn on Vilnius. For volatilities, both Riga and Vilnius depend on Tallinn. In addition, we find evidence of asymmetric effects of shocks arising in Moscow and in Baltic States on both returns and volatilities.

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1. Introduction

The main motivation for this study is the importance of simultaneity in financial assets or markets for various investment and risk management decisions. Portfolio or fund managers, for example, often invest in several markets at the same time. This investment strategy may not provide the diversification and risk reduction that managers are seeking, if there are strong linkages between markets. In addition, risk managers need to understand the nature of cross market linkages in order to appropriately assess their risk exposures and capital adequacy (Fleming et al., 1998).

Cross market linkages or information spillovers are of two types. The first is the common information that simultaneously affects expectations in more than one market. The second type of information spillovers is caused by cross-market hedging. Fleming et al. (1998) argue that information spillovers are strongest when linkages between markets are not limited by institutional constraints, and other practical considerations. These include, for example, a common trading platform, and other factors that lower the settlement risk and information costs for investors. Fazio (2007) argues that investors following an international diversification strategy may be exposed to unhedged risk when assuming that different countries are unrelated. He also finds that countries belonging to the same region are more likely to suffer from dependence in the case of extreme market movements. This implies that countries located in the same region may have stronger linkages than anticipated by investors. Also, Koch and Koch (1991) find simultaneity in returns within geographic regions but not across regions.

Another lesson from the intra-day trading literature concerning some marketplaces is that information processing is very fast (e.g., Engle and Russell, 1998). Even if there are unidirectional causations within the day, a study based on a daily sampling frequency cannot but find an average effect that may go both ways. The sampling frequency scenario is in fact a main motivation in macro-econometrics for employing structural systems which can incorporate simultaneous endogenous effects. More recently, Rigobon and Sack (2003) and others have reported on model-based studies allowing for simultaneity in returns.

Obviously, and perhaps more interestingly from a risk management point of view, there is also reason to expect simultaneous effects in volatilities. Rigobon and Sack (2003) were the first ones to find simultaneity in volatilities. But, as in the studies of De Wet (2006) and Lee (2006), the simultaneity arises in a very restrictive way, and only as a consequence of the simultaneity in returns. Gannon and Choi (1998) and Gannon (2004, 2005)

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detect simultaneity for some Asian markets using realized volatilities. Engle and Kroner (1995) suggested a related framework but focus theoretically on simultaneity in returns only.

Here, our main focus will be on the joint modelling of, and the allowance for, simultaneity in both returns and volatilities along with asymmetry, and exogenous effects. The model platform is the univariate ARasMA-asQGARCH of Brännäs and De Gooijer (1994, 2004). This model combines an asymmetric ARMA model with an asymmetric and quadratic GARCH model and it is here given its first multivariate form. Notably, extensions of this type introduce additional parameters into an already richly parameterized model. Kroner and Ng (1998), De Goeij and Marquering (2005) and others discussed ways of parameterizing, in particular, the volatility functions for models to be estimable. To allow for simultaneity we will have to be restrictive in terms of correlation structure, lag lengths, and asymmetric effects. We employ the methodology to jointly study the closely related Baltic States' stock market indices and their potentially asymmetric dependence on the Russian stock market.

The paper is organized as follows. In Section 2 we introduce the model and discuss some of its properties. Section 3 presents the estimator along with the employed stepwise model specification procedure. The section discusses testing against simultaneous, asymmetric effects, and the impact of exogenous variables. In addition, the use of the model for portfolio allocation and value at risk (VaR) studies are outlined. Section 4 introduces the empirical study and presents the data-set. The empirical findings are given in Section 5. The final section concludes and relates our findings to other studies.

2. A Structural Vector ARasMA-asQGARCH Model

2.1 The Model

Consider an m-dimensional time series $\mathbf{y}_t = (y_{1t}, \ldots, y_{mt})'$. In this study $\{\mathbf{y}_t\}$ contains the variables of interest, i.e. the returns at time t of m stock market indices. The vector time series process $\{\mathbf{y}_t\}$ is assumed to be weakly stationary. Let $\mathbf{x}_t = (x_{1t}, \ldots, x_{kt})'$ denote a vector of exogenous variables that may affect the process $\{\mathbf{y}_t\}$; see Section 4 for more details on these series. To introduce the asymmetric structure of the proposed model we first need to define an m-dimensional vector discrete-time stochastic process generated by $\mathbf{u}_t = (u_{1t}, \ldots, u_{mt})'$ defined by

$$\mathbf{u}_t = \mathbf{H}_t^* \boldsymbol{\varepsilon}_t,$$

where $\{\boldsymbol{\varepsilon}_t\} \sim WN(\mathbf{0}, \mathbf{I})$, $\mathbf{H}_t^* = \{h_{ij,t}^*\}$ $(i, j = 1, 2, \ldots, m)$, and with $\mathcal{F}_{t-1}$ denoting the history of the time series up to and including time $t-1$. The conditional variance is $V(\mathbf{u}_t|\mathcal{F}_{t-1}) = \mathbf{H}_t^* \mathbf{H}_t^{*\prime} \equiv \mathbf{H}_t$. Now a simultaneous or structural vector ARasMA model can be defined as

$$\begin{aligned} \mathbf{A}_0 \mathbf{y}_t &= \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \mathbf{u}_t + \sum_{i=1}^{q} \left(\mathbf{B}_i^+ \mathbf{u}_{t-i}^+ + \mathbf{B}_i^- \mathbf{u}_{t-i}^- \right) + \mathbf{c}_0 \\ &\quad + \sum_{i=0}^{r} \left(\mathbf{C}_i^+ \mathbf{x}_{t-i}^+ + \mathbf{C}_i^- \mathbf{x}_{t-i}^- \right), \end{aligned} \tag{1}$$

where $\mathbf{u}_t^+ = \max(\mathbf{0}, \mathbf{u}_t)$, $\mathbf{u}_t^- = \min(\mathbf{0}, \mathbf{u}_t)$, $\mathbf{x}_t^+ = \max(\mathbf{0}, \mathbf{x}_t)$, and $\mathbf{x}_t^- = \min(\mathbf{0}, \mathbf{x}_t)$. Model (1) accounts for asymmetric effects unless for all i, $\mathbf{B}_i^+ = \mathbf{B}_i^-$ and $\mathbf{C}_i^+ = \mathbf{C}_i^-$. If appropriate, the threshold level for the exogenous process $\{\mathbf{x}_t\}$ may be set at another value than $\mathbf{0}$. It is easy to see that the threshold levels in $\{\mathbf{u}_t^+\}$ and $\{\mathbf{u}_t^-\}$ can be accommodated by the vector of constants $\mathbf{c}_0$.

The $m \times m$ non-symmetric matrix $\mathbf{A}_0$ in (1) contains the simultaneity parameters,

$$\mathbf{A}_0 = \begin{pmatrix} 1 & a_{12}^0 & \cdots & a_{1m}^0 \\ a_{21}^0 & 1 & \cdots & a_{2m}^0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1}^0 & a_{m2}^0 & \cdots & 1 \end{pmatrix},$$

where an assumption of normalization has been imposed, i.e. coefficients along the diagonal are equal to 1. Assume $\mathbf{A}_0$ is nonsingular. Then the conditional mean (return) of $\{\mathbf{y}_t\}$ follows directly from the conditional reduced form of (1) as

$$\begin{aligned} E(\mathbf{y}_t|\mathcal{F}_{t-1}) &= \sum_{i=1}^{p} \mathbf{A}_0^{-1} \mathbf{A}_i \mathbf{y}_{t-i} + \sum_{i=1}^{q} \mathbf{A}_0^{-1} \left(\mathbf{B}_i^+ \mathbf{u}_{t-i}^+ + \mathbf{B}_i^- \mathbf{u}_{t-i}^- \right) \\ &\quad + \mathbf{A}_0^{-1} \mathbf{c}_0 + \sum_{i=0}^{r} \mathbf{A}_0^{-1} \left(\mathbf{C}_i^+ \mathbf{x}_{t-i}^+ + \mathbf{C}_i^- \mathbf{x}_{t-i}^- \right). \end{aligned}$$

Similarly, the conditional variance (volatility or risk) is given by

$$V(\mathbf{y}_t|\mathcal{F}_{t-1}) = \mathbf{A}_0^{-1} \mathbf{H}_t (\mathbf{A}_0^{-1})'$$

from which, e.g., the conditional correlation matrix can be obtained. Various options are available to specify an asymmetric model for $\mathbf{H}_t$; see De Goeij and Marquering (2005). The specifications for $\mathbf{H}_t$ suggested by these authors contain off-diagonal elements. Thus there are conditional and possibly unconditional correlations among the elements of $\{\mathbf{u}_t\}$, and consequently among those of $\{\mathbf{y}_t\}$. There is no simultaneity in conditional volatility behavior in the sense that the conditional variance of, say, u_{it} would be a direct function of the corresponding conditional variance of u_{jt} $(i \neq j)$ in the same time period.

As we wish to have simultaneity in conditional volatility as an integral part of the model we need to consider an extension of the univariate asQGARCH model. One avenue that appears feasible is to view the structures of De Goeij and Marquering (2005) as "reduced forms". Note that structural forms may make economic sense but that only the reduced form gives the conditional variance interpretation. The situation resembles closely that of the simultaneous and reduced forms in classical macro-econometrics. Similarly, we view simultaneity to arise mainly due to the relatively low sampling frequency of one day while real trading occurs in continuous time, and partly due to common investors on different stock exchanges.

Our general simultaneous specification for the conditional variance is very much in the same spirit as model (1). Given a vector time series process $\{\mathbf{z}_t\}$ of exogenous variables, the vector asQGARCH model for $\mathbf{h}_t = vech(\mathbf{H}_t)$ is given by

$$\begin{aligned}\mathbf{D}_0\mathbf{h}_t &= \sum_{i=1}^{P}\mathbf{D}_i\mathbf{h}_{t-i} + \sum_{i=1}^{Q}\left(\mathbf{F}_i^{+}\mathbf{u}_{t-i}^{+} + \mathbf{F}_i^{-}\mathbf{u}_{t-i}^{-}\right) + \sum_{i=1}^{Q}\mathbf{K}_i\mathbf{u}_{t-i}^{*,2} \\ &\quad + \mathbf{g}_0 + \sum_{i=0}^{R}\left(\mathbf{G}_i^{+}\mathbf{z}_{t-i}^{+} + \mathbf{G}_i^{-}\mathbf{z}_{t-i}^{-}\right), \end{aligned} \tag{2}$$

where $\mathbf{g}_0$ is an $\frac{1}{2}m(m+1)\times 1$ vector of constants, $\mathbf{z}_t^{+} = \max(\mathbf{0},\mathbf{z}_t)$, $\mathbf{z}_t^{-} = \min(\mathbf{0},\mathbf{z}_t)$, and the vector $\mathbf{u}_t^{*,2}$ has elements u_{it}^2 $(i = 1,\ldots,m)$.

The reduced form of (2) is

$$\begin{aligned}\mathbf{h}_t &= \sum_{i=1}^{P}\mathbf{D}_0^{-1}\mathbf{D}_i\mathbf{h}_{t-i} + \sum_{i=1}^{Q}\mathbf{D}_0^{-1}\left(\mathbf{F}_i^{+}\mathbf{u}_{t-i}^{+} + \mathbf{F}_i^{-}\mathbf{u}_{t-i}^{-}\right) + \sum_{i=1}^{Q}\mathbf{D}_0^{-1}\mathbf{K}_i\mathbf{u}_{t-i}^{*,2} \\ &\quad + \mathbf{D}_0^{-1}\mathbf{g}_0 + \sum_{i=0}^{R}\mathbf{D}_0^{-1}\left(\mathbf{G}_i^{+}\mathbf{z}_{t-i}^{+} + \mathbf{G}_i^{-}\mathbf{z}_{t-i}^{-}\right) \end{aligned} \tag{3}$$

from which the corresponding $\mathbf{H}_t$ matrix can be obtained. The matrix $\mathbf{D}_0$ captures simultaneity, whereas the matrices $\mathbf{D}_i$ $(i \geq 1)$ are useful to represent persistence and possible cyclical features in the process $\{\mathbf{h}_t\}$. Also asymmetric effects are characterized through the matrices $\mathbf{F}_i^{+}$ $(\mathbf{F}_i^{-})$ and $\mathbf{G}_i^{+}$ $(\mathbf{G}_i^{-})$. Empirically, it is important to realize that the estimation of (3) may become infeasible with too generously parameterized specifications. Reducing lag lengths and introducing sparse matrix specifications are two ways of reducing the number of parameters; see Section 3 for a data-driven model specification procedure. Note also that the specification in (2) allows for time-varying covariances. Additional simplifications include setting these to constants, by restricting the parameter matrices.

Various moment properties, and distributional results for ARasMA models have been reported by Brännäs and De Gooijer (1994) and Brännäs and Ohlsson (1999), and for univariate ARasMA-quadratic GARCH models by Brännäs and De Gooijer (2004). Since $V(\mathbf{y}_t) = \mathbf{A}_0^{-1} E_{\mathcal{F}_{t-1}}(\mathbf{H}_t)(\mathbf{A}_0^{-1})' + V_{\mathcal{F}_{t-1}}[E(\mathbf{y}_t|\mathcal{F}_{t-1})]$ by a decomposition of the variance, obtaining an explicit expression for the unconditional variance of $\{\mathbf{y}_t\}$ is a far from trivial problem.

3. Estimation and Model Use

Given a multivariate normality assumption on $\{\boldsymbol{\varepsilon}_t\}$ the prediction error

$$\mathbf{y}_t - E(\mathbf{y}_t|\mathcal{F}_{t-1}) = \mathbf{A}_0^{-1}\mathbf{u}_t = \mathbf{A}_0^{-1}\mathbf{H}_t^*\boldsymbol{\varepsilon}_t \equiv \mathbf{v}_t$$

is conditionally $N(\mathbf{0}, \boldsymbol{\Gamma}_t)$ distributed with $\boldsymbol{\Gamma}_t = \mathbf{A}_0^{-1}\mathbf{H}_t(\mathbf{A}_0^{-1})'$; recall (3). Here, $\mathbf{H}_t$ is the conditional variance expression in reduced form, containing among other things the $\mathbf{D}_0$ matrix. Given observations up till time T, the log-likelihood function takes the form

$$\begin{aligned} \ln L &\propto -\frac{1}{2}\sum_{t=s}^{T} \ln|\boldsymbol{\Gamma}_t| - \frac{1}{2}\sum_{t=s}^{T} \mathbf{v}_t'\boldsymbol{\Gamma}_t^{-1}\mathbf{v}_t \\ &\propto (T-s)\ln|\mathbf{A}_0| - \frac{1}{2}\sum_{t=s}^{T}\left(\ln|\mathbf{H}_t| + \mathbf{u}_t'\mathbf{H}_t^{-1}\mathbf{u}_t\right), \end{aligned}$$

where $s = \max(p, q, r, P, Q, R) + 1$. For practical quasi maximum likelihood estimation we use the RATS 6.0 package and employ robust standard errors.

To obtain the final model specification we advocate the following stepwise procedure.

1. Restrict all matrices in the mean and variance equations to be diagonal and select the model that minimizes AIC or some other appropriate model selection criterion. In this step we implicitly assume that there are no interactions between the series. It is equivalent to finding the "best" univariate ARasMA-asQGARCH models.

2. Take the model from step 1 and expand to non-diagonal matrices in the mean equation. First allow for simultaneity, i.e. estimate $\mathbf{A}_0$. Consider thereafter the expansion of the remaining matrices. Choose the specification that minimizes AIC. The $\mathbf{A}_0$ is the final parameter matrix to be reduced. The volatility functions obtained in step 1 are taken as given, but $\{\hat{\mathbf{u}}_t\}$ changes in the iterative steps.

3. Take the $\{\hat{\mathbf{u}}_t\}$-sequence from step 2 as given and expand to non-diagonal matrices in the variance equation. First allow for simultaneity, i.e. estimate $\mathbf{D}_0$. Consider thereafter the expansion of the remaining matrices. Choose the specification that minimizes AIC. The $\mathbf{D}_0$ is the final parameter matrix to be reduced.

4. In a final step all parameters are estimated jointly.

Given the estimated model, it is of interest to test hypotheses about simultaneity and asymmetric effects in the $\mathbf{x}$ and $\mathbf{z}$ variables. Given the likelihood framework and our specification procedure, Wald and likelihood ratio (LR) test statistics are relatively easy to implement.

We first consider tests of simultaneity and do so in terms of the $\mathbf{A}_0$ matrix. The reasoning with respect to $\mathbf{D}_0$ is analogous. We say that there is a simultaneous effect between markets i and j if $(\mathbf{A}_0)_{ij} \neq 0$ and $(\mathbf{A}_0)_{ji} \neq 0$. When $(\mathbf{A}_0)_{ij} \neq 0$ but $(\mathbf{A}_0)_{ji} = 0$ there is a recursive structure and causation is unidirectional from market j to market i. When $(\mathbf{A}_0)_{ij} = (\mathbf{A}_0)_{ji} = 0$ there is no causation between returns. When all off-diagonal elements equal zero $\mathbf{A}_0 = \mathbf{I}$ and the structural and reduced forms are identical.

Next we consider testing against asymmetric effects and do so in terms of the $\mathbf{B}_i^+$ and $\mathbf{B}_i^-$ matrices. We may form $\mathbf{B}_i^{\bigtriangledown} = \mathbf{B}_i^+ - \mathbf{B}_i^-$ $(i = 1, \ldots, q)$, and test whether this matrix is equal to zero or whether it is nonzero. We then make no distinction between the case of both matrices having nonzero parameters $(\mathbf{B}_i^+)_{ij}$ and $(\mathbf{B}_i^-)_{ij}$ in all places and the case where, say, $(\mathbf{B}_i^-)_{ij} = 0$. Testing against asymmetric effects of exogenous variables is in terms of the parameter matrices $\mathbf{C}_i^+$ and $\mathbf{C}_i^-$ $(i = 1, \ldots, r)$. For asymmetric effects in volatility the parameter matrices $\mathbf{F}_i^+$ and $\mathbf{F}_i^-$ as well as $\mathbf{G}_i^+$ and $\mathbf{G}_i^-$ are focused.

For no effects of exogenous variables on returns all matrices $\mathbf{C}_i^+$ and $\mathbf{C}_i^-$ must be identical to a zero matrix, while for volatility all $\mathbf{G}_i^+$ and $\mathbf{G}_i^-$ must be zero.

When we wish to use or, as here, evaluate the model in financially interesting and meaningful ways, portfolio allocation and VaR measures are of obvious interest. Two problems both stemming from the use of index series arise; how to get back to the index and what price related to the index should we consider.

First, the index is determined from the inverse of the change variable $y_{it} = 100 \cdot \ln(I_{it}/I_{it-1})$, i.e. as $I_{it} = I_{it-1}\exp(y_{it}/100)$ for stock market i. We get $E(I_{it}|\mathcal{F}_{t-1}) = I_{it-1}E(\exp(y_{it}/100)|\mathcal{F}_{t-1}) \approx I_{it-1}(1 + E(y_{it}|\mathcal{F}_{t-1})/100)$ where the first order approximation of the exponential function is reasonable for the small values of $y_{it}/100$. Using the same first order approximation we get $V(\mathbf{I}_t|\mathcal{F}_{t-1}) = \mathbf{I}^{\circ}_{t-1}V(\mathbf{y}_t|\mathcal{F}_{t-1})\mathbf{I}^{\circ}_{t-1}/100^2$, where $\mathbf{I}^{\circ}_t$ is a matrix with elements I_{it} on the diagonal and zeroes elsewhere. These expressions are useful if we wish to forecast the index and to give its forecast variance. Second, trading is not directly in terms of the index. The presence of index funds and standard options tied to the index are reasonable justifications for using the index as a price. The chosen approach is to use the return series as is and then emphasize the return as an indicator of market risk (e.g., McNeil and Frey, 2000).

For portfolio allocation we adopt the tangency portfolio (e.g., Campbell et al., 1997, ch 5). At time $T+1$ we have

$$\mathbf{a}_{T+1} = V^{-1}(\mathbf{y}_{T+1}|\mathcal{F}_T) \cdot [E(\mathbf{y}_{T+1}|\mathcal{F}_T) - R_f\mathbf{1}]/A,$$

where $A = \mathbf{1}'V^{-1}(\mathbf{y}_{T+1}|\mathcal{F}_T) \cdot [E(\mathbf{y}_{T+1}|\mathcal{F}_T) - R_f\mathbf{1}]$, R_f is the risk free rate, and $\mathbf{1}$ is a column vector of ones. Hence, $\mathbf{1}'\mathbf{a}_{T+1} = 1$. For the VaR-measure under normality, a time invariant allocation vector $\mathbf{a}$, and a probability α, Gourieroux and Jasiak (2001, ch 16) give:

$$R_{T+1} = -\mathbf{a}'E(\mathbf{y}_{T+1}|\mathcal{F}_T) + \Phi^{-1}(1-\alpha)\left[\mathbf{a}'V(\mathbf{y}_{T+1}|\mathcal{F}_T)\mathbf{a}\right]^{1/2},$$

where $\Phi(.)$ is the standard normal distribution function. This VaR measure is in terms of returns; one in terms of indices can also be devised by simply replacing $\mathbf{y}_{T+1}$ by $\mathbf{I}_{T+1}$ and using the expressions given above. Using shock scenarios in terms of the $\mathbf{u}_t$ vector or in terms of $\mathbf{x}_t^{+/-}$ and $\mathbf{z}_t^{+/-}$, the $\mathbf{a}_{T+1}$ and R_{T+1} can be calculated and then evaluated and subjected to comparisons. To cast light on effects of simultaneity, the univariate models can be compared to the simultaneous model system in terms of the portfolio or VaR metrics either as above or over some historical period. Note, that both measures are subject to sampling variation in estimated mean return and risk functions. Britten-Jones (1999) and others have discussed the variation in allocation weights, while Christoffersen and Gonçalves (2005) among others have discussed the issue for VaR measures.

4. Empirical Study and Data

The framework described above is used to study the indices of the Baltic States' stock exchanges. There are several common features, by which the Baltic States' stock exchange indices are likely to move together simultaneously. First, these relatively small marketplaces are geographically closely located. Second, they have the same owner (Nasdaq-OMX) and share a common trading platform. In addition, many of the largest traders are common to all three marketplaces. In fact, foreign institutional investors, predominately European ones, represent 40-47 percent of the market value in the Baltic States' stock markets, whereas foreign and domestic institutional investors combined control about 90 percent of the market value.

To study the joint evolution of returns and volatilities in the Baltic States' stock markets, we use capitalization weighted daily stock price indices of the Estonian (Tallinn, TALSE), Latvian (Riga, RIGSE), Lithuanian (Vilnius, VILSE) and Russian (Moscow, RTS) stock markets. All prices are transformed into Euros from local currencies, except for Estonia where stock market trading is in Euro. Using a common currency implies that the analyzed return series also contain variation due to exchange rate movements. Hence, this paper takes an international investor perspective, when interest is in Euro returns, and the effect of these variations is therefore included in the analysis. Also, since Estonia and Lithuania joined the ERM II during 2004 and Latvia in 2005 the exchange rates have been rather stable during, at least, the later parts of the return series.[1] The data-set covers January 3, 2000 to August 16, 2006, for a total of $T = 1729$ observations, cf. Figure 1 for the three Baltic States' indices. Both indices and exchange rates are collected from DataStream. The irregularity in the summer of 2001 in the Riga index (RIGSE) is due to a power struggle in its largest company (Latvijas Gaze). Instead of elaborating on modelling to contain this irregular period, the Riga series is adjusted in the following simplistic way: For a speculation period from July 25 to September 3, 2001, observations are replaced by interpolated values.

Following Brännäs and Soultanaeva (2010), the Russian stock market index is used as a exogenous variable that may have an impact on the Baltic

[1] The Latvian currency was pegged to the SDR basket (the unit of accounting of the IMF) consisting of the four major currencies: the US dollar, the Euro, the British pound sterling and the Japanese yen, since February 1994. The fixed exchange rate with the Euro was implemented on January 1, 2005. The Estonian currency was pegged to the Deutsche Mark since 1992, and moved to the Euro peg after the introduction of the Euro. Lithuania introduced a US dollar-based currency board in 1994 and changed the peg to the Euro in February 2002.

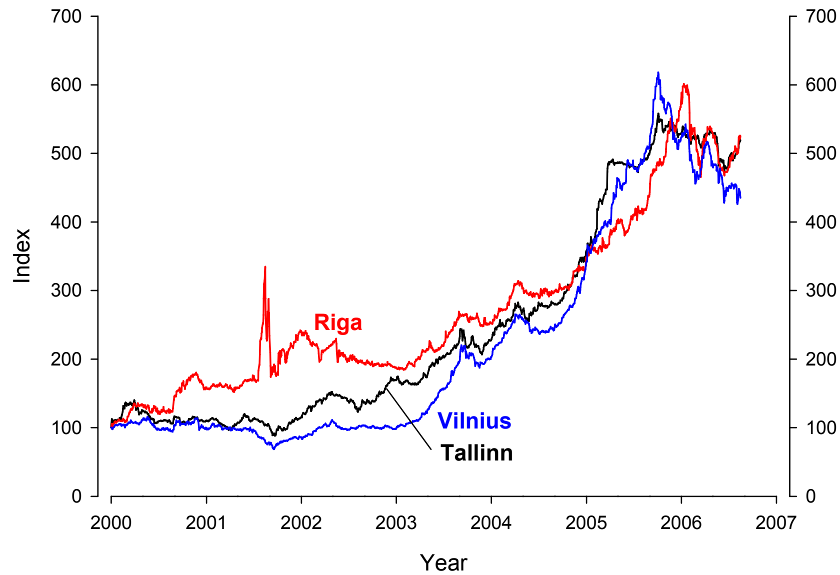

Figure 1: Indices of the Baltic stock exchanges (December 31, 1999 = 100).

States' stock markets. In general, spillovers from the Russian stock market can be explained by economic, historical and political ties between the countries (e.g., Koch and Koch, 1991). Pajuste et al. (2000) find, for example, that East European countries are likely to be affected by news coming from Russia. Moreover, Brännäs and Soultanaeva (2010) demonstrated that good and bad news arriving from Russia (Moscow) have asymmetric impacts on the volatility in the Baltic States' stock markets. Thus, within the context of the empirical analysis, the time series processes $\{\mathbf{x}_t^+\}$ and $\{\mathbf{x}_t^-\}$ represent positive and negative returns at time t in the Russian Stock Exchange (RTS) index, whereas the series $\{\mathbf{z}_t\}$ will enter (2) as the demeaned moving variance series of the RTS index. In more detail, to obtain the z_t variable, we construct a new series by obtaining moving variances of Moscow returns for a window length of 10 observations and deduct the mean. The z^+ then takes on positive values and is indicative of high-risk, and z^- in a corresponding way takes on negative values and indicates a lower risk in Moscow.

Table 1: Descriptive statistics for return series.

Exchange	Mean	Variance	Min/Max	Skewness	Kurtosis	LB_{10}
Riga	0.10	1.77	-9.27/10.29	0.18	10.72	45.93
Tallinn	0.10	1.05	-5.87/12.02	1.09	15.94	51.43
Vilnius	0.09	1.05	-12.12/5.32	-0.91	13.82	46.87
Moscow	0.12	4.93	-11.92/10.23	-0.47	3.27	16.37

Note: LB_{10} is the Ljung-Box statistic evaluated at 10 lags.

Table 2: Cross correlations for Baltic stock markets returns and squared returns.

	Returns			Squared Returns		
	Riga	Tallinn	Vilnius	Riga	Tallinn	Vilnius
Riga	1			1		
Tallinn	0.134	1		0.161	1	
Vilnius	0.141	0.208	1	0.023	0.032	1

Table 3: Auto and cross correlations for Baltic stock markets returns (in the order Riga, Tallinn and Vilnius). Significant entries are indicated by signs and subindex indicates lag.

$$\begin{pmatrix} 1 & + & + \\ . & 1 & + \\ . & + & 1 \end{pmatrix}_0, \begin{pmatrix} - & . & . \\ . & . & + \\ . & + & + \end{pmatrix}_1, \begin{pmatrix} . & . & + \\ . & . & + \\ . & . & + \end{pmatrix}_2, \begin{pmatrix} + & . & . \\ . & . & + \\ . & . & . \end{pmatrix}_3,$$
$$\begin{pmatrix} - & . & . \\ . & . & . \\ . & . & + \end{pmatrix}_4$$

Due to some differences in holidays for the involved countries the series have different shares of days for which index stock price are not observable. Linear interpolation was used to fill the gaps for all series. The resulting series are then throughout for a common trading week. All returns are calculated as $y_t = 100 \cdot \ln(I_t/I_{t-1})$, where I_t is the daily price index. Table 1 reports descriptive statistics for the daily returns. The Ljung-Box statistics for 10 lags

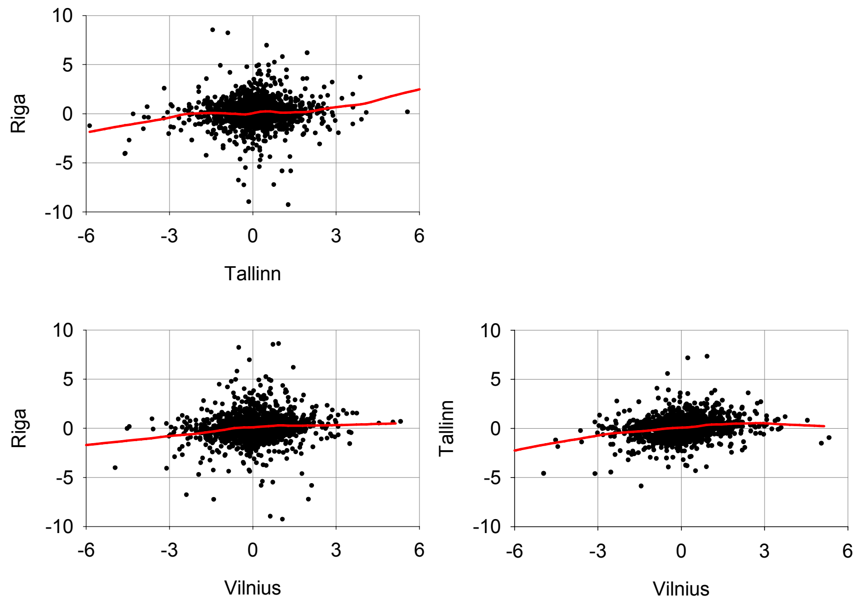

Figure 2: Cross plots for Baltic returns series. One negative outlier for Vilnius is outside the figure and three positive ones for Tallinn.

(LB_{10}) indicate significant serial correlations. The large kurtoses for Riga, Tallinn and Vilnius indicate leptokurtic densities. Table 2 presents cross correlations for the Baltic States' return series and for a squared returns. Table 3 gives auto and lagged cross correlations. For instance, the table indicates that Tallinn is positively affected by Vilnius both within the day and with up to three lags. There appears to be no impact from Riga.

Figure 2 gives scatterplots for pairs of returns series with a nonparametric regression line (LOWESS). Visual inspection indicates that there is weak dependence between Riga and Tallinn for the majority of observations, while for the other plots there appear to be positive relationships.

5. Results

The empirical results are presented first in terms of the return function and later in terms of the volatility function. Table A in the Appendix contains estimated univariate models. The empirical specifications are obtained by the steps outlined in Section 3.

For the return function of $\{\mathbf{y}_t\}$, cf. eq (1), when returns are in the order Riga, Tallinn and Vilnius, the estimated function is

$$\begin{pmatrix} 1 & \underset{(0.034)}{-0.06} & \underset{(0.043)}{-0.09} \\ 0 & 1 & \underset{(0.025)}{-0.11} \\ 0 & 0 & 1 \end{pmatrix} \hat{\mathbf{y}}_t = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \underset{(0.023)}{0.06} \end{pmatrix} \hat{\mathbf{y}}_{t-2}$$

$$+ \begin{pmatrix} \underset{(0.050)}{-0.17} & 0 & 0 \\ 0 & \underset{(0.044)}{0.24} & 0 \\ 0 & 0 & \underset{(0.048)}{0.15} \end{pmatrix} \hat{\mathbf{u}}^+_{t-1} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & \underset{(0.039)}{0.12} & 0 \\ 0 & 0 & 0 \end{pmatrix} \hat{\mathbf{u}}^+_{t-2}$$

$$+ \begin{pmatrix} 0 & 0 & 0 \\ \underset{(0.023)}{0.07} & \underset{(0.048)}{0.09} & \underset{(0.026)}{0.07} \\ 0 & 0 & 0 \end{pmatrix} \hat{\mathbf{u}}^-_{t-1} + \begin{pmatrix} 0 & \underset{(0.046)}{0.12} & \underset{(0.041)}{0.08} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \hat{\mathbf{u}}^-_{t-2}$$

$$+ \begin{pmatrix} \underset{(0.043)}{0.21} \\ \underset{(0.026)}{0.12} \\ \underset{(0.027)}{0.14} \end{pmatrix} + \begin{pmatrix} \underset{(0.021)}{0.06} \\ 0 \\ 0 \end{pmatrix} x^+_t + \begin{pmatrix} 0 \\ 0 \\ \underset{(0.018)}{0.04} \end{pmatrix} x^+_{t-1}$$

$$+ \begin{pmatrix} \underset{(0.024)}{0.07} \\ \underset{(0.011)}{0.09} \\ \underset{(0.016)}{0.12} \end{pmatrix} x^-_t + \begin{pmatrix} 0 \\ \underset{(0.012)}{0.03} \\ 0 \end{pmatrix} x^-_{t-1} + \begin{pmatrix} 0 \\ \underset{(0.014)}{0.02} \\ 0 \end{pmatrix} x^-_{t-2}.$$

With respect to simultaneity, the $\hat{\mathbf{A}}_0$ matrix indicates a recursive structure; the returns of the Riga index depends within the day positively on both the index returns of Tallinn and Vilnius, while returns in Tallinn are positively influenced by those of Vilnius. Riga returns have no impact on the returns of neither Tallinn nor Vilnius, and Tallinn returns have no influence on those of Vilnius. The only lagged influence arises for Vilnius at lag two, cf. the $\hat{\mathbf{A}}_2$ matrix.

For Riga returns, Moscow has a quite symmetric and positive effect within the day. For Tallinn, we instead find asymmetric effects spread over lags $0-2$. The effects are much stronger for a negative shock. For Vilnius, negative shocks out of Moscow appear to have stronger impact than positive shocks. For shocks arising in the three Baltic States' stock exchanges we find that a positive shock in Riga at lag one has a negative impact on current returns, and in addition, negative lag two shocks of Tallinn and Vilnius have negative effects. Positive shocks in Tallinn have stronger effects than equally sized negative shocks, and there are negative shocks of both Riga and Vilnius at lag 2. The off-diagonal elements of lagged shocks suggests that there are some shock-spillovers; Riga returns are negatively influenced by Tallinn and Vilnius shocks at lag two, while Tallinn is impacted by Riga and Vilnius shocks at lag one.

For the volatility function the conditional covariances are assumed time-invariant and insignificantly estimated as $\hat{\mathbf{h}}_{t,4} = 0.003$ (s.e. $= 0.023$), $\hat{\mathbf{h}}_{t,5} = 0.000$ (0.033) and $\hat{\mathbf{h}}_{t,6} = 0.000$ (0.025). The estimated conditional variances has the form

$$
\begin{aligned}
\begin{pmatrix} 1 & \underset{(0.004)}{-0.01} & 0 \\ 0 & 1 & 0 \\ 0 & \underset{(0.016)}{0.03} & 1 \end{pmatrix} \hat{\mathbf{h}}_t &= \begin{pmatrix} \underset{(0.006)}{0.95} & 0 & 0 \\ 0 & \underset{(0.009)}{0.93} & 0 \\ 0 & 0 & \underset{(0.029)}{0.82} \end{pmatrix} \hat{\mathbf{h}}_{t-1} \\
&+ \begin{pmatrix} \underset{(0.018)}{-0.02} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & \underset{(0.025)}{-0.12} & \underset{(0.035)}{0.27} \end{pmatrix} \hat{\mathbf{u}}^{+}_{t-1} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & \underset{(0.016)}{0.15} & 0 \\ 0 & 0 & 0 \end{pmatrix} \hat{\mathbf{u}}^{+}_{t-2} \\
&+ \begin{pmatrix} \underset{(0.076)}{0.37} & 0 & 0 \\ 0 & \underset{(0.017)}{-0.15} & 0 \\ 0 & 0 & \underset{(0.033)}{-0.26} \end{pmatrix} \hat{\mathbf{u}}^{-}_{t-1} + \begin{pmatrix} \underset{(0.073)}{-0.29} & 0 & \underset{(0.008)}{-0.06} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \hat{\mathbf{u}}^{-}_{t-2} \\
&+ \begin{pmatrix} \underset{(0.039)}{0.36} & 0 & 0 \\ 0 & \underset{(0.037)}{0.13} & 0 \\ 0 & \underset{(0.007)}{0.03} & \underset{(0.033)}{0.12} \end{pmatrix} \hat{\mathbf{u}}^{*,2}_{t-1} + \begin{pmatrix} \underset{(0.037)}{-0.31} & 0 & 0 \\ 0 & \underset{(0.034)}{-0.14} & \underset{(0.001)}{-0.01} \\ 0 & 0 & \underset{(0.028)}{-0.13} \end{pmatrix} \hat{\mathbf{u}}^{*,2}_{t-2} \\
&+ \begin{pmatrix} \underset{(0.011)}{0.02} \\ \underset{(0.004)}{-0.02} \\ \underset{(0.026)}{0.07} \end{pmatrix} + \begin{pmatrix} \underset{(0.000)}{-0.002} \\ 0 \\ \underset{(0.006)}{0.04} \end{pmatrix} z_t^{+} + \begin{pmatrix} \underset{(0.017)}{0.08} \\ \underset{(0.012)}{0.04} \\ 0 \end{pmatrix} z_t^{-}
\end{aligned}
$$

$$+\begin{pmatrix} 0 \\ 0 \\ \underset{(0.006)}{-0.04} \end{pmatrix} z_{t-1}^{+} + \begin{pmatrix} \underset{(0.016)}{-0.08} \\ \underset{(0.012)}{-0.04} \\ \underset{(0.004)}{0.01} \end{pmatrix} z_{t-1}^{-}.$$

Only two elements in $\hat{\mathbf{D}}_0$ are significant, the volatility of Vilnius depends negatively but weakly on that of Tallinn in the same time period, while Riga depends positively on Tallinn. As expected volatilities are quite persistent, cf. the $\hat{\mathbf{D}}_1$-matrix estimates. The patterns for Riga and Tallinn are quite similar and asymmetric; a higher than average Moscow risk marginally reduces risk in Riga and there is no effect for Tallinn, and in both cases there is a strong negative direct effect of a lower than average Moscow risk that turns positive and then dies out. For Vilnius the direct effects are quite asymmetric and both are positive. Thereafter the effects are negative and gradually die out. The effect is an enhancing one for Vilnius.

The model evaluation phase considers formal tests against simultaneity in returns and in risk as well as tests against asymmetric effects arising from Moscow or from the innovations of the model system. As a first but informal test supporting the joint models rests on the likelihoods under the univariate models and the joint model; the likelihood ratio statistic is then $LR = 181.8$. Table 4 summarizes the Wald test results and also gives the serial correlation properties and the goodness-of-fit for the model. The Wald tests are all significant with p-values less than 0.02. There is then evidence of simultaneity as well as of asymmetric effects. When it comes to serial correlation properties in standardized and squared standardized residuals there appears to be remaining serial correlation in only one series, the standardized residuals of Vilnius. The standardized residuals are nonnormal and leptokurtic.

Next, we consider the estimated volatility functions in some more detail in Figures 3-4. Figure 3 shows the estimated $\mathbf{H}_{t,i,i}$ functions for the final part of the series. It is quite clear from this figure that the volatilities of Riga and Vilnius are larger than those of Tallinn. This pattern reenforces the sample variance ordering of Table 1. The estimated volatility functions are positively correlated, cf. Figure 4. Since covariance estimates $\mathbf{H}_{t,i,j}$ between the innovations of stock exchanges are very small the resulting time-varying conditional correlations are also very small and always smaller than 0.05. The implied estimated conditional correlations between $\{\mathbf{y}_t\}$ variables are much larger and also positive throughout, cf. Figure 5. Average conditional correlations are relatively close to the sample correlations of Table 2.

Table 4: Simultaneity and asymmetry tests together with model evaluation measures.

Hypothesis	Wald	df	Measure	Riga	Tallinn	Vilnius
Simultaneity-Returns	27.0	3	LB_{10}	10.08	5.82	22.75
Simultaneity-Risk	7.81	2	LB^2_{10}	11.77	1.63	1.14
Asymmetry-Return-Moscow	160.9	6	Skewness	0.47	0.54	-0.30
Asymmetry-Return-Innovation	74.4	8	Kurtosis	4.33	6.31	6.06
Asymmetry-Risk-Moscow	92.8	6	JB	1403.7	2936.8	2659.2
Asymmetry-Risk-Innovation	6033	7	R^2	0.05	0.18	0.06

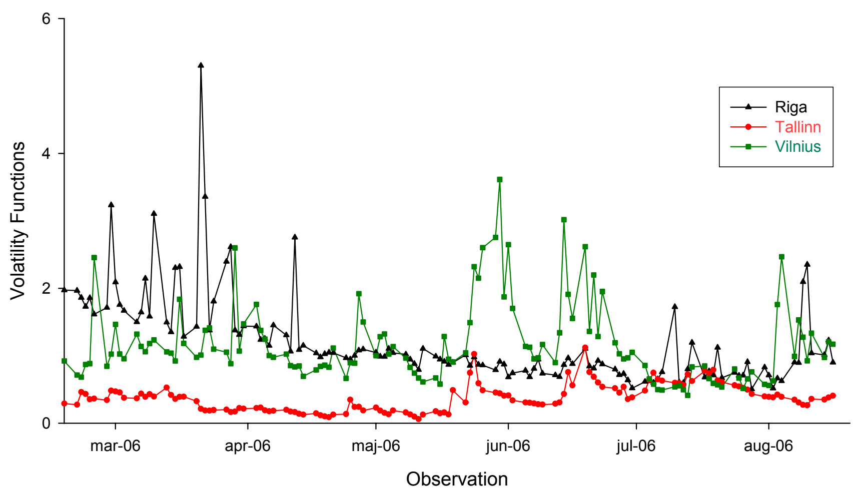

Figure 3: Estimated volatility functions for the final part of the sample period.

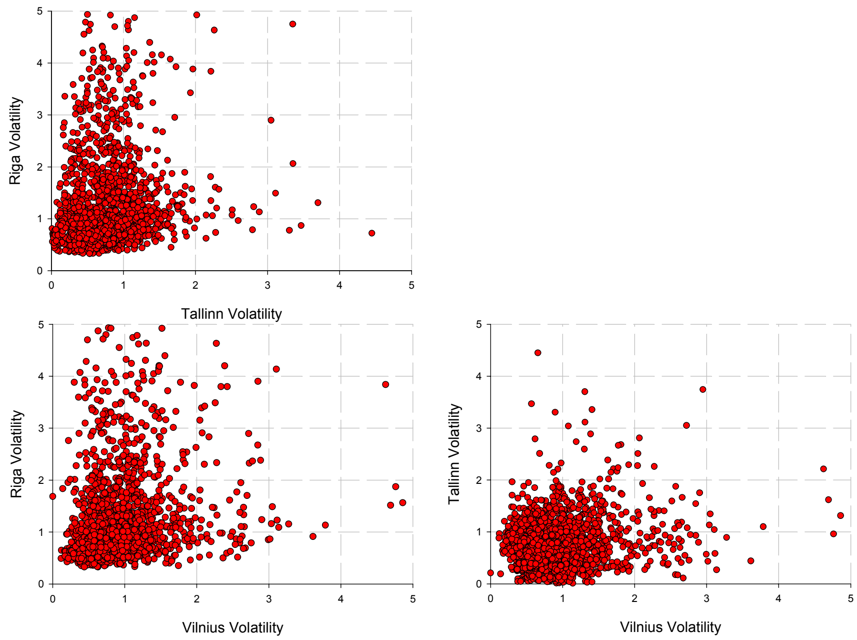

Figure 4: Plots of estimated volatilities (some outlying volatilities fall outside the graphs).

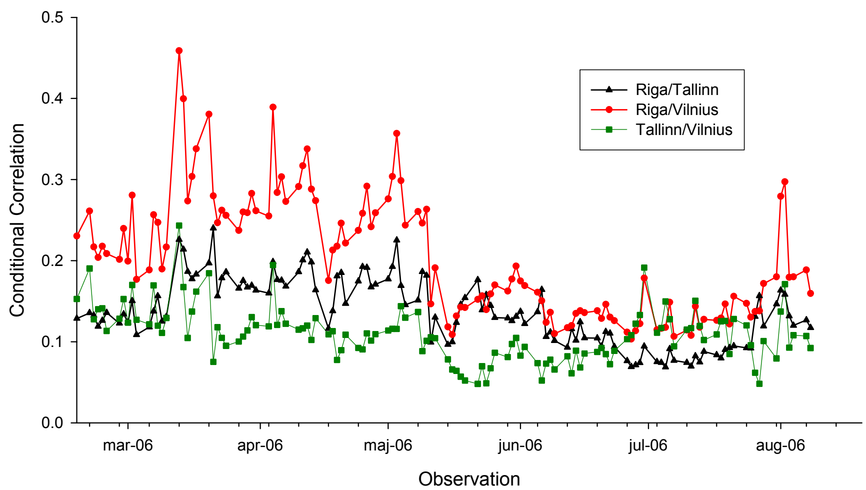

Figure 5: Estimated conditional correlations between the returns of the stock markets for the final part of the sample period.

Table 5: Portfolio and VaR effects of shocks in innovations and Moscow (Joint), together with a univariate model (Single) case. The VaR is based on probability 0.025 and a portfolio with weights 0.333 for each index (VaR-A) and with the weights obtained in the Base case (VaR-B).

	Portfolio Allocation						VaR			
	Joint			Single			A		B	
	Riga	Tallinn	Vilnius	Riga	Tallinn	Vilnius	Joint	Single	Joint	Single
Base case	0.24	0.66	0.10	0.32	0.50	0.18	1.23	0.91	1.66	0.83
Shock-Riga	0.27	0.64	0.09	0.19	0.60	0.21	1.19	1.15	1.65	0.98
-Tallinn	0.30	0.54	0.16	0.35	0.45	0.19	1.23	0.99	1.64	1.06
-Vilnius	0.26	0.72	0.02	0.37	0.58	0.05	1.42	0.99	2.02	0.81
-Moscow(x)	0.23	0.67	0.10	0.31	0.51	0.18	1.25	0.90	1.67	0.82
-Moscow(z)	0.24	0.62	0.14	0.27	0.50	0.23	1.36	1.07	1.77	1.03

Portfolio allocations and VaR measures one-step-ahead are shown in Table 5. These measures are based on forecast equations

$$\begin{aligned} E(\mathbf{y}_{T+1}|\mathcal{F}_T) &= \hat{\mathbf{A}}_0^{-1}\left[\hat{\mathbf{A}}_2\mathbf{y}_{T-1} + \sum_{i=1}^{2}\left(\hat{\mathbf{B}}_i^{+}\hat{\mathbf{u}}_{T+1-i}^{+} + \hat{\mathbf{B}}_i^{-}\hat{\mathbf{u}}_{T+1-i}^{-}\right)\right. \\ &\quad \left. +\hat{\mathbf{c}}_0 + \sum_{i=0}^{2}\left(\hat{\mathbf{C}}_i^{+}\mathbf{x}_{T-i}^{+} + \hat{\mathbf{C}}_i^{-}\mathbf{x}_{T-i}^{-}\right)\right] \\ V(\mathbf{y}_{T+1}|\mathcal{F}_T) &= \hat{\mathbf{A}}_0^{-1}\hat{\mathbf{H}}_{T+1}(\hat{\mathbf{A}}_0^{-1})' \end{aligned}$$

and depend on the histories of $\mathbf{y}_t$, $\hat{\mathbf{u}}_t$, and $\mathbf{x}_t$ for the conditional return and additionally on the histories of $\mathbf{H}_t$ and $\mathbf{z}_t$ for the conditional volatility. Since the impact of Moscow is in the same period we set future values (x_{T+1} and z_{T+1}) for Moscow close to their values at the end of the series, i.e. as $x_{T+1}^{+} = 0.1$ and $z_{T+1}^{-} = -4$. This is the Base case design. For the portfolio allocation exercise the risk free rate is set at 1.07, which is the level of the Euro market government bond yield by the end of the sample period.

The allocation for the Tallinn stock exchange is 0.66, while 0.24 of the portfolio should be placed in Riga and 0.10 in Vilnius. Using the same setup but using instead the univariate models (Single) of Table A, gives a much lower allocation for Tallinn and higher ones for both Riga and Vilnius. The two model forms differ in simultaneity but also with respect to other features of the dynamic model. Therefore, we cannot infer with certainty that the differences are due solely to simultaneous effects. The VaR measures for probability 0.025 are for the simultaneous model with equal weights 1.23 and

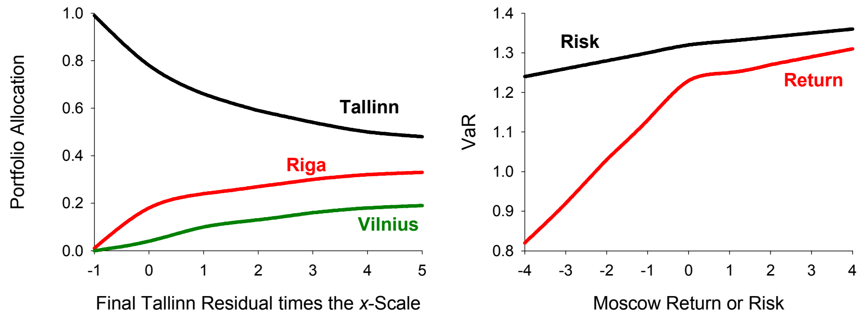

Figure 6: Allocations after shocking the final negative residual for Tallinn (left exhibit, a value on the x-scale larger than $+1$ means a larger negative shock). VaR effects of shocks to Moscow return, for given $z^- = -4$ and risk for given $x^+ = 0.1$(right exhibit).

for the univariate models 0.91. For the weights obtained with the weights of the Base case we get 1.66 and 0.82, respectively.

To study the sensitivity of the Base case results we next shock the individual elements of $\hat{\mathbf{u}}_T$ (the final residuals are individually multiplied by a factor 3). Note that the underlying sizes of residuals in the univariate models have not been changed but shocks are throughout in the direction of the joint model. For shocks in the Tallinn and Vilnius stock markets the allocations for these markets are reduced. Figure 6 illustrates this for an increasingly negative shock in Tallinn. With a decrease in the Tallinn weight comes relatively more weight for Riga than for Vilnius. The allocations obtained using the univariate models differ from those based on the joint model, mainly such that the weights for Riga and Vilnius are larger and those for Tallinn are smaller.

We also consider shocks arising in Moscow returns (x^+_{T+1} is set to 1). This appears to have only minor impact. For Moscow risk we change from $z^-_{T+1} = -4$ to $z^+_{T+1} = 4$ and note an increase for Vilnius and a reduction for Tallinn allocations.

The VaR measure changes little for shocks in Tallinn but responds more to shocks in Vilnius and in Moscow risk. The VaR:s based on the univariate models are smaller than the corresponding measures for the joint model. When the weights of the Base case are used the VaR:s increase markedly throughout. Figure 6 studies the impacts on VaR of Moscow shocks in more detail. Changes in risk have rather small effects, while Moscow return changes have a more sizeable and asymmetric effect.

6. Conclusion

The paper has introduced simultaneity into a multivariate and nonlinear time series model framework to study jointly the indices of the Baltic States' stock exchanges. Unlike previous studies (e.g., Rigobon and Sack, 2003, De Wet, 2006, Lee, 2006), we allow for simultaneity in returns and volatility separately. The model allows us to capture "within a day" information transmission between the stock markets under study. Since information transmission between markets is virtually instantaneous (e.g., Engle and Russell, 1998) a study based on daily sampling frequency should take into account simultaneous reactions to movements in other relevant assets or markets. Moreover, the model is able to capture asymmetric impacts of lagged positive and negative shocks on returns and volatility processes. We argue that measuring simultaneous and asymmetric spillovers is important for a number of reasons, including optimal portfolio allocation and risk management.

In summary, the empirical analysis provides support for the simultaneity in return and volatility. Accounting for simultaneity is of particular importance for markets located in the same geographic region or closely related due to institutional structure or other practical considerations as for example common trading platform. Given the fact that investors diversify their holdings across markets in order to reduce the risk of the portfolio, accounting for information which simultaneously alters the expectations of different markets is important for asset allocation and risk management strategies.

Empirically, we illustrate the importance of simultaneity with respect to Baltic States' stock markets. In these closely related markets simultaneity is likely to arise due to geographical proximity, common institutional setup as well as common large traders, among other things. We found strong evidence of simultaneous effects in both returns and volatility. In returns, Riga is dependent on the indices of Tallinn and Vilnius, Tallinn is dependent on Vilnius, while Vilnius is not influenced by the other two markets. For volatility, we find within a day spillovers from Tallinn to both Riga and Vilnius. In addition, we found asymmetric effects of Moscow returns on the index returns in the Baltic States' exchanges, and asymmetric effects of Moscow risk on volatilities.

To illustrate the importance of simultaneous interaction between markets we obtain the portfolio allocations and value at risk measures for the multivariate and univariate models. Portfolio allocation results indicate that optimal portfolio weights are more sensitive to shocks when simultaneity is not accounted for. VaR measures indicate that the variability in losses that may occur due to shocks to the market are larger when simultaneity is not accounted for.

The simultaneous and dynamic econometric model generalizes previous univariate models by allowing for simultaneity but also for cross-effects of innovations. As in any simultaneous model we can therefore talk about direct, indirect and total effects in the return and volatility functions. The direct effects can be seen in the estimation results, while the portfolio and value at risk results build on total effects. To estimate the model we employ full information maximum likelihood. The suggested stepwise specification procedure resulted in a model with important deviations from corresponding univariate models. Estimation of the final model does not result in numerical problems despite the fact that the model is quite richly parametrized.

Table A: Estimation results for univariate models.

	Riga				Tallinn				Vilnius			
Variables	Return		Risk		Return		Risk		Return		Risk	
y_{t-2}									0.057	0.021		
u^+_{t-1}	-0.146	0.048	-0.072	0.018	0.252	0.041			0.162	0.045	0.273	0.030
u^+_{t-2}					0.117	0.037	0.021	0.022				
u^+_{t-3}												
u^-_{t-1}			0.394	0.071	0.119	0.046	-0.190	0.181			-0.279	0.023
u^-_{t-2}			-0.283	0.064								
h_{t-1}			0.944	0.005			0.917	0.009			0.829	0.024
u^2_{t-1}			0.389	0.034			0.113	0.034			0.093	0.031
u^2_{t-2}			-0.322	0.031			-0.135	0.031			-0.113	0.026
x, z^+_t	0.050	0.021	-0.001	0.001							0.034	0.005
x, z^+_{t-1}									0.046	0.0167	-0.032	0.005
x, z^-_t	0.105	0.021	0.121	0.0167	0.120	0.011	0.046	0.012	0.126	0.015	0.007	0.004
x, z^-_{t-1}			-0.114	0.0167	0.046	0.012	-0.050	0.012				
x, z^-_{t-2}					0.029	0.013						
Constant	0.177	0.033	0.079	0.012	0.114	0.027	-0.035	0.004	0.141	0.027	0.004	0.020
AIC	2086.9				1164.5				1446.8			
$\ln L, R^2$	-1029.5		0.03		-566.87			0.16	-709.41			0.06
LB_{10}	10.84		8.83		7.01		1.53		21.57		1.53	
Skew, Kurt, JB	0.43	5.60	2303.5		0.439	6.86	3446.6		-0.23	6.48	3030.7	

References

Brännäs, K., and J.G. De Gooijer (1994): Autoregressive-asymmetric moving average models for business cycle data. *Journal of Forecasting*, 13, 529-544.

Brännäs, K., and J.G. De Gooijer (2004): Asymmetries in conditional mean and variance: modelling stock returns by asMA-asQGARCH. *Journal of Forecasting*, 23, 155-171.

Brännäs, K., and H. Ohlsson (1999): Asymmetric time series and temporal aggregation. *Review of Economics and Statistics*, 81, 341-344.

Brännäs, K., and A. Soultanaeva (2010): Influence of news from Moscow and New York on returns and risks on Baltic States' stock markets. To appear in *Baltic Journal of Economics*

Britten-Jones, M. (1999): The sampling error in estimates of mean-variance efficient portfolio weights. *Journal of Finance*, LIV, 655-671.

Campbell, J.Y., Lo, A.W., and A.C. MacKinlay (1997): *The Econometrics of Financial Markets.* 2nd edition, Princeton: Princeton University Press.

Christoffersen, P., and S. Gonçalves (2005): Estimation in financial risk management. *Journal of Risk*, 7, 1-28.

De Goeij, P., and W. Marquering (2005): The generalized asymmetric dynamic covariance model. *Finance Research Letters*, 2, 67-74.

De Wet, W.A. (2006): A structural GARCH model: An application on South African data. *Economic Modelling*, 23, 775-791.

Engle, R.F., and K.F. Kroner (1995): Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11, 122-150.

Engle, R.F., and J.R. Russell (1998): Autoregressive conditional duration: A new model for irregularly spaced transaction data. *Econometrica*, 66, 1127-1162.

Fazio, G. (2007): Extreme interdependence and extreme contagion between emerging markets. *Journal of International Money and Finance*, 26, 1261-1291.

Fleming, J., Kirby, C., and B. Ostdiek (1998): Information and volatility linkages in the stock, bond and money markets. *Journal of Financial Economics*, 49, 111-137.

Gannon, G.L. (2004): Simultaneous volatility transmission and spillover effects. School Working Paper Series 2004/10, Deakin University.

Gannon, G.L. (2005): Simultaneous volatility transmissions and spillover effects: U.S. and Hong Kong stock and futures markets. *International Review of Financial Analysis,* 14, 326-336.

Gannon, G.L., and D. Choi (1998): Structural models: Intra/inter-day volatility transmission and spillover persistence of the HSI, HSIF and S&P500 futures. *International Review of Financial Analysis*, 7, 19-36.

Gourieroux, C., and J. Jasiak (2001): *Financial Econometrics*. Princeton: Princeton University Press.

Koch, P.D., and T.W. Koch (1991): Evolution in dynamic linkages across daily national stock indexes. *Journal of International Money and Finance*, 10, 231-251.

Kroner, K.F., and V.K. Ng (1998): Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, 11, 817-844.

Lee, K.Y. (2006): The contemporaneous interactions between the U.S., Japan and Hong Kong stock markets. *Economics Letters*, 90, 21-27.

McNeil, A.J., and R. Frey (2000): Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of Empirical Finance*, 7, 271-300.

Pajuste, A., Kepitis, G., and P. Högfeldt (2000): Risk Factors and Predictability of Stock Returns in Central and Eastern Europe. *Emerging Markets Quarterly* Summer: 7-24.

Rigobon, R. (2003): Identification through heteroskedasticity. *The Review of Economics and Statistics*, LXXXV, 777-792.

Rigobon, R., and B. Sack (2003): Spillovers across U.S. financial markets. NBER Working Paper 9640.