The Impact of Stock Market Jumps on Time-Varying Return Correlations: Empirical Evidence from the Baltic Countries

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Abstract

In this paper we study the impact of market jumps on the time varying return correlations between stock market indices in the Baltic countries. An EARJI-EGARCH model facilitating direct modelling of the time varying return correlations is introduced. The empirical results indicate that there is a quite large number of identified jumps in the emerging Baltic stock markets. The main finding is that isolated market jumps in one of the markets generally have no or small effects on the time-varying correlations. In contrast, simultaneous jumps of equal sign increase the average correlation, in some cases with as much as 100 percent.

Keywords: Correlated jumps, contagion.

JEL: C32, C52.

1 Introduction

Does international portfolio diversification give investors protection from extreme movements (or jumps) in local stock market prices? An answer to this question obviously depends on the correlation between returns in different markets included in the portfolio.

Empirical evidence concerning financial asset and market returns (e.g., Fustenberg and Jeon, 1989; Koch and Koch, 1991; Erb *et al.*, 1994) often points towards time-varying correlation structures that tend to increase during unstable periods. Karolyi and Stulz (1996), Ramchand and Susmel (1998) and Longin and Solnik (1995, 2001), among others, found that the correlations between major stock markets rose during periods of high volatility or during market crises. In general, the literature on contagion[1] (e.g., Claessens, 2001; Forbes and Rigobon, 2002) often finds that the cross-market correlation coefficients in a stable environment are statistically different (lower) from the correlation coefficients during unstable periods. Even though international stock market correlations have received a lot of attention in the literature, due to its importance in portfolio and risk management (e.g., Fazio, 2007; Knif and Pynnönen, 2007; Campbell *et al.*, 2008), less is known about correlation responses to large shocks (jumps) in stock market returns.

To shed some light on this issue, the current paper studies the impact of large discrete changes in stock market prices (jumps) on time-varying return correlations. More specifically, we study whether the correlations of stock market returns differ when there are smooth changes in market returns or large discrete changes (jumps). The study is performed on stock market data for the Baltic countries (Estonia, Latvia and Lithuania) which have previously received little attention in the financial literature. Despite the benefits of diversifying into emerging markets (see, Bekaert and Harvey, 2002), portfolio managers often shy away from these markets due to the high volatility. Thus, improved knowledge about emerging stock markets, in this case the Baltic stock markets, may reduce the uncertainty about such an investment.

In the empirical analysis a bivariate Exponential Autoregressive Jump Intensity (EARJI)-EGARCH model, based on Chan (2004), is introduced to identify stock market jumps as well as to estimate time varying return correlations. The possible effect of the identified stock market jumps on the time varying return correlations are then analyzed in separate regressions.

This paper contributes to the existing literature in several ways. First, in contrast to

[1] Contagion is commonly defined as an increase in stock market co-movements after a shock or a financial crisis.

the earlier literature on contagion, where shocks or periods of financial turmoil usually are pre-defined by the authors, we utilize a data driven procedure to identify large shocks labelled as jumps. Thus, the results of this paper are, in this regard, more general and pertain to any market shocks rather than to prespecified shocks or to periods of financial turmoil. Second, the effects of market jumps on the dynamics of time-varying return correlations have not previously, to the authors knowledge, been addressed as directly as in this paper. In the literature on jump spillovers, Asgharian and Bengtsson (2006) found earlier that the correlation structure between the jump processes of returns differs significantly from the correlation between the regular return components (i.e. the parts that are not jumps). In comparison to Asgharian and Bengtsson (2006), we focus directly on the question of how jumps affect the return correlations, whereas they are mainly concerned with the correlation between jumps, as well as, spillovers of jumps between international markets. Note that a high correlation between jumps does not necessarily imply a high correlation between returns, since jumps may be in different directions, i.e. correspond to large positive and negative changes in stock market prices. Third, in this paper the class of mixed GARCH-jump models (e.g., Chan and Maheu, 2002) is extended to a specification with a time varying return correlation. The earlier multivariate models by e.g., Chan (2004), have instead implicitly modelled time varying return correlation through correlated jump components. Fourth, empirical evidence on the Baltic stock markets, which are less studied in the financial literature, is provided.

In Section 2 of the paper the econometric framework is outlined. Section 3 describes the data set used in the empirical study. Section 4 reports on the empirical results, while the final section discusses the results and concludes the paper.

2 A bivariate EARJI-EGARCH model with time-varying correlation

2.1 Background

The model used in the empirical analysis belongs to the class of GARCH-Jump mixture models originating from Press (1967), who introduced a jump model, where the arrival of jumps is governed by a Poisson distribution.[2] The early version of the model assumed that there is a constant number of large discrete price movements (jumps) within a fixed time

[2]The basic jump model by Press has been used in mainly financial applications by, e.g., Jorion (1988), Vlaar and Palm (1993) and Nieuwland *et al.*, (1994).

interval. The average number of jump events in a time interval is called the jump intensity. Chan and Maheu (2002) extended the model to include time-varying (ARMA) jump intensities, whereas Hellström *et al.*, (2008) introduced an exponential version of the time-varying jump intensity to account for asymmetric responses to jump innovations. Chan (2003, 2004) considered bivariate extensions of the model with correlated jump dynamics. However, their study, based on the multivariate GARCH parametrization (BEKK) is limited to the analysis of the correlation between jump components only. In contrast to the earlier studies, we focus directly on the correlation between market returns through a reparameterization of the covariance matrix for the market returns (e.g., Tsay, 2002, ch. 10). Thus, the covariances and correlations between market returns capture the co-movements driven by both the innovations not associated with jumps and by the jump innovations. This allows us to directly study the impact of market jumps on the return correlation. To explore the effect of market jumps on the time-varying return correlations, actual jumps are first identified and then in a second step used to explain the time-varying correlation.

2.2 A bivariate EARJI-EGARCH model

To study the time-varying correlation between the stock market returns r_{1t} and r_{2t} a bivariate model based on Chan (2004) is outlined. The bivariate model structure, opposed to a trivariate structure, is chosen to simplify the identification of the time-varying second order moments.[3] Given the information set at time $t-1$, $\Phi_{it-1} = \{r_{it-1}, ..., r_{i1}\}$ for $i = 1, 2$,[4] the model is specified as:

$$\mathbf{R}_t = \boldsymbol{\mu}_t + \boldsymbol{\epsilon}_{1t} + \boldsymbol{\epsilon}_{2t}. \tag{1}$$

Here $\mathbf{R}_t$, $\boldsymbol{\mu}_t$, $\boldsymbol{\epsilon}_{1t}$ and $\boldsymbol{\epsilon}_{2t}$ are 2×1 vectors denoting the returns, the conditional mean functions specified as $\mu_{it} = \alpha_{0i} + \sum_{l=1}^{L} \alpha_{li} r_{it-l}$, the random disturbances, and the jump innovations, respectively.

The jump innovation component is defined as:

$$\boldsymbol{\epsilon}_{2t} = \begin{bmatrix} \sum_{k=1}^{n_{1t}} Y_{1t,k} - E_{t-1}\left(\sum_{k=1}^{n_{1t}} Y_{1t,k}\right) \\ \sum_{l=1}^{n_{2t}} Y_{2t,l} - E_{t-1}\left(\sum_{l=1}^{n_{2t}} Y_{2t,l}\right) \end{bmatrix}, \tag{2}$$

[3] Since the model is already highly parameterized in its univariate form and is estimated by integrating over the jump distribution, a trivariate structure would be numerically more complicated to estimate compared to the bivariate structure.

[4] Throughout the rest of the paper $i = 1, 2$.

where each of the jump size variables $Y_{it,j}$ is assumed to be independent and normally distributed with mean θ_i and variance δ_i^2. The jumps, n_{it}, in the market returns are assumed to be generated independently of each other by an independent bivariate Poisson distribution with time-varying jump intensity parameters λ_{it}. The parameter λ_{it} is the expected conditional number of jumps, n_{it} over the time interval $(t-1,t)$, i.e. $\lambda_{it} \equiv E\left[n_{it}|\Phi_{it-1}\right]$. The bivariate Poisson density is specified as:

$$\Pr(n_{1t}=k, n_{2t}=l \mid \mathbf{\Phi}_{t-1}) = \frac{\exp(-\lambda_{1t})\lambda_{1t}^{k}}{k!}\frac{\exp(-\lambda_{2t})\lambda_{2t}^{l}}{l!}. \tag{3}$$

To allow the jump intensities to vary over time, λ_{it} is specified in an Exponential Autoregressive Jump Intensity (EARJI) form given by:

$$\ln(\lambda_{it}) = \gamma_{0i} + \gamma_{1i}\ln(\lambda_{it-1}) + \gamma_{2i}\xi_{it-1}.$$

In this specification, the parameter γ_{1i} measures the persistence and γ_{2i} measures the possible asymmetric effect of shocks to the jump intensity (λ_{it}). That is, a positive parameter value for γ_{2i} indicates that a positive shock produces a larger impact on the conditional jump intensity than a negative shock of an equal magnitude. The ξ_{it-1} represents the innovation to λ_{it-1}, measured *ex post.* This measurable shock (intensity residual), which is the unpredictable component affecting the jump intensity is given by:

$$\xi_{it-1} = E\left[n_{it-1} \mid \Phi_{it-1}\right] - \lambda_{it-1} = \sum_{\eta=0}^{\infty} \eta \times \Pr\left(n_{it-1}=\eta \mid \Phi_{it-1}\right) - \lambda_{it-1}.$$

$E\left[n_{it-1} \mid \Phi_{it-1}\right]$ is the *ex post* assessment of the expected number of jumps that occurred from $t-2$ to $t-1$, whereas, λ_{it-1} is the conditional *ex ante* expectation of n_{it-1}, given the information set Φ_{it-2}, and $\Pr\left(n_{it-1}=\eta \mid \Phi_{it-1}\right)$ is the *ex post* distribution of n_{it-1}, given the information at time $t-1$. Having observed r_{it} and using Bayes' rule, the *ex post* probability that η jumps occurred at time t is given by:

$$\Pr\left(n_{it}=\eta \mid \Phi_{it}\right) = \frac{f\left(r_{it} \mid n_{it}=\eta,\ \Phi_{it-1}\right)\Pr\left(n_{it}=\eta \mid \Phi_{it-1}\right)}{f\left(r_{it} \mid \Phi_{it-1}\right)}, \quad \eta = 0,1,2,.... \tag{4}$$

Here, $f\left(r_{it} \mid n_{it}=\eta,\ \Phi_{it-1}\right)$ is the marginal conditional density function for r_{it} given that η jumps occurred, $\Pr\left(n_{it}=\eta \mid \Phi_{it-1}\right)$ is the marginal Poisson density function for $n_{it}=\eta$ implied by eq.(3), and $f\left(r_{it} \mid \Phi_{it-1}\right)$ is the conditional density function for r_{it}. The conditional density function for r_{it} is specified and discussed in Section 2.2.

2.3 Time-varying return correlation

Given that the random disturbances in $\boldsymbol{\epsilon}_{1t}$ and the jump innovation components in $\boldsymbol{\epsilon}_{2t}$ are contemporaneously independent of each other, i.e. $E(\varepsilon_{1it}\varepsilon_{2jt}) = 0$ for $i,j = 1,2$, the

covariance matrix of returns may be expressed as:

$$\text{Var}(\mathbf{r}_t|\Phi_{it-1}) = Var(\boldsymbol{\varepsilon}_{1t}|\Phi_{it-1}) + Var(\boldsymbol{\varepsilon}_{2t}|\Phi_{it-1}).$$

The disturbances in $\boldsymbol{\epsilon}_{1t}$ are assumed to be normal i.i.d. mean-zero innovations with the conditional covariance matrix:

$$\tilde{\mathbf{H}}_t = Var(\boldsymbol{\varepsilon}_{1t}|\Phi_{it-1}) = \begin{bmatrix} \sigma_{1t}^2 & \sigma_{12t}^{\varepsilon_1} \\ \sigma_{12t}^{\varepsilon_1} & \sigma_{2t}^2 \end{bmatrix}.$$

The disturbances are specified as $\varepsilon_{1it} = \sigma_{it} z_t$, where $z_t \sim N(0,1)$, and σ_{it} is assumed to follow an EGARCH(1,1) process (Nelson, 1991). The process for the conditional variance is specified as:

$$\ln(\sigma_{it}^2) = \omega_{0i} + \omega_{1i}\psi_{it-1} + \omega_{2i}\ln(\sigma_{it-1}^2) + \omega_{3i}\left(|\psi_{it-1}| - \sqrt{2/\pi}\right),$$

where $\psi_{it} = \varepsilon_{1it}/\sigma_{it}$ is the normalized residual. The $\sigma_{12t}^{\varepsilon_1}$ is the covariance between ε_{11t} and ε_{12t}.

Conditional on k jumps in stock market index 1 and l jumps in stock market index 2, the jump innovations in ϵ_{2t} (cf. eq. (2)) have a bivariate normal distribution with zero mean and a covariance matrix given by:

$$\bar{\mathbf{H}}_t = Var(\boldsymbol{\varepsilon}_{2t}|\Phi_{it-1}) = \begin{bmatrix} k\delta_1^2 & \sigma_{12t}^{\varepsilon_2} \\ \sigma_{12t}^{\varepsilon_2} & l\delta_2^2 \end{bmatrix}.$$

The conditional variances for the jump components are given by $k\delta_1^2$ and $l\delta_2^2$ while the covariance between ε_{21t} and ε_{22t} is denoted with $\sigma_{12t}^{\varepsilon_2}$. Note that $\sigma_{12t}^{\varepsilon_2}$ is thought to capture the possible covariance between either the jump sizes (θ_i) or jump intensities (λ_{it}), or both. In contrast, Chan (2004) lets n_{it}, the frequency of jumps between $t-1$ and t, be correlated through a bivariate Poisson distribution (through trivariate reduction). Hence, the jump intensities, λ_{it}, are allowed to be positively correlated. Chan (2004) assumes that the jump sizes, θ_i, have a constant correlation across contemporaneous equations and are zero across time. An advantage with the approach used in this paper, compared to modelling correlation through underlying parameters, i.e. correlation between σ_{it}^2, and/or through correlated jump intensities λ_{it} and/or jump sizes θ_i, is that we avoid increasing the numbers of parameters in an already richly parameterized model. Also, the main interest of this paper is on the correlation between market returns rather than between the underlying components.

The covariance matrix for returns is given by:

$$\begin{aligned}\mathbf{H}_t &= \tilde{\mathbf{H}}_t + \bar{\mathbf{H}}_t \\ &= \begin{bmatrix} \sigma_{1t}^2 & \sigma_{12t}^{\varepsilon_1} \\ \sigma_{12t}^{\varepsilon_1} & \sigma_{2t}^2 \end{bmatrix} + \begin{bmatrix} k\delta_1^2 & \sigma_{12t}^{\varepsilon_2} \\ \sigma_{12t}^{\varepsilon_2} & l\delta_2^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_{1t}^2 + k\delta_1^2 & \sigma_{12t} \\ \sigma_{12t} & \sigma_{2t}^2 + l\delta_2^2 \end{bmatrix},\end{aligned} \tag{5}$$

where the covariance between the market returns, $\sigma_{12t} = \sigma_{12t}^{\varepsilon_1} + \sigma_{12t}^{\varepsilon_2}$, is the sum of the covariance between the random disturbances ($\sigma_{12t}^{\varepsilon_1}$) and the jump innovations ($\sigma_{12t}^{\varepsilon_2}$). To derive a model with time-varying return correlation, the covariance for the returns is reparameterized in the spirit of Tsay (2002, ch. 10), as $\sigma_{12t} = \rho_t \sqrt{\sigma_{1t}^2 + k\delta_1^2}\sqrt{\sigma_{2t}^2 + l\delta_2^2}$. Thus, the covariance is replaced by a parameter, ρ_t, for the time-varying correlation times the standard deviation of each return series. To accommodate that $|\rho_t| < 1$, we use the reparametrization[5]:

$$\rho_t = \frac{\check{\rho}_t}{\sqrt{1 + \check{\rho}_t^2}}.$$

The $\check{\rho}_t$ is parameterized as:

$$\check{\rho}_t = \beta_0 + \beta_1 \varepsilon_{11t-1}^* \varepsilon_{12t-1}^* + \beta_2 \rho_{t-1},$$

where $\varepsilon_{11t-1}^* \varepsilon_{12t-1}^* = \varepsilon_{11t-1}\varepsilon_{12t-1} / \sqrt{\sigma_{1t-1}^2 \sigma_{2t-1}^2}$ and β_2 measures the persistence of the correlation over time. Note here that we use the lagged normal disturbances, ε_{1it-1}, instead of the total residuals, $\varepsilon_{it-1} = \varepsilon_{1it-1} + \varepsilon_{2it-1}$, in this specification. The reason for this is that identification of the jump parameters (θ_i, λ_{it}) is based on the normal disturbances, ε_{1it-1}, cf. eq.(7).[6]

To study the contemporaneous effects of jumps on the return correlations, the *ex post* probability is used in the identification of actual jumps.[7] Following Maheu and McCurdy (2004), we consider actual jumps to have occurred if the *ex post* probabilities of at least one jump is larger than 0.5, i.e. $\Pr(n_{it} \geq 1 \mid \Phi_{it}) = 1 - \Pr(n_{it} = 0 \mid \Phi_{it}) > 0.5$. The identified jumps are then related to the estimated time-varying return correlations using regression analysis.

[5] Tsay (2002) restricts ρ by a Fisher transformation given by $\rho = (\exp(\tilde{\rho}) - 1)/(\exp(\tilde{\rho}) + 1)$. Baur (2006) reports that the Fisher transformation is more restrictive than the transformation used in this paper and thus less adequate.

[6] Direct testing of the effect of jump innovations on the time-varying return correlation dynamics resulted in unstable models with poor convergence properties.

[7] This approach is similar to that used by Asgharian and Bengtsson (2006).

2.4 Estimation

The probability density function for $\mathbf{R}_t$, given k independent jumps in stock market index 1 and l independent jumps in stock market index 2 is given by:

$$f(R_t|n_{1t}=k,n_{2t}=l,\Phi_{t-1})=\frac{1}{2\pi^{N/2}}|\mathbf{D}_{ijt}\boldsymbol{\rho}_t\mathbf{D}_{ijt}|^{-1/2}\exp[-1/2\boldsymbol{\epsilon}_{1t}\mathbf{D}_{ijt}\boldsymbol{\rho}_t\mathbf{D}_{ijt}\boldsymbol{\epsilon}_{1t}], \quad (6)$$

where

$$\boldsymbol{\epsilon}_{1t} = \mathbf{R}_t-\boldsymbol{\mu}_t-\boldsymbol{\epsilon}_{2t}=\begin{bmatrix} r_{1t}-\mu_{1t}-k\theta_1+\lambda_{1t}\theta_1 \\ r_{2t}-\mu_{2t}-l\theta_2+\lambda_{2t}\theta_2 \end{bmatrix}, \quad (7)$$

$$\mathbf{D}_t = \begin{bmatrix} \sqrt{\sigma_{1t}^2+k\delta_1^2} & 0 \\ 0 & \sqrt{\sigma_{2t}^2+l\delta_2^2} \end{bmatrix}, \quad (8)$$

and $\boldsymbol{\rho}_t$ is the conditional correlation matrix

$$\boldsymbol{\rho}_t=\begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}.$$

The conditional density of returns is defined by:

$$\Pr(\mathbf{R}_t|\boldsymbol{\Phi}_{t-1})=\sum_{k=0}^{\infty}\sum_{l=0}^{\infty}f(R_t|n_{1t}=k,n_{2t}=l,\Phi_{t-1})\times\Pr(n_{1t}=k,n_{2t}=l\mid\boldsymbol{\Phi}_{t-1}) \quad (9)$$

and the corresponding log likelihood function is simply the sum of the log conditional densities:

$$\ln L=\sum_{t=1}^{T}\ln\Pr(\mathbf{R}_t|\boldsymbol{\Phi}_{t-1}).$$

In practice, the maximum number of jumps may be truncated to a large value τ, so that the probability of τ or more jumps is zero. In the empirical estimation $\tilde{\tau}>\tau$ is investigated to ensure that the likelihood and parameter estimates do not change. In the estimations reported in the results section, $\tau=15$.

3 Data

The data used in this paper are capitalization weighted daily stock price indices of the Estonian (Tallinn, TALSE), Latvian (Riga, RIGSE)[8] and the Lithuanian (Vilnius, VILSE)

[8] There is an irregularity in the summer of 2001 in the Riga index (RIGSE), due to a power struggle in its largest company (Latvijas Gaze). Instead of modelling this irregular period, the observations from July 25 to September 3, 2001, are replaced by interpolated values in the same way as in Brännäs *et al.*, (2008).

stock markets. All prices are expressed in Euro.[9] The data set, obtained from Datastream, covers January 3, 2000 to July 9, 2007, for a total of $T = 1960$ observations. Due to some differences in holidays for the involved countries, the series have different shares of days for which index stock prices are not observable. Linear interpolation was used to fill the gaps for all series, where 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 and cross correlations for the daily return series. The Ljung-Box statistics for 10 lags (LB_{10}) indicate significant serial correlations. The large kurtoses for Riga, Tallinn, and Vilnius indicate leptokurtic densities. Cross-correlations indicate that the largest unconditional correlation is between Tallinn and Vilnius return series.

Table 1: Descriptive statistics and unconditional correlations between return series.

Exchange	Mean	Variance	Min/Max	Skewness	Ex. Kurtosis	Riga	Tallinn	Vilnius
Riga	0.09	1.64	-9.27/10.29	0.18	11.29	1		
Tallinn	0.10	1.06	-5.87/12.02	0.66	14.86	0.134	1	
Vilnius	0.09	1.00	-12.12/5.32	-0.95	13.68	0.145	0.242	1

4 Empirical results

4.1 Basic models

In the empirical investigation of the correlation structure between the Baltic stock market indices, a number of different model specifications were estimated, including different lag structures for the mean, conditional variance and autoregressive jump intensity functions. Although, in some specifications with more lags, the Akaike Information Criteria (AIC) and autocorrelation properties were slightly improved, the identification of the parameters

[9] This implies that the analyzed return series also contain variation due to exchange rate movements. Since the paper is written from an international investor perspective, i.e. we are interested in Euro returns, the effects of these variations are included in the analysis. Also, the currencies of the considered countries have been pegged (Latvian to a basket of major currencies since 1994, and to the Euro from 2005; Estonian to the Deutsche Mark since 1992, and later to the Euro after its introduction; Lithuania had a US dollar-based currency board arrengement since 1994, moved to the Euro peg in 2002) under the period of study and have been rather stable during, at least, the later parts of the sample period.

in the time-varying correlation function became numerically unstable with more elaborate lag structures. Hence, as the focus of this paper is mainly on the correlation functions, the more simple model specifications were favored and utilized in the analysis. Overall, the EGARCH specification for the conditional variance was favored in terms of AIC compared to corresponding GARCH specifications.

Initially, we considered models without jumps (for the purpose of comparison), i.e. with residuals specified as $\boldsymbol{\epsilon}_t = \mathbf{R}_t - \boldsymbol{\mu}_t$. Table 2 reports on the estimation results for this model specification with time-varying correlations.

The results indicate that the average correlation between Tallinn-Riga, Tallinn-Vilnius, and Vilnius-Riga is 0.120 (s.d. 0.065), 0.217 (s.d. 0.106), and 0.115 (s.d. 0.065), respectively.[10] Note that for each series, we obtain two sets of parameter estimates due to the bivariate structure of the models. That is, for the Riga series, we obtain one set of estimates from the bivariate model with Tallinn, and another set of estimates from the bivariate model for Riga and Vilnius. However, the estimates for the same series do not differ much between the models. Figure 1 displays the time-varying correlations.

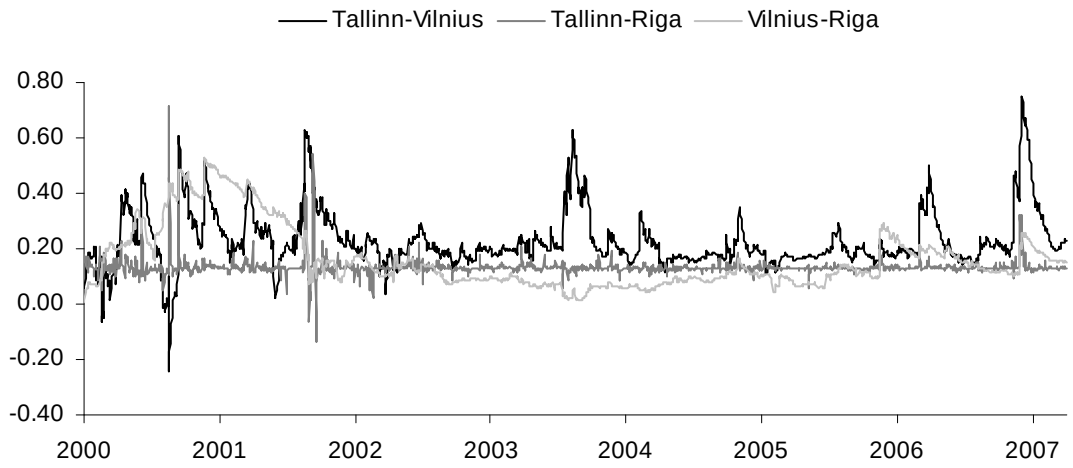

Figure 1: Time-varying return correlations.

Notably, there is a number of sharp spikes, both positive and negative, in the time-varying correlations for all considered indices, possibly due to market jumps. This is most pronounced for the time-varying correlation between the Tallinn and Vilnius stock market returns. The persistence in the time-varying correlations are high, as indicated by the significant lagged correlation parameters (β_2 in Table 2) that takes on values above 0.9 for all the models.

[10] Constant correlation models without jumps gave similar parameter estimates and correlations close to the mean of the time-varying correlations.

Table 2: Estimation results for time-varying return correlation models without jump component (robust standard errors in parantheses).

	Tallinn		Riga		Tallinn		Vilnius		Vilnius		Riga	
$\mu_{it} = \alpha_{0i} + \alpha_{1i} r_{it-1}$												
α_0	0.054*	(0.018)	0.158*	(0.024)	0.056*	(0.018)	0.123*	(0.020)	0.134*	(0.020)	0.174*	(0.023)
α_1	0.113*	(0.008)	-0.061*	(0.025)	0.109*	(0.004)	0.093*	(0.025)	0.104*	(0.026)	-0.062*	(0.014)
$\ln(\sigma^2_{1it}) = \omega_{0i} + \omega_{1i}\psi_{it-1} + \omega_{2i}\ln(\sigma^2_{1it-1}) + \omega_{3i}\left(\lvert\psi_{it-1}\rvert - \sqrt{2/\pi}\right)$												
ω_0	0.017*	(0.003)	0.097*	(0.009)	0.017*	(0.002)	0.007	(0.007)	0.001	(0.007)	0.094*	(0.008)
ω_1	0.002	(0.007)	-0.024	(0.015)	0.004	(0.006)	-0.076*	(0.012)	-0.076*	(0.013)	-0.020	(0.013)
ω_2	0.974*	(0.004)	0.800*	(0.012)	0.975*	(0.003)	0.864*	(0.014)	0.853*	(0.016)	0.807*	(0.010)
ω_3	0.244*	(0.012)	0.411*	(0.025)	0.241*	(0.012)	0.386*	(0.027)	0.385*	(0.028)	0.412*	(0.022)
$\rho_t = \breve{\rho}_t/\sqrt{1+\breve{\rho}_t^2}$, $\breve{\rho}_t = \beta_0 + \beta_1 \varepsilon_{1t-1}\varepsilon_{2t-1} + \beta_2 \breve{\rho}_{t-1}$												
β_0	0.003	(0.006)			0.013*	(0.005)			0.001	(0.001)		
β_1	-0.000	(0.002)			0.028*	(0.008)			0.005*	(0.003)		
β_2	0.978*	(0.049)			0.915*	(0.028)			0.980*	(0.014)		
$\bar{\rho}$	0.120	(0.065)			0.217	(0.106)			0.115	(0.065)		
Log-L	-5572.18				-5117.01				-5639.70			
AIC	11.154				10.252				11.297			
LB_{10}	16.243		20.325		17.803		35.132		36.078		23.157	
LB^2_{10}	15.821		78.653		16.337		29.321		32.223		83.728	

* Significant at the 5 percent level. $\bar{\rho}$ = mean of the time-varying correlations.

Table 3 report estimates for constant correlation models including the jump component. Including a jump component in the models notably improves the AIC, compared to the models with constant correlation and no jump component.[11] It is worth noting that the estimated mean jump sizes (θ_i) are small, and significant only for Riga in the bivariate model for the Vilnius and Riga series, as the estimated standard deviations are, in general, quite large. However, the estimated jump parameters (θ_i,λ_{it}) are jointly significant, as indicated by a LR test, when comparing with models with no jumps and constant correlations.[12] The parameter estimates for the conditional mean jump intensities (λ_t) indicate that the persistence in jump intensity is high (and statistically significant) both for Riga (0.974, 0.978) and Vilnius (0.986, 0.991), while it is lower for Tallinn (0.481, 0.485). The inclusion of the jump component in the models also removed some of the autocorrelations present in the models without a jump component, as indicated by the Ljung-box statistics (LB_{10} and LB^2_{10}). However, there is little autocorrelation remaining in the final models.[13]

Table 4 reports estimates for the time-varying correlation models including the jump components. Since the parameter estimates for the mean, EGARCH, and jump components are similar to that reported in Table 3, only the parameters pertaining to the specification of the time-varying correlation are reported.

For the model specification with the time-varying correlation, the AIC improves slightly for all models. However, LR tests indicate that there are doubts about whether including time-varying correlations improve the model fit for the bivariate model for Tallinn and Riga series. The LR test value is 2.7832, 22.7752, and 21.2336 for the model with Tallinn and Riga, Tallinn and Vilnius, and Vilnius and Riga series, respectively. The persistence parameter for the time-varying correlation specification is quite high and ranges between 0.924 and 0.987. A number of different specifications for the time-varying correlation was tried during estimation. None of these specifications, including jump residuals, $\hat{\boldsymbol{\epsilon}}_{2t-1} = E[\boldsymbol{\epsilon}_{2t-1}|\Phi_{it-1}]$, the *ex post* assessment of the expected number of jumps $E\left[n_{it-1} \mid \Phi_{it-1}\right]$, as well as the lagged conditional variance, σ^2_{t-1}, improved the fit of the model and mostly rendered numerically unstable models. Hence, to study the effect of market jumps on the time-varying return correlations, we instead turn our attention towards the identification of actual jumps.

[11] The estimation results available from authors upon request.

[12] The LR test statistics are 951, 639 and 855 for the Tallinn-Riga, Tallinn-Vilnius and Vilnius-Riga sample, respectively.

[13] Other lag structures for the mean, conditional variance, and the autoregressive jump intensity have been tried without fully removing the autocorrelations. The more parsimonious lag structures, reported in the paper, were therefore chosen.

Table 3: Estimation results for models including jump components and constant correlation (robust standard errors in parantheses).

	Tallinn		Riga		Tallinn		Vilnius		Vilnius		Riga	
$\mu_{it} = \alpha_{0i} + \alpha_{1i} r_{it-1} + \varepsilon_{2it}$												
α_0	0.056*	(0.016)	0.070*	(0.020)	0.065*	(0.014)	0.104*	(0.018)	0.102*	(0.012)	0.075*	(0.014)
α_1	0.197*	(0.022)	-0.084*	(0.020)	0.186*	(0.021)	0.120*	(0.022)	0.130*	(0.015)	-0.078*	(0.019)
$\ln(\sigma^2_{1it}) = \omega_{0i} + \omega_{1i}\psi_{it-1} + \omega_{2i}\ln(\sigma^2_{1it-1}) + \omega_{3i}\left(\lvert\psi_{it-1}\rvert - \sqrt{2/\pi}\right)$												
ω_0	-0.064*	(0.014)	-0.258*	(0.060)	-0.069*	(0.016)	-0.308*	(0.111)	-0.406*	(0.113)	-0.238*	(0.020)
ω_1	-0.027	(0.016)	0.029	(0.025)	-0.013	(0.016)	-0.040	(0.026)	-0.026	(0.029)	0.031	(0.018)
ω_2	0.982*	(0.008)	0.715*	(0.062)	0.974*	(0.008)	0.733*	(0.086)	0.679*	(0.080)	0.732*	(0.021)
ω_3	0.198*	(0.029)	0.342*	(0.042)	0.204*	(0.032)	0.317*	(0.048)	0.336*	(0.048)	0.341*	(0.029)
$\ln(\lambda_{it}) = \gamma_{0i} + \gamma_{1i}\ln(\lambda_{it-1}) + \gamma_{2i}\xi_{it-1}$												
γ_0	-0.705*	(0.361)	-0.039	(0.025)	-0.760	(0.426)	-0.012	(0.010)	-0.014	(0.011)	-0.048*	(0.021)
γ_1	0.485*	(0.204)	0.978*	(0.015)	0.481*	(0.241)	0.991*	(0.007)	0.986*	(0.009)	0.974*	(0.012)
γ_2	1.264*	(0.256)	0.552*	(0.166)	1.148*	(0.284)	0.365*	(0.100)	0.373*	(0.073)	0.587*	(0.050)
θ	0.063	(0.079)	0.120	(0.101)	0.076	(0.075)	0.054	(0.067)	0.048	(0.054)	0.140*	(0.067)
δ	1.203*	(0.058)	1.867*	(0.068)	1.261*	(0.063)	1.197*	(0.067)	1.106*	(0.055)	1.966*	(0.029)
ρ	0.133*	(0.024)			0.236*	(0.024)			0.187*	(0.024)		
Log-L	-5096.69				-4804.70				-5219.01			
AIC	10.217				9.633				10.462			
LB_{10}	5.931		10.123		6.375		14.278		20.451		12.011	
LB^2_{10}	8.968		31.136		10.995		11.280		20.662		30.576	

* Significant at the 5 percent level.

Table 4: Estimation results for models including jump components and time-varying return correlations (robust standard errors in parantheses).

	Tallinn (1) - Riga (2)	Tallinn (1) - Vilnius (2)	Vilnius (1) - Riga (2)
$\breve{\rho}_t = \beta_0 + \beta_1 \varepsilon^*_{11t-1}\varepsilon^*_{12t-1} + \beta_2 \rho_{t-1}$			
β_0	0.069* (0.029)	0.013 (0.007)	0.001 (0.001)
β_1	0.014 (0.008)	0.025* (0.009)	0.008* (0.002)
β_2	0.968* (0.201)	0.924* (0.034)	0.987* (0.004)
Log-L	-5095.29	-4793.32	-5210.01
AIC	10.213	9.609	10.448

* Significant at the 5 percent level.

4.2 The effect of jumps on time-varying return correlations

Actual jumps are determined to have occurred if the *ex post* probability of at least one jump is larger than 0.5, i.e. $\Pr(n_{it} \geq 1 \mid \Phi_{it}) = 1 - \Pr(n_{it} = 0 \mid \Phi_{it}) > 0.5$.[14] The *ex post* jump probabilities during 2006-2007 for the Riga stock market are displayed in Figure 2 along with the daily return series. Over this period, 23 return observations are determined to be jumps according to the chosen criteria.

[14] To study the sensitivity of the results to the chosen criteria the analysis was repeated with $\Pr(n_{it} \geq 1 \mid \Phi_{it}) = 1 - \Pr(n_{it} = 0 \mid \Phi_{it}) > 0.7$. This specification did not change the results.

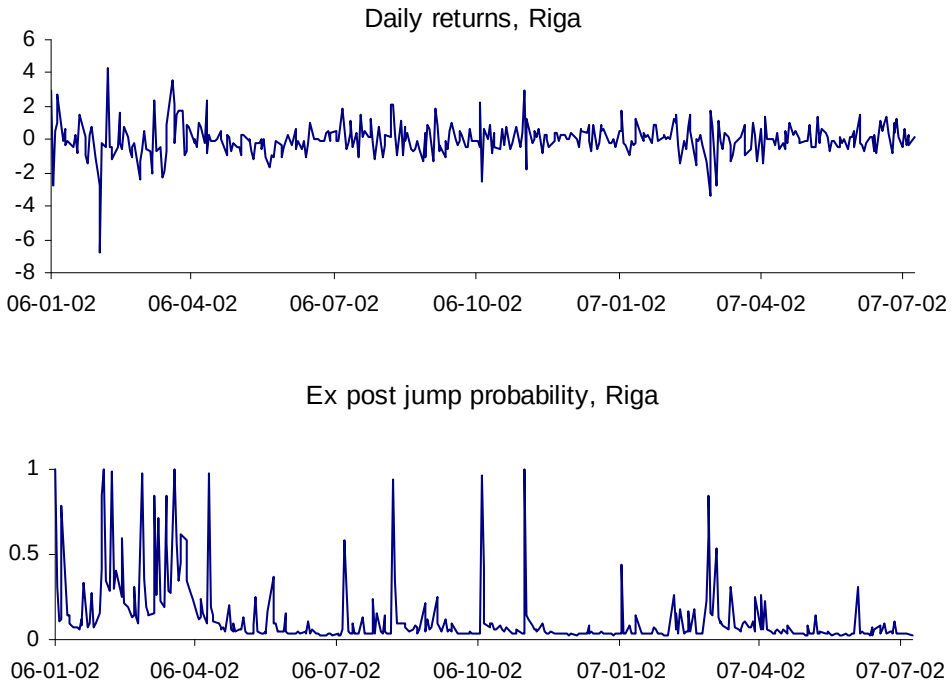

Figure 2: Return and *ex post* jump probability, Riga.

Using the above criterion to identify actual jumps, we find that there are 270 and 95 jumps for the bivariate model for Tallinn and Riga, 195 and 296 jumps for the model of Tallinn and Vilnius, and 353 and 95 jumps for the Vilnius and Riga model.[15] Of these, there are 12, 33, and 21 simultaneous jumps in the three corresponding bivariate models. Based on the signs of the return series, we determine that there are 2, 9, and 8 simultaneous negative jumps while there are 5, 10, and 4 simultaneous positive jumps for the models for Tallinn and Riga, Tallinn and Vilnius, and Vilnius and Riga series. Thus, on a number of occasions, there are simultaneous jumps in opposite directions.

To examine the impact of the identified jumps on the time-varying return correlations, we run different linear regression models for the estimated time-varying correlation, $\hat{\rho}_{ijt}$,

[15] As mentioned before, due to the bivariate structure of the model, we obtain two estimated series of jump probabilities (and series of identified jumps) for each return series. For example, for Tallinn we identify one series of jump probabilities based on the bivariate model with Riga and another series based on the bivariate model of Tallinn and Vilnius. The correlations (Spearman's rho) between the two identified series of jump probabilities for each return series are 0.97, 0.99, and 0.99 for Tallinn, Riga and Vilnius, respectively. The Spearman's rho for the actually identified jump series are 0.83, 0.96, and 0.86 for the Tallinn, Riga, and Vilnius series. This indicates that the level of the identified jump probabilities differs to some degree depending on the combination of the series in the model. This also explains the difference in the number of actual identified jumps (depending on combination) for the same series.

Table 5: Effect of identifed jumps on time-varying return correlations (robust standard errors in parantheses).

	Tallinn (1) - Riga (2)		Tallinn (1) - Vilnius (2)		Vilnius (1) - Riga (2)	
$const$	0.051*	(0.002)	0.008*	(0.001)	0.001	(0.000)
$\hat{\rho}_{t-1}$	0.908*	(0.017)	0.959*	(0.005)	0.994*	(0.002)
$djump_{1t}^{+}$	0.001	(0.002)	0.007*	(0.002)	0.001	(0.001)
$djump_{1t}^{-}$	0.004	(0.002)	-0.002	(0.003)	0.004*	(0.001)
$djump_{2t}^{+}$	0.015*	(0.003)	0.004	(0.002)	0.000	(0.001)
$djump_{2t}^{-}$	0.015*	(0.004)	0.017*	(0.002)	0.001	(0.002)
$dsimjump_{t}^{+}$	0.129*	(0.011)	0.052*	(0.008)	0.017*	(0.005)
$dsimjump_{t}^{-}$	0.061*	(0.024)	0.083*	(0.009)	0.026*	(0.004)
$dsimjump_{t}^{+/-}$	-0.077*	(0.011)	-0.094*	(0.007)	-0.033*	(0.003)
R^2	0.446		0.949		0.993	
DW	1.961		1.899		1.966	

* Significant at the 5 percent level.

on a number of dummy variables that reflect the number of jumps in the series. The dummy variables for individual jumps in each series are $djump_{it}$, $djump_{it}^{+}$ and $djump_{it}^{-}$, which take on a value of one if there is a jump at time t in series i, a positive jump in series i, or a negative jump in series i, respectively, and zero otherwise. The dummy variable controlling for simultaneous jumps are $dsimjump_{ijt}$, $dsimjump_{ijt}^{+}$, $dsimjump_{ijt}^{-}$, and $dsimjump_{ijt}^{+/-}$, which take on a value of one if there are simultaneous jumps in series i and j, simultaneous positive jumps in series i and j, and simultaneous negative jumps in series i and j, and simultaneous jumps of opposite sign in series i and j, respectively, and zero otherwise.[16] Table 5 report estimation results for the model specification with the highest adjusted R^2.

[16] The lagged correlation $\hat{\rho}_{t-1}$ is also included in all regressions to control for serial correlation.

From Table 5 we see that a jump in one series, controlling for simultaneous jumps, contributes positively (when significant) to the time-varying correlations. On average, the time-varying correlation between Tallinn and Vilnius series increases with 0.007 when there are positive jumps on the stock market in Tallinn. Both positive as well as negative jumps on the Riga stock market increase the correlation between Tallinn and Riga by on average 0.015. Negative jumps on the Vilnius stock exchange on average increase the correlation between both the Tallinn and Vilnius (with 0.017), as well as the Vilnius and Riga (with 0.004) series. Overall, the effects of the individual jumps, when controlling for simultaneous jumps, is rather small. For example, the correlation between the Tallinn-Vilnius return series increase on average from 0.228 to 0.245 when there are isolated jumps on the Vilnius stock market.

For simultaneous jumps in the series, the effect on the time-varying correlations depends on the direction of the jumps. For example, the time-varying correlation increases on average with 0.129 for simultaneous positive jumps, and with 0.061 for simultaneous negative jumps in the Tallinn-Riga model. Thus, the average correlation almost doubles (compared to the model with constant correlation) on days when there are simultaneous positive jumps. Notably the impact on the correlation between the Tallinn and Riga series is much larger when markets are jointly rising, compared to when markets are jointly falling. The opposite is true for Tallinn-Vilnius and Vilnius-Riga models, where the correlation increases on average with 0.052 and 0.017 for simultaneous positive jumps, and 0.083 and 0.026 for simultaneous negative jumps. These changes correspond to a correlation increase ranging from 11 to 34 percent. Note that these results could be related to the contagion literature, where positive contagion is defined as an increase in the correlation caused by positive shocks, while an increase in the correlation due to negative shocks is usually referred to as negative contagion (Baur and Fry, 2005).

On the occasions when there are simultaneous jumps in opposite directions, the correlations decreases on average with 0.077, 0.094, and 0.033 for the Tallinn-Riga, Tallinn-Vilnius, and Vilnius-Riga correlation series, respectively. Including $dsimjump_{ijt}$, i.e. controlling for simultaneous jumps with no regard to the direction of the jumps, in general, yields an insignificant impact on the time-varying correlations.

5 Concluding remarks

The results of this paper show a strong support for models including a jump component (compared to the EGARCH-alternatives), as well as support for time-varying return cor-

relations over constant correlation models. In general, the number of identified jumps during the period may seem large, at least, compared to results for developed markets. For example, Bollerslev *et al.*, (2008) find on average 7 major jumps in equity market indices for a number of developed countries during the period 2001-2005. Kim and Mei (2001), however, report 71 identified price jumps for the Hong Kong stock market during 1989-1993. Thus, our results are in line with the idea that the emerging stock markets are, in general, more volatile and have empirical return distributions with fatter tails than more developed markets (e.g., Harvey, 1995; Bekaert and Harvey, 2002). A possible explanation to the large number of identified jumps is that, the markets under study are relatively small with a few large institutional traders active on all three markets. Thus, a number of these jumps may be driven by liquidity motivated trading.

The time-varying return correlations increase slightly when there are individual market jumps (i.e. conditional on being non-simultaneous jumps) for some of the markets. For simultaneous jumps, we find that the effect of these on the return correlations depend on the jump signs. This is particularly important to keep in mind when studying jump correlations (e.g., Chan, 2004; Asgharian and Bengtsson, 2006), as a positive jump correlation, i.e. the correlation between jump intensities with no regard to the sign of a jump, often is taken as a sign of increasing return correlations. This becomes even more important for emerging markets, where more jumps in both directions could be expected. In this paper, we find that on average 58 percent of the simultaneous jumps (over all samples) are of the same sign, and as many as 42 percent are of opposite sign. In addition, we find that the correlation increases by as much as 100 percent on average due to simultaneous positive jumps (for the Tallinn-Riga model), but by 47 percent due to simultaneous negative jumps.[17]

Overall, we find that stock market return correlations increase mainly due to simultaneous market jumps, that may depend on other factors than market crises, while individual (non-simultaneous jumps) only have small effects. The underlying model could also be of use for studies of the correlation between stock and bond markets, thus, of the so called flight-to-quality effect. For example, if there is a negative jump in the stock market together with a decrease in the correlation coefficient, this may indicate the flight-to-quality from stocks to bonds. Similar patterns on two stock markets are harder to interpret, as investor's preferences could also be affected by the liquidity on the markets. However,

[17] However, since the results are based on a few observations, as there is only a small number of simultaneous jumps, conclusions should be interpreted with some caution.

studying the possible impact of market jumps on return correlation dynamics and, in particular, how these effects may differ between financial assets and markets, is useful for risk management and portfolio diversification.

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