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MATEMATIKOS IR INFORMATIKOS FAKULTETAS

Magistrinis darbas

Baltijos šalių statybų sektoriaus kainų kintamumo analizė naudojant VAR, GARCH ir DCC modelius

Analysis of volatility of Baltic States construction sector stock market using VAR, GARCH and DCC models

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Santrauka

Šiame darbe yra analizuojamas sąryšis tarp didžiausių Baltijos šalių statybų įmonių grąžų kintamumo. Analizuojamas laikotarpis yra nuo 2008-11-01 iki 2016-05-06. Sudaromas VAR modelis, kuris parodo jog įmonės akcijų grąžai daro įtaką kitos šalies bendrovės ankstesnių dienų grąža. Vėliau yra naudojami GARCH ir DCC modeliai ištirti sąlyginėmis koreliacijoms tarp įmonių grąžų porų. Parodyta, jog įmonių akcijų grąžos nereikšmingai teigiamai koreliuoja poromis, išskyrus Panevėžio Statybų Trestas ir Latvijos Tilti grąžos, šios koreliuoja neigiamai. Sudarius GARCH(1,1) ir sGARCH(1,1) kiekvienai įmonei atskirai, parodyta, jog Panevėžio Statybų Tresto grąžos buvo jautriausios išoriniams šokams. Šis jautrumas persidavė daugiamačiams modeliams: DCC modeliai, kuriuose buvo analizuojamos šios įmonės sąlyginės koreliacijos su kitomis įmonėmis (poromis) turėjo didžiausius α parametro įverčius (0,035074) ir koreliacijos laikui bėgant kito labiausiai.

Raktiniai zodziai : Baltijos šalys, statybų sektorius, VAR, GARCH, DCC

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Abstract

In this paper we investigate the relationship among the biggest Baltic States construction sector companies daily returns. The sample period is from 2008-11-01 to 2016-05-06. An adequate VAR model is constructed after analyzing the stationarity of the variables and performing lag selection. It appears that one company's return values depend on foreign company's past values. Later GARCH and DCC

models are used to study the conditional correlations among the paired firms. It is discovered that all companies returns correlate positively insignificantly, except Panevėžio Statybos Trestas and Latvijos Tilti returns, which correlate negatively. After construction of GARCH(1,1) and sGARCH(1,1) models for each of the company, it is found out that Panevėžio Statybos Trestas returns are the most sensitive to the external shocks. This sensitivity influences multivariate models: DCC models, where Panevėžio Statybos Trestas conditional correlation with other company's returns are analysed, have the highest α parameter estimators (0.035074) and the correlations vary the most.
Key words : Baltic States, Construction Sector, VAR, GARCH, DCC

Contents

1 Introduction

Multivariate GARCH model has been used widely across the world in order to interpret the volatilities of stock exchange markets. The relationship among Baltic States stock markets has been analyzed in various ways. However often a national index of each country is taken into consideration as a representative.

In this research we analyze the movements of the Baltic States construction sector – one of the principal branches of the national financial markets. It has heavily influenced the national economy, GDP growth and labour force since the financial crisis of 2008 in the Baltic States.

We study the relationship of construction sector stock returns volatilities. 4 construction companies (2 Estonian- Nordecon and Merko, 1 Latvian - Latvijas Tilti and 1 Lithuanian - Panevėžio Statybų Trestas) are taken into consideration. The sample period is from 2008-01-11 to 2016-05-06. We take into consideration the financial crisis of USA in 2007 which spilled over into European countries in 2008. The GARCH(1,1), sGARCH(1,1), DCC and VAR (Vector autoregression) models are constructed.

A VAR model is constructed after analyzing the stationarity of the variables, performing lag selection and testing autocorrelation of the residuals. An adequate VAR(5) model shows that one company's price values depend on foreign companies's past values.

Later GARCH(1,1), sGARCH(1,1) and eGARCH(1,1) are constructed for each of the company. It is found out that Panevėžio Statybų Trestas returns are the most sensitive to the external shocks (had the highest α parameter). This sensitivity influences the volatility in multivariate models: DCC-sGARCH and DCC-eGARCH models, where Panevėžio Statybų Trestas returns are paired with other company's returns, have the highest α parameter estimators (0.035074) and the correlations vary the most. In addition to that, it is discovered that all of the companies's returns correlate positively insignificantly, except Panevėžio Statybų Trestas and Latvijos Tilti returns, which correlate negatively.

The work is structured as follows: Section 2 presents Literature overview, where Baltic states stock volatilities and GARCH models research are desribed, Section 3 – Baltic States financial markets development and the studied construction sector companies, Section 4 defines univariate and multivariate models, Section 5 presents VAR, GARCH(1,1), sGARCH(1,1) and DCC models construction using empirical data, Section 6 concludes the work with the results and their interpretations, Section 7 shows Bibliography and Section 8 portrays the graphs and the tables.

2 Literature overview

In the previous researches GARCH models were used to analyse the relationships among bigger and smaller financial markets around the world. The financial crisis in 2008, various other political and economical news together with entrance to European Union, Eurozone were taken into consideration while analysing the changes in the returns. The adjustments in equity prices have been compared to the changes in bond returns.

In the works of Kuusk et al. (2008), Soultanaeva (2008), Brännäs and Soultanaeva (2011), Deltuvaitė (2016), Brännäs et al. (2012) and Jakučionytė (2011) the volatilities of Baltic States financial markets were analysed. The national indexes were taken as the representatives of the markets and the relationships among the foreign companies were studied. Brännäs and Soultanaeva (2011) analysed the influence of Russian (Moscow) and USA (New York) stock exchanges to the Baltic stock markets. Jakučionytė (2011) analyzed the influence of changes in trading currency (to EUR) in Baltic states markets to the international investors interests. Next, their works are described.

Kuusk et al. (2008) performed a research on whether the USA crisis of 2007-2008 spread over to the Baltic States. Kuusk et al. (2008) used correlation coefficients based methods adjustment together with heteroskedasticity evaluation and ARCH-GARCH models. The findings were diverse and contradictory. As predicted, the USA and Baltic States stock returns' correlations were discovered to have increased during the turbulent times. However, the volatility had not spread over to the European countries.

Soultanaeva (2008) analysed the relationship among the political news releases and the returns and volatilities in the stock markets of Baltic States. Political news releases captured the information of political risk. The results revealed that political news about domestic and foreign, excluding Russia, problems reduced the unpredictability in Latvian and Estonian markets during the years of 2001-2003. On the other hand, political risk from Russia boosted the volatility of Tallinn stocks. In this paper a weak relationship between political risks of individual causalities and the stock market volatility was discovered. Additionally, an important Monday effect was captured.

Brännäs and Soultanaeva (2011) studied the influence of Russian (Moscow) and USA (New York) stock exchanges on the daily returns and volatilities of Baltic stock market indices. The sample period from January 2000 to April 2005 was taken. Brännäs and Soultanaeva (2011) used the autoregressive asymmetric moving average (ARasMA) model for each Baltic stock exchange and then later it was augmented to the asymmetric quadratic generalized ARCH (asQGARCH). Later they introduced Moscow and New York data in the conditional mean and conditional variance functions in other to check if Russia and USA influence mean returns or volatilities. Finally they included New York and Moscow into the model. It was discovered that news from USA had affected Tallinn returns stronger than Russia. The NYC shocks of a higher risk had a bigger influence on Tallinn returns volatility, while Vilnius stock market was more vulnerable to the shocks from Russia. Latvian equity returns did not seem to be touched by the external sources.

Deltuvaitė (2016) analysed the regional integration of the stock markets in Lithuania, Latvia and Estonia. The author performed various methodology, which included DCC model and Granger causality test. The sample period from January 2000 to June 2014 was taken. The results of this research indicated three major conclusions: a) all of the Baltic stock markets were closely linked, b) nonetheless, the Latvian stock market was more segregated and c) Estonian and Lithuanian stock markets were more connected. The author suggested that Estonian and Lithuanian stock market interdependence might be interpreted as a result of a couple of facts: firstly, the residents of

Lithuania were the principal foreign shareholders of equity securities issued by Estonians and vice versa. Secondly, NASDAQ OMX Baltic main list contained significantly more Lithuanian (16) and Estonian (13) companies than Latvian companies (5).

Brännäs et al. (2012) analyzed the simultaneity in returns and in volatilities in Baltic states and Russia stock markets. They used ARasMA-asQGARCH model and the data taken was from January 2000 to August 2006. Brännäs et al. (2012) discovered that Riga stock returns depended on Vilnius and Tallinn and Tallinn stock returns were impacted by Vilnius returns. The volatilities of Tallinn influenced both Vilnius and Riga volatilities.

Jakučionytė (2011) analyzed whether the international investors interests were influenced by the Estonian entrance to euro area in 2011 and the change of the trading and clearing currency to euro at the NASDAQ OMX Vilnius on 22 November 2010. The author used structural break tests. Jakučionytė (2011) discovered that the news about the turbulence in foreign economics and politics were rather more important than the shift to the new currency in the NASDAQ OMX stock exchanges in Lithuanian and Estonian stock markets.

In Aielli (2013) it was found that in DCC models, the innovation parameter α of the DCC model influenced the volatility of the conditional correlation function. He discovered that the variance of the correlation process was an increasing function of α. The increase of α parameter shifted the mean of the conditional correlation process. It was found that the typical innovation parameter values were $\alpha \leq 0{,}04$. The increase of $\alpha+\beta$ (where β is the volatility decay paramter in DCC) raised the volatility of conditional correlation process.

Thalassinos et al. (2015) used a three-variate M-GARCH model to capture the risk of a bank's investment portfolio. They modelled the correlation structure, applied the Gaussian and t distribution and the multivariate conditional volatilities and correlations. The authors aimed to reveal the fact that the bond returns and equity prices were correlated in a complex way. The adjustments in stock prices had significant influence on the value of government bonds. The authors analysed the relationship between GR2 (bonds of Greece), FR4 (bonds of France), GM4 (bonds of Germany) and three equity indexes in Greece, France and Germany: ASE, CAC40, and DAX. According to the given results, although the unconditional correlation coefficient between bonds and stock market indexes were pretty low and negative in the sample, the conditional correlations fluctuated significantly over the period from January 2008 to May 2014.

In Gencer (2014), the importance of the oil market was highlighted: as the variability of oil prices rose, the national financial market became less stable. Therefore in Gencer (2014) the shock and volatility spillovers between the oil market and five other financial sectors in Turkey were analysed. They used a bivariate GARCH-BEKK model to evaluate the mean and conditional variances. The sample period from 2005-01-04 to 2013-06-12 was studied. They stressed the importance of the oil market: as the variability of prices rose, the national financial market stability diminished. A significant unidirectional volatility transmission from oil market to all the sectors (Banking, Industrials, Services, chemicals-petroleum-plastics, BIST100-a capitalization-weighted index composed of National Market companies except investment trusts) was discovered. They also found a significant unidirectional shock transference from oil market to some of the sectors.

Mircheva (2015) analysed the possible spillovers from euro area and Russia to Nordic countries (Denmark, Finland, Norway, and Sweden). They used IMF's Global Integrated Monetary and Fiscal model (GIMF). The researchers took into consideration the drop of global oil prices. They revealed that the influences differed, even though there existed a high degree of integration among the four countries' economies. The diversity was a result of the fact that Denmark and Finland had no independent monetary policy, and Denmark and Norway exported energy while Finland and Sweden imported energy.

Hyyten (1999) analysed the development of the (conditional) volatility of returns on the Scandinavian markets from 1987 to 1997. The main results of this research were these: 1) (T)GARCH model appeared to be sufficient for capturing conditional volatility even during the years of crisis; 2) bank crisis affected the shifts in volatility; 3) there existed cross-country volatility spillovers among Scandinavian markets during that time; 4) the volatility of returns was higher during the financial crisis, however the volatility peaks appeared later, after the most problematic events had happened.

3 Baltic States financial markets

3.1 Baltic States financial markets development in the 21^{st} century

Baltic States economy is influenced by both the USA and Western and Eastern Europe (particularly Russia). For such small countries with similar history and development after Soviet Union, their economy is often compared and the stock markets relate mutually. According to the daily returns of all four construction companies, the financial crisis which appeared in USA in 2007 hit the prices of European companies heavily 2008, when all of the markets went down. They took more than a year to recover and the fastest one was Estonia.

According to Staehr (2015), the global financial crisis most severely affected construction, manufacturing and retail sales sectors in the Baltic States. Overall, the GDPs of Baltic countries fell the most in the first quarter of 2009.

Lithuanian commercial bank system which is mostly dominated by Scandinavian banks, debt (loans) portfolio grew more than 40% each year from 2003 until 2009. This growth was risky – it was twice as fast than financial deposits and even six times faster than the real GDP growth. Most of the loans taken were on the real estate and this created the housing bubble.

The banks loans portfolio started to shrink in 2008. During the first two years it shrank by 15%. The loans portfolio in 2007 and the one in 2009 differed by 20 billion litas. Lithuanian government debt reached 36 billion litas in 2010. Due to this bank system shrinkage Lithuanian construction sector possibly fell the most in the entire European Union. The most significant financial crisis in Lithuania was happening from October in 2008 until 2009 first quarter.

The financial crisis in Latvia continued for a bit longer, until the end of 2009. On February, 2009, during the turbulent period, the country borrowed 7.5 billion euros from IMF and European Union. In addition to that, Latvia nationalised Parex bank. The unemployment rate had risen from 7% in 2007 to 22.8% in the fourth quarter of 2009. Latvian economical situation fully recovered in 2010. Then the ratings agency Standard and Poor's announced Latvian economy to be stable.

Estonia was the fastest country of the Baltic States to recover from the financial crisis. In 2010 its GDP rose by 3.1% and in 2011 – 8.3%. The labor power grew faster than the real wages. This caused the competitiveness of Estonian companies in the international market at the time [1]. The national export rose by 22% in 2010 and 25% in 2011. This was probably the most important factor for Estonian economic development. On the 11th of August in 2011 Standard and Poor's raised the Estonian credit rating from A to AA-.

3.2 Construction sector stock markets

AS Merko Ehitus Eesti is the market leader of the construction sector in Estonia. The company operates both smaller construction tasks as well as larger-scale, complex and innovative programs. AS Merko Ehitus Eesti is one of the principal residential developers in the country. It has been administering all stages of new buildings – planning, designing, building, sales and warranty service.

This company incorporates both Tallinna Teede AS, which main priority is road construction and AS Merko Infra, which is responsible for infrastructure and civil engineering work.

AS Merko Ehitus Eesti is part of AS Merko Ehitus, the principal construction company in the Baltics. The shares of AS Merko Ehitus has been on the NASDAQ Tallinn in 1997. There are more than 790 employees of this firm in the Baltics. The revenue of 2015 was 251 million euros.

[1] Parts (2013)

Another Estonian construction company Nordecon AS, established in 1989 (and formerly named Eesti Ehitus), has grown to be one of the largest construction groups in the country at the moment. Its work covers various tasks in most of the sectors of this market.Nordecon is a member of the Estonian Association of Construction Entrepreneurs and the Estonian Chamber of Commerce and Industry. The shares of Nordecon AS have been listed on Tallinn Stock Exchange since 18 May 2006.

The joint-stock company Panevėžio Statybų Trestas is Lithuanian construction company established in 1957. This company has started its work under the name of National construction trust Number 9. During its history the firm has carried out many significant and complex projects which have contributed to Lithuanian economy growth and environmental wellness. In this way Panevėžio Statybų Trestas has created a higher quality of living surroundings for all the people of Lithuania. The company's stocks are in the market of NASDAQ Vilnius. On the 30rd of June in 2015 the number of all of the shareholders was 1718.

Another joint-stock company Latvijas Tilti is one of the biggest Latvian construction companies. Itspecializes in building and reconstructing bridges, roads, bypasses, viaducts and tunnels. They also perform projects on sea piers and shores sustainability. During the last 70 years the firm has built several thousands of bridges andhydro technical objects in Latvia and in foreign countries. As a result of developed manufacturing and professional bases, Latvijas Tilti insure full construction service for their clients, participating in projects of various complexity.

4 Methods

4.1 Data

In order to analyze the changes in returns and volatilities of Nordecon, Merko, Latvijas Tilti and Panevėžio Statybų Trestas, the daily returns of the firms were taken into consideration. The sample period was from 2008-11-01 to 2016-05-06. The movements of the prices during the 8 year period were shown below (Figure 1). The prices on 2008-11-01 were taken as the initial values of 100% and all the prices after that were converted into percentages accordingly.

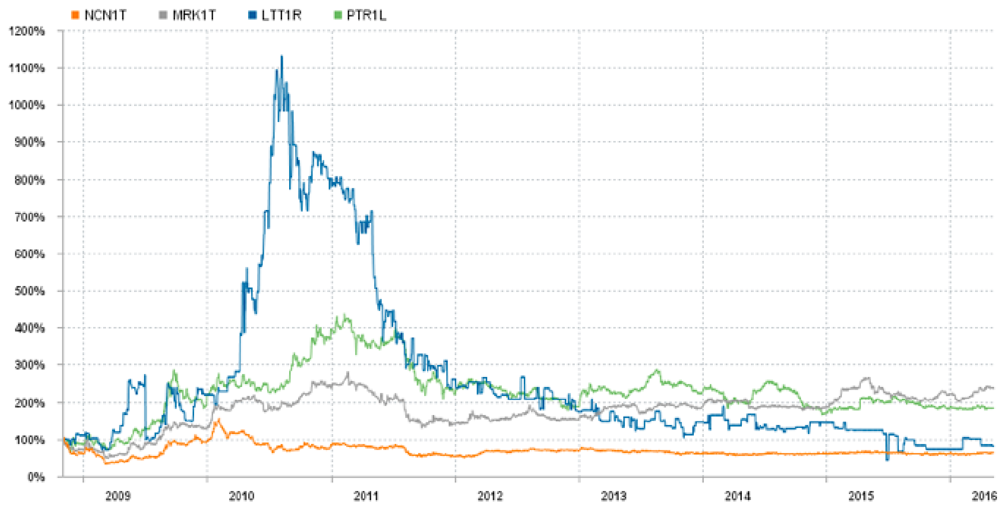

Figure 1: Nordecon, Merko, Latvijas Tilti and Panevėžio Statybų Trestas prices over the period of 2008-11-01 to 2016-05-06 from NASDAQ OMX.

4.2 VAR model

Vector autoregressive model is often used to analyse multivariate time series and study the dynamic relationships among stationary variables.

Definition 6.1 A stationary vector Y_t is a multivariate VAR (vector autoregressive) model and it is defined in this way [2]:

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + v_t \tag{1}$$

where $v_t \sim WN(0, \sigma_v)$, $p > 0$ and Y_t, c and v_t are $n \times n$ dimensional variables, constants and white noise residuals respectively. A_i is a quadratic $n \times n$ dimensional parameters matrix and $\sum_v$ is a quadratic $n \times n$ dimensional white noise residual matrix and p is the order of the process.

[2] Kvedaras (2015)

A vector Y_t is stationary when the roots of the equation:

$$\left| I - \sum_{i=1}^{p} A_i z^i \right| = 0 \tag{2}$$

are bigger than 1 in their absolute values.

4.3 ARCH model

Before analysing the multivariate DCC model for all of the companies, we define univariate models that can be constructed for each of the series separately. We introduce ARCH(p), GARCH(p,q), eGARCH(p,q) and sGARCH(p,q).

Autoregressive conditional heteroscedasticity (ARCH) is one of the first models widely used to describe financial returns. It was introduced by Engle in 1982.

- Autoregressive (AR) part suggests that tomorrow's variance (volatility) is a regressed function of today's variance;
- Conditional (C) – tomorrow's variance depends on the most recent variance.
- Heteroscedastic (H) – the variances change over time.

Engle (1982) proposed a model with returns r_t depicted in this way:

$$r_t = \sigma_t \epsilon_t, \ t \ \in Z, \tag{3}$$

where ϵ_t are independent random variables with distribution $N(0, 1)$.

The conditional variance σ_t^2 has a form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + ... + \alpha_p r_{t-p}^2. \tag{4}$$

Here,

$$\alpha_0 > 0, \alpha_1 \geq 0, ...\alpha_p \geq 0 \ .$$

Therefore, ARCH(1) model is defined in this way:

$$\begin{cases} r_t = \sigma_t \epsilon_t, \\ \sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2. \end{cases} \tag{5}$$

4.4 GARCH model

Generalized autoregressive conditional heteroscedasticity (GARCH) model was introduced by Bollerslev in 1986.

Definition 6.2 GARCH(p, q) is defined in this way [3]:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j r_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{6}$$

where $r_t = \sigma_t \epsilon_t, t \in Z$ and $\epsilon_t \sim iid(0, 1)$.

If

$$\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j < 1,$$

The GARCH model has stationary solution and the unconditional variance is equal to

$$Var(r_t) = \frac{\alpha_0}{1 - (\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j)} < \infty.$$

GARCH(p,q) process has the following properties:

- ***Definition 6.3*** A series Z_t is called white noise with a mean 0 and a variance σ^2, if $EZ_t = 0$ and:

  $$r(h) = \begin{cases} \sigma^2 \ if\, h = 0 \\ 0 \ if\, h \neq 0 \end{cases}$$

  Then it is defined $Z_t \sim WN(0, \sigma^2)$.

  GARCH series is a series of white noise.

[3] Leipus (2010)

- If r_t is GARCH(p,q) process, then r_t^2 is ARMA(m,p) process, where $m = max(p, q)$.

  Definition 6.4 Process $X_t,\ t \in Z$ is called autoregressive moving – average series, if X_t is stationary. It is defined in this way:

  $$X_t - \phi_1 X_{t-1} - ... - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + ... + \theta_q Z_{t-q},$$

  where $Z_t \sim WN(0, \sigma^2)$. This series is named ARMA(p,q). It can be rewritten in this form:

  $$\phi(B)X_t = \theta(B)Z_t,\ t \in Z;$$

  where

  $$\phi(z) = 1 - \phi_1 z - ... - \phi_p z^p \theta(z) = 1 + \theta_1 z + ... + \theta_q z^q$$

  and B is the back shift operator: $B^j X_t = X_{t-j},\ j \in Z$. Polynomials $\phi(\cdot)$ and $\theta(\cdot)$ are autoregressive and moving average polynomials respectively.

- r_t is not independent series because it depends on its past values.

- When $p = q = 1$ we have a widely used GARCH(1,1) model which is defined in this way:

  $$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \tag{7}$$

  This model is stationary in a strict sense if $E\ln(\beta_1 + \alpha_1 \epsilon_t^2) < 0$.

  When

  $$\alpha_1 + \beta_1 = 1,$$

  we have an integrated GARCH model (iGARCH(1,1)). This model is a restricted version of the previous GARCH(1,1) model. Consequently the process does not present second moments.

4.5 GARCH limitations

It is known that there exists a negative correlation among stock returns and changes in daily returns' volatility. The volatility tends to rise in response to "bad news" (excess returns lower than expected) and to fall in response to "good news" (higher than expected).

GARCH models, however, assume that only the magnitude and not the positivity or negativity of unanticipated excess returns determines feature of α_t^2.

The asymmetric models provide an explanation for the leverage effect. They are able to show that an unexpected price drop increases volatility more than an analogous unexpected price increase. The following chapter will describe GARCH transformations: exponential GARCH and the skewed GARCH.

4.6 eGARCH (exponential GARCH)

Nelson introduced Exponential GARCH (eGARCH) in 1991. This model analyzes the asymmetry effect in GARCH. The returns are portrayed as in ARCH model (3). The volatility is defined in this way:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \gamma_j \ln(\sigma_{t-j}^2). \tag{8}$$

Here,

$$g(z_t) = \theta z_t + \gamma(|z_t| - E\,|z_t|), \theta, \gamma \in R,$$

and

$$z_t = \epsilon/\sigma.$$

Furthermore, $E\,|z_t| = (2/\pi)^{1/2}$ if $z_t \sim N(0,1)$. z_t and ϵ_t are independent.

eGARCH model has the following characteristics:

- When $0 <_t < \infty$, then $g(_t)$ is a linear combination with a slope coefficient $\theta + \gamma$;
- When $-\infty <_t \leq 0$, then there is a linear combination with a slope coefficient $\theta - \gamma$.

- Suppose $\theta = 0$. Large innovations increase the conditional variance if $|z_t| - E\,|z_t| > 0$ and decrease the conditional variance if $|z_t| - E\,|z_t| < 0$.
- Suppose that $\theta < 1$. The innovation in variance, $g(z_t)$, is positive if the innovations z_t are less than $(2/\pi)^{1/2}/(\theta - 1)$. The negative innovations in returns, ϵ_t, cause the innovation to the conditional variance to be positive if θ is less than 1.

In this way $g(z_t)$ allows for the conditional volatility σ_t^2 to react asymmetrically for prices inclination and declivity.

4.7 sGARCH (skewed-GARCH)

The sGARCH model reveals the skewness and kurtosis of the returns series. In the GARCH model, the initial values are set to the empirical variance of the time series (as suggested by Bollerslev (1986)). However in sGARCH the initial observations are fit to the stable distribution. If we have such a GARCH model:

$$\begin{cases} r_{j,t} = \delta_j Z_{j,t-1} + \epsilon_{j,t}, \\ \epsilon_{j,t} = \sigma_{j,t} z_{j,t}, \\ z_{j,t}|\Omega_{t-1} \sim \O(0, 1, \psi), \\ \sigma_{j,t}^2 = \omega_j + \alpha_j \sigma_{j,t-1}^2 + \beta_j \epsilon_{j,t-1}^2. \end{cases}$$

where $j = 1, ..., N$, $r_{j,t}$ - returns, $z_{j,t}$ - standardized residuals (residual $\epsilon_{j,t}$ is divided by the standard deviation $\sigma_{j,t}$, Ω_{t-1} is a set of information available at the beginning of time t, $\O(\cdot)$ denotes a conditional density function and ψ denotes a vector of parameters that may be needed to fully characterize the probability distribution.

The stable distribution of sGARCH is defined in this way:

$$\begin{cases} \epsilon_{j,t} = (\sigma_{j,t})^{1/\psi} z_{j,t}, \\ \ln[E(e^{iXt})] = -|t|^{\psi}. \end{cases}$$

In GARCH model ψ would be 2.

4.8 DCC

Dynamic conditional correlation (DCC) model was introduced by Engle in 2002. It is a nonlinear combination of univariate GARCH models.

Definition 6.3 The Engle DCC model is depicted in this way:

$$H_t = D_t R_t D_t, \text{ where } D_t = diag(h_{11t}^{1/2}, ..., h_{NNt}^{1/2}). \tag{9}$$

Each h_{iit} is described by univariate GARCH model and R_t is the conditional correlation matrix.

5 Modelling

5.1 Data preparation

Firstly, we obtained the daily returns of the Baltic States companies. It was possible to either choose the daily changes of the prices provided by NASDAQ OMX or do the transformations ourselves: $r_t = \ln p_t - \ln p_{t-1}$, where p_t were the prices. The graph of the daily returns suggested the stationarity of the series thus we tested it using the Augmented Dickey-Fuller test and KPSS test.

The Augmented Dickey-Fuller (ADF) test is a widely used method. However it has a drawback, since its null hypothesis is that is $I(1)$ (nonstationary). A stronger test is Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test which has a null hypothesis of $I(0)$ (stationarity) – an absence of a unit root. The non-appearance of a unit root is a proof of trend-stationarity. This means that the series are mean-reverting (if the shock occurs, the time series are going to converge towards the growing mean, which was not affected by the shock). According to both ADF and KPSS tests the return series were all stationary (Table 2 and Table 3 in Appendix).

Later we investigated if the time series had the features of ARCH structure. This would imply the changing of volatility. We tested the series with several of lags (1, 5 and 10). Two statistics: Q(m) of squared series (LM test) statistic and Rank-based test statistic were provided. ARCH LM test analyzed whether the coefficients in the regression below:

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + ... + \alpha_p a_{t-p}^2 + e_t \tag{10}$$

were zero, where a_t was the studied series. The null hypothesis of no ARCH effects was defined in this way:

$$0 = \alpha_1 = ... = \alpha_p \tag{11}$$

In this research, the null hypothesis of no ARCH effects was rejected by LM test in all of the series except from Merko (lag 1) and Panevėžio Statybos (lag 1 and 5). However, the Rank-based test rejected the hypothesis of no ARCH effects in all of the series.

5.2 VAR modelling

After analyzing the stationarity of the variables, a beneficial lag number (VAR order) had to be chosen. VARselect program proposed four possible options: Akaike informational criteria suggested 10, Hannan-Quinn – 7, Schwartz – 3.

We started our modeling with the smallest VAR order of 3. VAR(3) had some parameters that were almost significant. Therefore we increased the order. The VAR model of order 5 had the most significant parameters thus we tested the adequacy of the model, where VAR(5) was studied for no serial correlation. We used the Durbin-Watson test for our model. It proposed a statistic of 1.9947, which was compared to the Durbin-Watson table. The necessary part of the table was portrayed (Table 5 in Appendix), where the number of parameters was four as we had 4 time series and the number of observations was from 1850 to 1900 as we had 1894 days.

Since 1.9947 was higher than the upper bound: $1,92773$ – the hypothesis of no positive autocorrelation was accepted. Since $4 - 1.9947 = 2,0053$ was higher than $1,92773$, the hypothesis of no negative autocorrelation was accepted. Therefore the VAR(5) model was adequate.

$$
\begin{cases}
nord_t = -0,076 - 0,1382 nord^{***}_{t-1} + 0,0814 panst^{***}_{t-1} \\
- \ 0,1046 nord^{***}_{t-2} + 0,0414 panst^{*}_{t-2} + 0,0138 tilti^{*}_{t-3} \\
+ \ 0,0135 tilti^{*}_{t-5} + \epsilon_{nord}, \\
\\
merko_t = 0,3547 - 0,1331 merko^{*}_{t-1} + 0,2024 nord^{*}_{t-2} - 0.3227 merko^{***}_{t-2} \\
- \ 0.2016 merko^{***}_{t-3} + 0.2281 merko^{***}_{t-5} + \epsilon_{merko}, \\
\\
tilti_t = 0,0439 + 0.1856 nord^{*}_{t-1} - 0.2090 tilti^{***}_{t-1} - 0.0486 tilti^{*}_{t-2} \\
- \ 0.0048 panst^{***}_{t-4} - 0.1751 tilti^{***}_{t-5} + \epsilon_{tilti}, \\
\\
panst_t = -0.1230 - 0.0785 panst^{***}_{t-2} + 0.0554 nord_{t-3} - 0.0542 panst^{**}_{t-5} \\
+ \ \epsilon_{panst}.
\end{cases}
\tag{12}
$$

Here significance is noted: 0 '***' 0.001 '**' 0.01 '*' 0.05. $nord_t$ notes the Nordecon returns, $merko_t$ – Merko returns, $tilti_t$ – Latvijas Tilti returns and $panst_t$ – Panevėžio Statybų Trestas returns.

Formula (24) portrays an adequate VAR(5) model for Nordecon, Merko, Latvijas Tilti and Panevėžio Statybų Trestas. The analysis concluded that one company's prices depended on other foreign companies's past prices. Estonian company Nordecon depended on its own, Latvijas Tilti and Panevėžio Satybos past values. Estonian company Merko was influenced by its own and Nordecon past values. Latvijas Tilti depended on its own and Nordecon past values. Panevėžio Statybos depended only on its own past values.

Overall, Estonian company Nordecon was influenced by Latvian and Lithuanian stock companies past values and Estonian Merko depended on Nordecon.

5.3 GARCH(1,1) and sGARCH(1,1)

Later in the research univariate GARCH models were constructed for each of the four of the time series. The normal distribution was considered. The stationarity was chosen as a primary condition.

GARCH(1,1) α and β parameters:

$$\alpha_{nord} = 0.2400,\ \beta_{nord} = 0.7757;\ \alpha_{merko} = 0.1824,\ \beta_{merko} = 0.6193;$$

$$\alpha_{tilti} = 0.1402,\ \beta_{tilti} = 10^{-10};\ \alpha_{panst} = 0.2393,\ \beta_{panst} = 0.7617.$$

GARCH(1,1) of Merko and Latvijas Tilti followed a stationarity condition of $\alpha + \beta < 1$. Therefore we constructed two GARCH(1,1) series for Merko and Latvijas Tilti daily returns:

$$\sigma^2_{merko,t} = 0.0084 + 0.1824 r^2_{t-1} + 0.6193 \sigma^2_{t-1},\ \epsilon_t \sim N(0,1), \tag{13}$$

$$\sigma^2_{tilti,t} = 0.1103 + 0.1402 r^2_{t-1} + 10^{-10} \sigma^2_{t-1},\ \epsilon_t \sim N(0,1). \tag{14}$$

Due to the $\alpha + \beta > 1$ property of GARCH(1,1) of Nordecon and Panevėžio Statybų Trestas, sGARCH(1,1) of the two firms were studied. The skewed-GARCH(1,1) for the firms obtained $\alpha + \beta = 0,999$.

Therefore two univariate sGARCH(1,1) for Nordecon and Panevėžio statybos were defined:

$$\sigma^2_{nord,t} = 0.000144 + 0.215554 r^2_{t-1} + 0.783446 \sigma^2_{t-1},\ \epsilon_t \sim N(0,1), \tag{15}$$

$$\sigma^2_{panst,t} = 0.000249 + 0.236216 r^2_{t-1} + 0.762784 \sigma^2_{t-1},\ \epsilon_t \sim N(0,1). \tag{16}$$

Panevėžio Statybų Trestas returns in the univariate sGARCH(1,1) model had the highest innovation parameter α of 0.236216. This comparatively high α possibly influenced the highest α in the multivariate models: DCC-sGARCH and DCC-eGARCH between Panevėžio Statybų Trestas and Latvijas Tilti and between Panevėžio Statybų Trestas and Nordecon: $\alpha = 0.035074$ in sGARCH and $\alpha = 0.021697$ in eGARCH.

Latvijas Tilti had the lowest $\beta = 10^{-10}$ which suggested the fastest volatility decay.

5.4 DCC α and β interpretation

It was found in Aielli (2013) that α and β parameters in DCC performed accordingly to the graphs below (Figure 2). When $\alpha + \beta$ increased, the volatility of the conditional correlation rose as well. As the α parameter grew, the volatility increased and the mean shifted too. They discovered that the variance of the correlation process was an increasing function of α.

This theory was strengthened in this research as DCC models for Latvijas Tilti and Panevėžio Statybų Trestas obtained the highest value of $\alpha = 0.035074$ in DCC-eGARCH and the second to the highest $\alpha = 0.021697$ in DCC-sGARCH while having the highest conditional correlation variances (0.16 in DCC-eGARCH and 0.00653 in DCC-sGARCH).

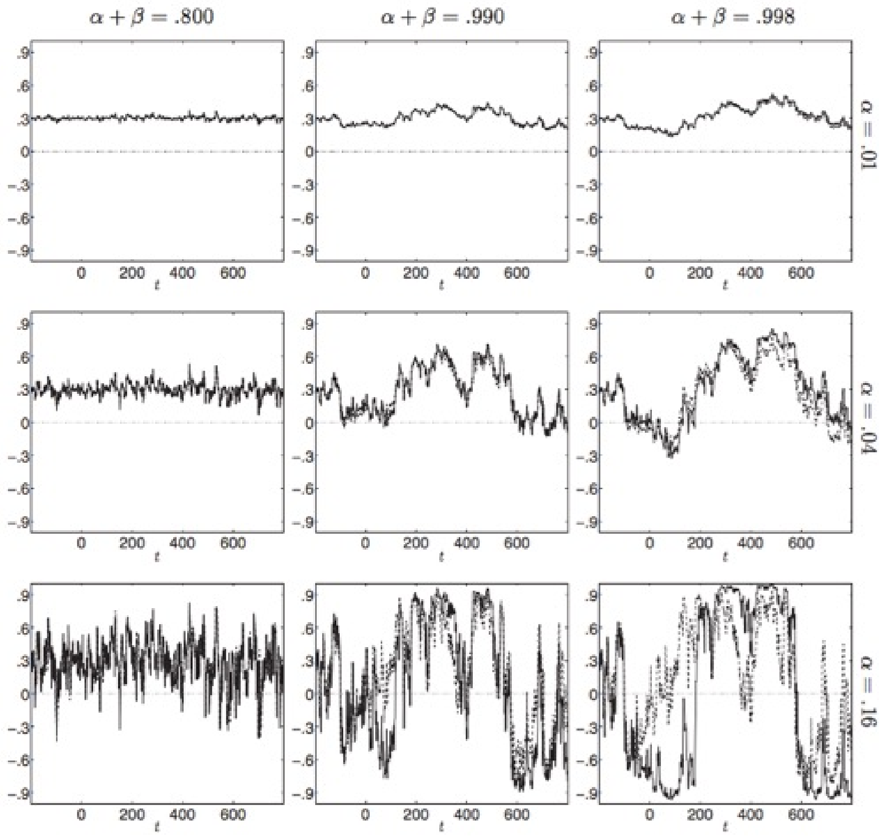

Figure 2: α and β analysis from Aielli (2013)

5.5 Analysis of DCC conditional correlation graphs

The conditional correlation graph of Panevėžio Statybų Trestas and Latvijas Tilti DCC-eGARCH model showed that the values deviated the furthest from the mean with the variance of 0.16. Panevėžio Statybų Trestas and Latvijas Tilti DCC-eGARCH model also obtained the highest α amongst all of the models: 0.035074, and the second to the highest α in their DCC-sGARCH model: 0.021697.

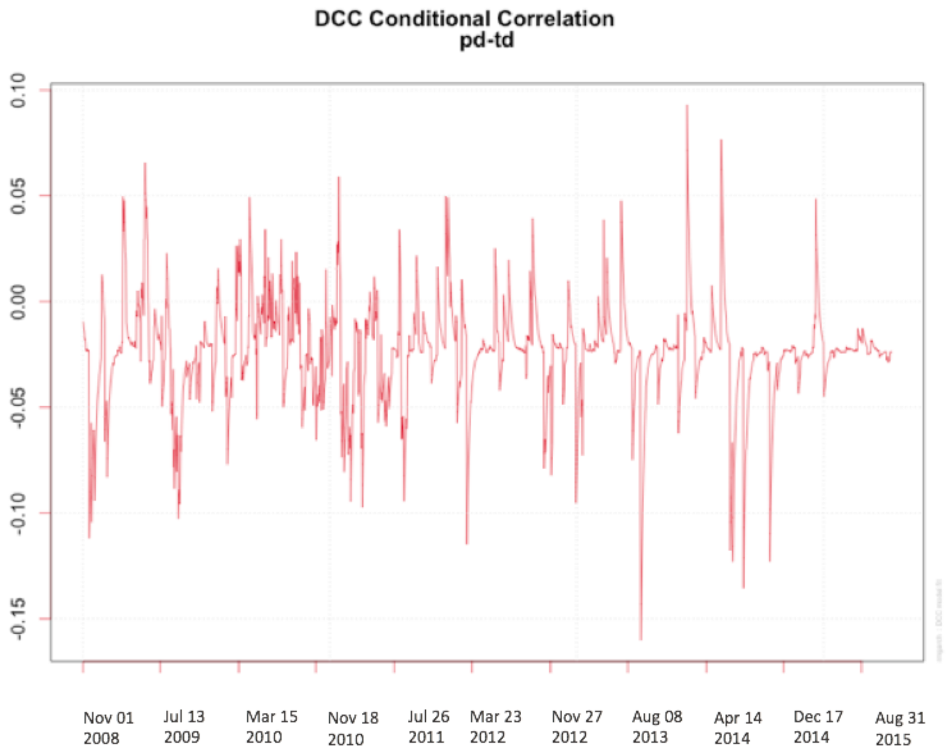

Figure 3: Latvijas Tilti and Panevėžio Statybų Trestas DCC-eGARCH

The conditional correlation graph of Estonian company Merko and Latvijas Tilti DCC-sGARCH had the variance of 10^{-10} and the model of these two firms obtained a low α: 0.00738.

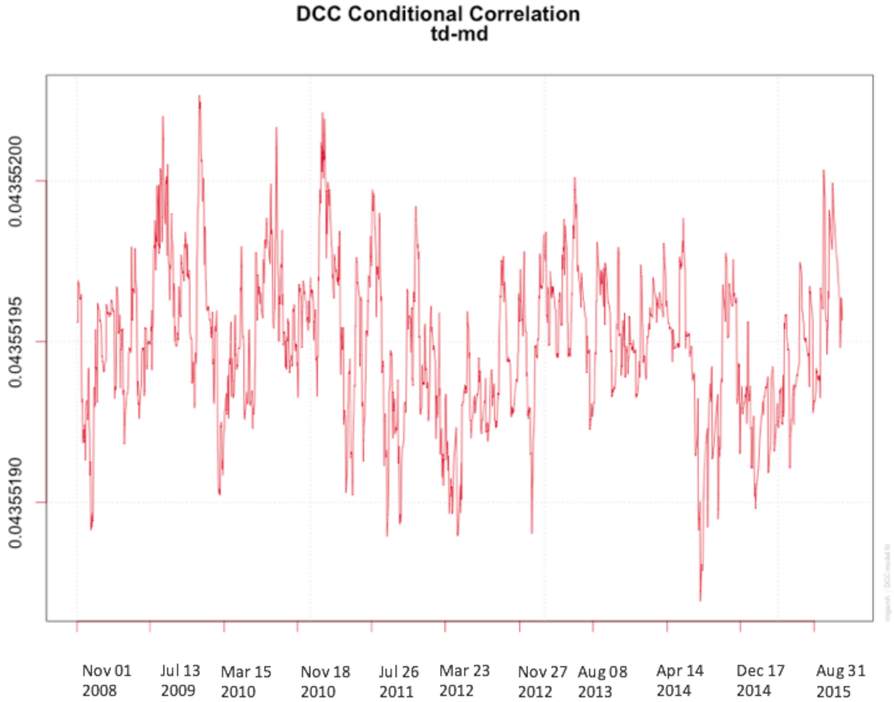

Figure 4: Merko and Latvijas Tilti DCC-sGARCH

The conditional correlation graph of two Estonian companies Nordecon and Merko had a variance of 0.005. The DCC-eGARCH model of these two firms obtained a low α: 0.004082. The α in DCC-sGARCH was rather low as well: 0.008602. The DCC-sGARCH conditional correlation model of these two firms showed the highest correlation of 0.3 in 2010. This was also the highest correlation overall attained among all of the firms indicating the important factor of the companies national relationship.

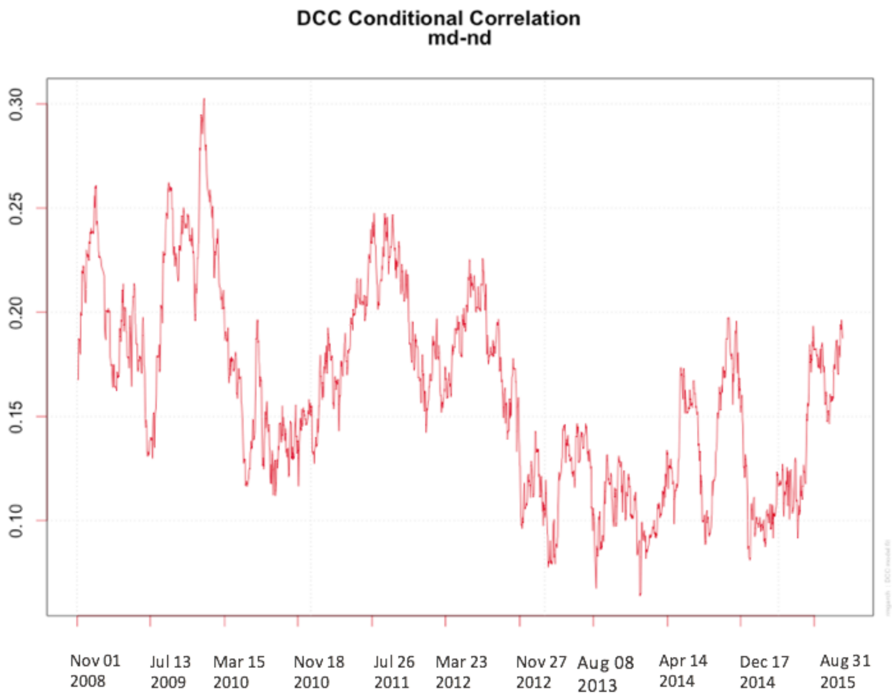

Figure 5: Nordecon and Merko DCC-sGARCH

6 Conclusions

6.1 VAR results

An adequate vector autoregression model VAR(5) suggested a significant relationship among the four of the Baltic States companies. It appeared that Nordecon depended on its own, Latvijas Tilti and Panevėžio Statybų Trestas past values. Estonian company Merko depended on its own and Nordecon past values. Latvijas Tilti was influenced by its own and Nordecon past values. Panevėžio Statybų Trestas depended only on its own past values.

The overall analysis suggested that Nordecon was influenced by all of the other stock companies past values and Merko depended on Nordecon.

6.2 DCC results

In conclusion, the innovation parameter α was quite low (< 0.0086) in most of the models. This suggested that the news did not influence the correlation in nearly all of the four series.

The highest α was among Latvijas Tilti and Panevėžio Statybų Trestas (0.035078 in DCC-eGARCH and second to the highest – 0.21697 in DCC-sGARCH). In relation to that, the highest conditional correlation variance appeared among Latvian and Lithuanian firms (0.16 in DCC-eGARCH and second to the highest: 0.00653 in DCC-sGARCH). This suggested the fact that the relation of Lithuanian and Latvian markets was sensitive to the innoviations and external shocks.

In addition, Panevėžio statybos trestas returns appeared to be comparatively volatile in the univariate model. This high level of volatility in Lithuanian stock market possibly augmented the volatility of conditional correlation between the Lithuanian and Latvian companies in the multivariate model as well.

The decay parameter β was quite large (> 0.97) in all of the multivariate models which proposed a slow volatility decay in the obtained correlations. This meant that the variances did not diminish fast and they stayed steady.

Although the mean conditional correlations among Nordecon and Latvijas Tilti, Nordecon and Panevėžio Statybų Trestas, Merko and Latvijas Tilti and Merko and Panevėžio Statybų Trestas were not significant (up to 0.24), they remained positive and steady throughout the entire sample period. Therefore even though all of the prices diminished after the crisis and then recovered afterwards, they did so in a similar manner and consequently the relationships stayed stable.

The conditional correlation among two Estonian construction companies: Nordecon and Merko reached the highest conditional correlation of 0.3 in the first quarter of 2010. This peak appeared during the recovery of Estonian financial markets. At the end of 2009 the national GDP started to rise and it plummeted subsequently in 2010. Estonian construction sector contribution to GDP growth increased significantly as well. At the beginning of 2010 the labour force, building machines and materials started to rise together with the construction prices.[4] Alongside this fast recovery of the national stock market and the construction sector, the Estonian construction companies prices performed the highest level of interaction.

Only Lithuanian Panevėžio Statybų Trestas and Latvijas Tilti appeared to have a slightly negative relationship, the conditional correlation mean stayed around -0.023. The relationship appeared to be affected by external shocks as well: the mean stayed unchanging, but the volatility was comparatively high. The negative conditional correlation might be explained by a couple of economical reasons: firstly, it suggested the competitiveness of the two markets and secondly, supported the fact that Lithuania has been developing a closer relationship to the Western Europe financial market while Latvia - to the Eastern Europe, particularly Russia.

[4] Swedbank Newsletter 2014

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8 Appendix

8.1 Tables

Value	Nordecon	Merko	Latv. Tilti	Pan. St.
ADF statistic	-11.016	-15.302	-18.422	-15.748
Lag order	12	12	12	12
p-value 0.01	0.01	0.01	0.01	

Table 1: Augmented Dickey-Fuller test for stationarity of Nordecon, Merko, Latvijas Tilti and Panevėžio Statybų Trestas daily returns.

Value	Nordecon	Merko	Latv. Tilti	Pan. St.
KPSS level	0.044796	0.13146	0.07069	0.27632
Lag order	10	10	10	10
p-value	0.1	0.1	0.1	0.1

Table 2: Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity of Nordecon, Merko, Latvijas Tilti and Panevėžio Statybų Trestas daily returns.

Value	Nordecon	Merko
Lag order 1		
LM test statistic and p-value	175.646, 0	0.0004, 0
Rank-based Test statistic and p-value	128.2247, 0	145.7127, 0
Lag order 5		
LM test statistic and p-value	703.2432, 0	562.2039, 0
Rank-based Test statistic and p-value	501.4728, 0	451.6749, 0
Lag order 10		
LM test statistic and p-value	829.2196, 0	802.8078, 0
Rank-based Test statistic and p-value	899.9417, 0	759.9867, 0

Table 3: Test for ARCH effects for Nordecon and Merko daily returns.

Value	Latvijas Tilti	Panevėžio Statybos
Lag order 1		
LM test statistic and p-value	46.0305, 0	0.0057, 0.9398
Rank-based Test statistic and p-value	82.8171, 0	140.3889, 0
Lag order 5		
LM test statistic and p-value	95.30405, 0	0.0379 0.9999
Rank-based Test statistic and p-value	299.1519, 0	549.3304, 0
Lag order 10		
LM test statistic and p-value	179.4896, 0	0.0433, 1
Rank-based Test statistic and p-value	526.5469, 0	881.8145, 0

Table 4: Test for ARCH effects for Latvijas Tilti and Panevėžio Statybų Trestas daily returns. The null hypothesis of no arch effects is rejected.

Number of observations	Number of parameters	Lower bound	Upper bound
1850	4	1.92031	1.92681
1900	4	1.92141	1.92773

Table 5: Durbin-Watson table for the hypothesis of noautocorrelation of residuals.

Series	GARCH(1,1)	eGARCH(1,1)	sGARCH(1,1)
Parameters	$\alpha + \beta$	$\alpha + \beta$	$\alpha + \beta$
Nordecon	1.0157	1.1467	0.999
Merko	0.801	0.8994	0.999
Tilti	0.14	0.9441	0.999
Panevėžio statybos	1.00102	1.14644	0.999

Table 6: principal, exponential and skewed GARCH(1,1) $\alpha + \beta$ estimators for each of the company's return series. Here β in eGARCH represents γ in eGARCH description in the Methods Section.

Companies	DCC(sGARCH)	DCC(eGARCH)
Nordecon Merko	α=0.008602 β=0.990397 α=0.007385 β=0.991615	α=0.004082 β=1 α=0.007881 β=0.990708
Nordecon Tilti	α=0.008602 β=0.990397 α=0.008602 β=0.990397	α=0.004082 β=1 α=0.004688 β=1
Nordecon Panst	α=0.008602 β=0.990397 α=**0.021697** β=0.972099	α=0.004081 β=1 α=**0.035078** β=0.988157
Merko Tilti	α=0.006519 β=0.992034 α=0.007385 β=0.991615	α=0.007852 β=0.990669 α=0.004688 β=1
Merko Panst	α=0.006519 β=0.992034 α=**0.021697** β=0.972099	α=0.007845 β=0.990751 α=0.006550 β= 0.988159
Tilti Panst	α=0.007385 β=0.991615 α=**0.021697** β=0.972099	α=0.004688 β 1 α=**0.035074** β=0.988158

Table 7: α and β estimators of multivariate models DCC-eGARCH and DCC-sGARCH for paired companies daily returns.

	Variance	sGARCH α
Nordecon, Merko	0.005	0.007
Nordecon, Tilti	0.005	0.007
Nordecon, Panst	0.004	<0.001
Merko, Tilti	0.005	<0.001
Merko, Panst	0.007	<0.001
Tilti, Panst	**0.007**	**0.035**

Table 8: Conditional correlation variance and α from DCC-sGARCH models. As α estimator grew, the conditional correlation variance rose.

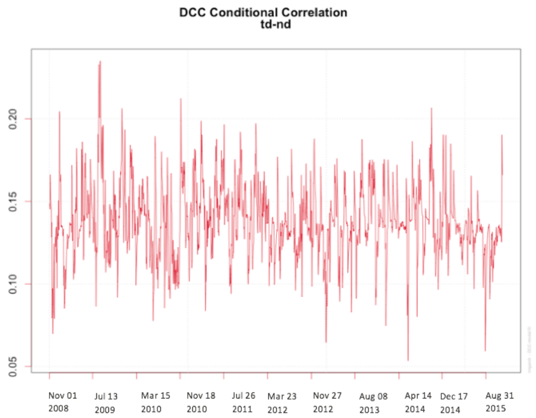

Figure 6: Nordecon and Latvijas Tilti DCC-sGARCH conditional correlation graph

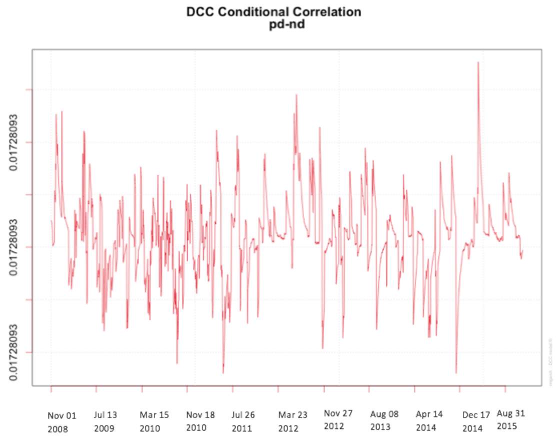

Figure 7: Nordecon and Panevėžio statybos DCC-sGARCH conditional correlation graph

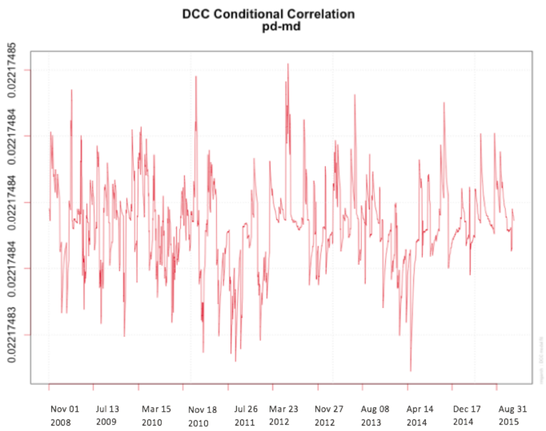

Figure 8: Merko and Panevėžio statybos DCC-sGARCH conditional correlation graph

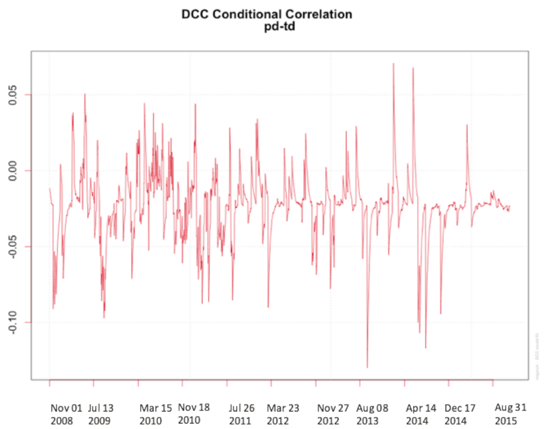

Figure 9: Panevėžio statybos and Latvijas Tilti DCC-sGARCH conditional correlation graph

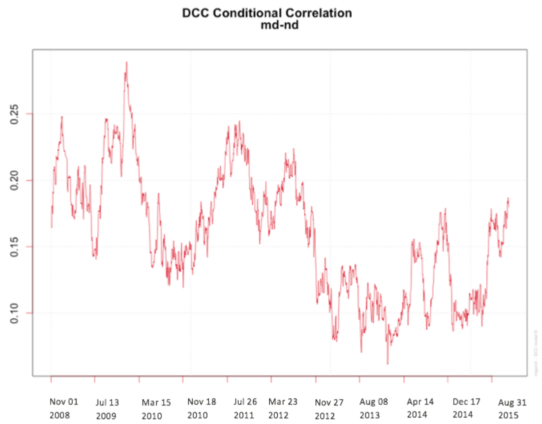

Figure 10: Nordecon and Merko DCC-eGARCH conditional correlation graph

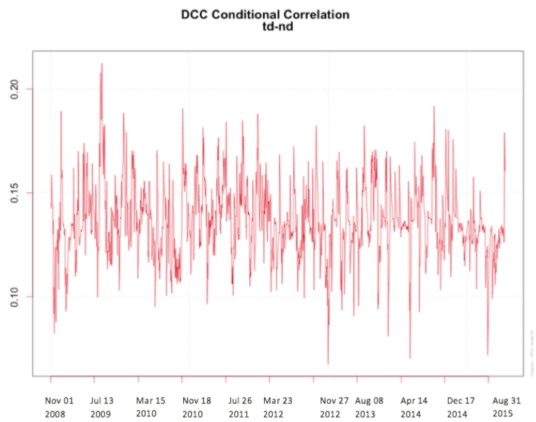

Figure 11: Nordecon and Latvijas Tilti DCC-eGARCH conditional correlation graph

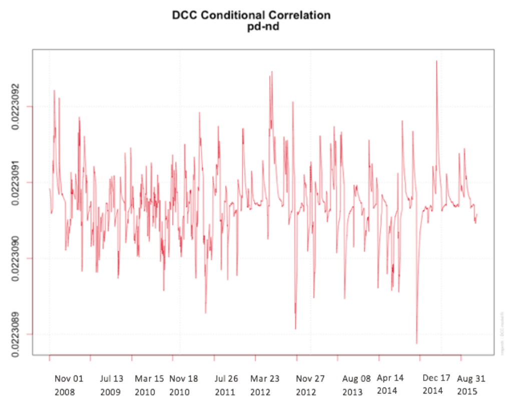

Figure 12: Nordecon and Panevėžio statybos DCC-eGARCH conditional correlation graph

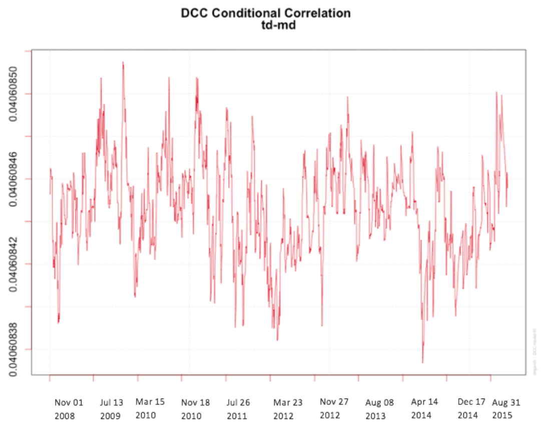

Figure 13: Merko and Latvijas Tilti DCC-eGARCH conditional correlation graph

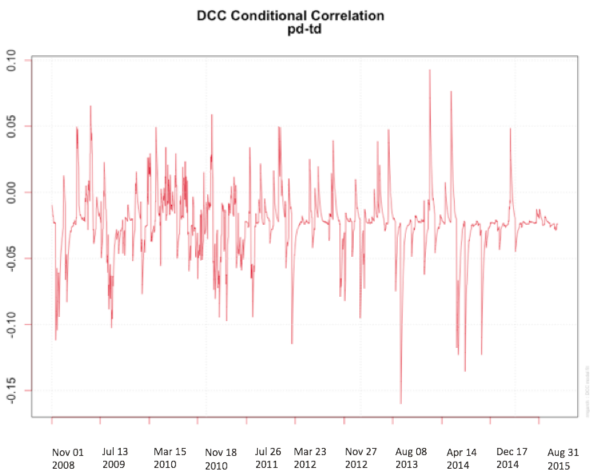

Figure 14: Merko and Panevėžio statybos DCC-eGARCH conditional correlation graph