Udvari B. – Voszka É. (eds) 2019: Proceedings of the 3rd Central European PhD Workshop on Economic Policy and Crisis Management. University of Szeged, Doctoral School in Economics, Szeged, pp. 78–88.

The financial integration of the Visegrád countries: Examining the co-movement of stock and bond market return and volatility by wavelet and copula tests

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The paper aims to explore financial integration between the Visegrád countries from a new perspective. Its purpose is to examine the short-term interdependency of stock exchange returns, volatility and long-term bond market volatility and market movement by applying three-dimensional continuous wavelet transformation to the daily market data. By using wavelet method, we can estimate the interdependence level and lag-lead relationship among the financial markets of the Visegrád countries for the post – crisis period (from January 2012 to February 2018). The level of interdependence for bond market movement varies over time as Hungary seems to be becoming more independent as a result of the programs launched by the National Bank of Hungary. In spite of the independent price return on bond markets, we can still detect interdependent volatility within the market, which means volatility on international markets continues to affect the Hungarian market. The level of interdependence for stock market movements and volatility are stable over time and were found to be stronger in the short term. The copula approach can help us to understand the causality between variables within the region and to understand whether the level of co-movement is temporary or not.

Keywords: Wavelet, Copula, Financial integration, Co-movement

1. Introduction

Many economists are concerned with the causal influence of one country's performance on other countries. In this paper, I focus on the Visegrád countries, especially on Hungary, and examine whether the Czech, Polish and Slovakian financial markets affect the Hungarian economy. Contrary to most of the literature, both stock and bond markets are examined from various aspects i.e. price and volatility.

The topic of price co-movement among international stock markets has been much analyzed recently and become a widely discussed topic in international finance. A knowledge of financial market linkage between national financial markets is very important for the investors' hedge strategy, who are thereby able to build optimal portfolios which fully reflect their risk appetite.

Bond market interdependency is a less popular research topic in the financial literature, even though the global financial crisis pointed out the importance of global financial networks. An appreciation of the linkage between bond markets, i.e. sovereign government bond markets, is very important for policy makers, as well as for fiscal and monetary policy decision makers. Bond market linkage can have an impact on the yield curve and exchange rate, and therefore co-movement can affect monetary policy, transmission mechanisms and thus financial stability. Bond market interdependency is also very important for fiscal policy as it can affect the cost of financing and the risk of refunding (liquidity risk).

2. Literature review

Co-movement within stock markets is a widely studied area among researchers. As early as the 1960s and 1970s, Grubel (1968) and Solnik (1974) studied the correlations between domestic stock markets and found that they were low in that instance. However, in a study two decades later, Goldstein and Michael (1993) found increasing linkages between international stock markets. In more recent years many have studied co-movement during times of financial crisis. An especially fertile ground for such studies was provided by the 1997 Asian financial crisis. Authors studying the Asian crisis also found that the crisis had an integrational effect, and Lee (2009) by applying a cointegration test found that interdependence among ASEAN countries had increased after 1997. Almost a decade later, Dewandaru et al. (2015) came to the same conclusion in their study. Lee (2009) uses a cointegration test to study the effect of financial crisis on the level of co-movement among ASEAN markets and finds that the level of interdependence increases after the 1997 financial crisis. Dewandaru et al. (2015) note that the 1997 financial crisis greatly increased interdependence in the Asian market. More recently, Jiang et al. (2017), found by utilizing wavelet and copula estimation methods that the countries in the region did not move in unison but in time lag in their stock markets' otherwise highly similar response.

Many studies have noted the strong relevance of domestic events in the US and their international effect on stock markets. Amongst others, Copeland and Copeland (1998), Janakiraman and Lamba (1998) and Jeong (1999) all found that there was a very noticeable co-movement between international stock markets and the US stock market, which some of the authors argued, shows a close interrelationship between the markets of different regions. Moreover, by applying the Copula-GARCH model to data they gained from the FTSE100 and S&P500 stock indices, Xiao and Dhesi (2010) show strong co-movement between the US and UK stock markets. Pilajk (2013) also found that co-movement between the seven government bond markets and that of the US is certainly present, however domestic macroeconomic factors influence how rapidly the adjustment takes place. Engsted and Tanggaard (2006) studied the co-movement of US and German bond markets between 1975 and 2003 and came to the conclusion that the most important macroeconomic factor influencing it was inflation data, usually that generated in the American economy. In an earlier study of the two authors (Engsted–Tanggaard 2001) used VAR models to determine the causes of co-movement in the Danish stock and bond markets and found that unlike in the US, news in Denmark about higher future inflation lead to an increase in expected future stock returns, and that excess stock return news and excess bond return news are negatively correlated. Meanwhile, relying on the same methodological approach as this paper does, Albulescu et al. (2015) found strong correlations among European stock markets after transforming time series data into a series of wavelet frequencies.

3. Methodology

In this paper, the analysis is mainly based on wavelet coherence method and copula methods. The co-movement of the analyzed variables is determined by wavelet method by transforming time series into frequencies. For ease of observation and implementation, color maps are used for the plots. In periods where significant co-movement was measured, various copulas are applied to investigate the dependence of the variables. A range of copulas including symmetric and asymmetric copulas help us to identify the nature of the dependence.

3.1. Wavelet analysis

Wavelet transform methods were favored over Fourier transform due to practical reasons. While the Fourier transform could possibly help the research by providing it with the ability to convert information from time domain into the frequency domain, however it could only do so much, i.e. only help us detect frequency. On the other hand, the wavelet transform is capable of exhibiting both spatial (time) and wave-number (frequency) information. Its benefit is therefore manifested in the fact that it can fulfil all the requirements of a comprehensive financial time series analysis at once. In addition, a further advantage of wavelet transformation stems from its special characteristic of it allowing the avoidance infinite differentiability and a smoother interpolation (In–Kim 2013, Sanderson 2010).

The name of the methodology was constructed to mean 'little waves'. The term itself was introduced by Morlet et al. (1982). Chui (1992), and Strang and Nguyen (1996) provide good introductions to wavelets. Gencay et al. (2002) discusses and illustrates how wavelets can be applied in economics and finance.

Wavelets can be thought of as small, localized oscillations. Unlike Fourier series, locality can be achieved in both the time and frequency domains simultaneously, providing a natural foundation for representing nonstationary functions. We define a wavelet $\varphi \in L^2(R)$

$$C_\varphi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega > 0 \qquad (1)$$

where $\psi(\omega)$ is the Fourier transform of $\varphi(\mathrm{x})$ and C_φ is the wavelet admissible constant. Condition (1) is referred to as the admissibility condition and ensures that the wavelet is localized in frequency. The admissibility condition also implies that $\psi(0) = 0$ so that

$$\int_{-\infty}^{\infty} \varphi(x)dx = 0 \qquad (2)$$

which ensures $\varphi(x)$ is localized in time (as it implies $\varphi \in L_1(R)$) and is oscillatory. The continuous wavelet transform (CWT) is defined as the integral over all time of the signal multiplied by scaled, shifted versions of the wavelet function φ (*scale, position, time*)

$$C\ (scale, position) = \int_{-\infty}^{\infty} x_t\ \varphi(scale, position, time)dt \qquad (3)$$

The results of the CWT are many wavelet coefficients *C*, which are a function of scale and position. The scale and position can take on any values compatible with the region of the time series x_t. Multiplying each coefficient by the appropriately scaled (dilated) and shifted wavelet yields the constituent wavelets of the original signal. If the signal is a function of a continuous variable and a transform that is a function of two continuous variables is desired, the continuous wavelet transform (CWT) can be defined as

$$F(a,b) = \int x_t\ \varphi\left(\frac{t-a}{b}\right) dt \qquad (4)$$

with an inverse transform of :

$$x_t = \iint \mathrm{F(a,b)}\ \varphi\left(\frac{t-a}{b}\right) da\ db \qquad (5)$$

where $\varphi(t)$ is the basic wavelet and a, b ∈ R are real, continuous variables. To capture the high and low frequencies of the signal, the wavelet transform utilizes a basic function (mother wavelet) that is stretched (scaled) and shifted.

3.2. Marginal distribution: GJR GARCH

In order to analyse the tail dependency, a copula-based estimation was applied, while to figure out the marginal distribution, the GJR-GARCH model was picked following the work of Glosten et al. (1993). Generalized autoregressive conditional heteroscedastic (GARCH) models have a long and comprehensive history, they are not free of limitations (for details, see Kiss 2017). For example, he documents that stock returns are negatively correlated to changes in returns volatility, implying that volatility tends to rise in response to bad news and fall in response to good news. An asymmetric GARCH model, popularly known as GJR-GARCH model, deals with the limitation of symmetric GARCH models. In accordance with Shahzad et al. (2016), we assume that the marginal distribution for each returns and volatility are characterized by the GJR-GARCH(1,1). This model is utilized to capture the asymmetric effect. The GJR-GARCH- skewed t model examines the asymmetric volatility by inserting a dummy variable into the standard conditional variance equation. The equations for this model are shown in Eq. (6-8).

$$r_{i,t} = \alpha_i + \varepsilon_{i,t} \qquad (6)$$

$$\varepsilon_t | I_{t-1} = h_{i,t} z_{i,t} \qquad z_{i,t} \sim \text{skewed} - \mathrm{t}(z_{i,t}, \lambda_i, \Phi_i) \qquad (7)$$

$${h_{i,t}}^2 = \omega_i + \theta_i {h_{i,t-1}}^2 + \zeta_i I(\varepsilon_{i,t-1} < 0)\varepsilon^2{}_{i,t-1} + \delta_i \varepsilon^2{}_{i,t-1} \qquad (8)$$

where $r_{i,t}$ denotes i stock returns at time t; I_{t-1} represents the information set at time t-1, ${h_{i,t}}^2$ denotes the conditional variance at time t. I(·) = 1 when $\varepsilon_{i,t-1}$ is negative, otherwise I(·)=0. If δ_i is larger than 0, then leverage effect is present in the conditional variance, and this means that a negative shock has a larger impact on returns and volatilities.

3.3. Copulas method

A symmetric copula method is applied in this paper in order to examine tail dependency. Copulas have recently become a sophisticated modelling asset in many fields where multivariate dependence is of interest. In finance, these models are primarily used for asset pricing, credit scoring, risk modelling, and risk management (e.g. Bouye et al. 2000, Embrechts et al. 2003).

The inversion method is used to acquire the copulas by substituting the information from the joint distribution with the marginal functions. This substitution is important for sorting out the effects of the marginal distribution on the tail dependence. Sklar theorem provides the theoretical explanation for copula applications and it is represented in equation (9) (Yan 2007). A copula is a multivariate distribution whose marginals are all uniform over (0, 1). For a p-dimensional random vector U on the unit cube, a copula C is

$$C(u_1, u_2, \dots, u_p) = \Pr(U_1 \leq u_1, U_2 \leq u_2, \dots, U_p \leq u_p) \tag{9}$$

Combined with the fact that any continuous random variable can be transformed to be uniform over (0, 1) by its probability integral transformation, copulas can be used to provide multivariate dependence structure separately from the marginal distributions. Copulas first appeared in the probability metrics literature. Let F be a p-dimensional distribution function with margins $F_1, \dots, F_p$. A p-dimensional copula C such that for all x in the domain of F,

$$F(x_1, x_2, \dots, x_p) = \mathrm{C}\{F_1(x_1), F_2(x_2), \dots, F_p(x_p)\} \tag{10}$$

In this paper, we will utilize the Gaussian copula to analyze the potential symmetric tail dependence, the Gaussian copula that is based on Gaussian-distribution and is specified in Eq (11).

$$C_\rho^{Ga}(u_1, u_2) = \Phi_\Sigma(\Phi^{-1}(u_1), \Phi^{-1}(u_2)) \tag{11}$$

where Σ is the 2 × 2 matrix with 1 on the diagonal and ρ otherwise. Φ denotes the cdf of a standard normal distribution while Φ_Σ is the cdf for a bivariate normal distribution with zero mean and covariance matrix Σ.

4. Data

Two kind of dataset were used for this paper. The dataset consists of daily stock and bond market data. Polish, Slovakian, Czech and Hungarian daily returns and volatility were gathered for both stock and bond market. Daily return means the logarithmic difference of the indices or price while the volatility is the difference of daily maximum and daily minimum price or index value from Reuters database.

Stock and long-term government bond market are different in structure as they are order and dealer driven markets respectively, and they differ in length time series. For bond markets, only the common and continuous periods were used for analysis.

Daily stock market indices were analyzed between January 2012 and February 2018, which means 1543 data points. Hungary was considered the most volatile index on average, which resulted in the highest average return.

Table 1 includes the descriptive statistics for stock data. Volatility is measured as the difference of daily maximum and daily minimum price as a percentage of closing price. Return is the changes in daily closing prices.

Table 1 Descriptive statistics for stock data

	N	Mean	Std. Deviation	Minimum	Maximum	Range
Hungary volatility (%)	1543	1.43	0.79	0.32	8.66	8.34
Czech volatility (%)	1543	1.17	0.67	0.28	10.30	10.01
Poland volatility (%)	1543	1.05	0.61	0.26	7.81	7.55
Slovakia volatility (%)	1543	0.64	0.77	-	6.29	6.29
Hungary return (%)	1543	0.05	1.18	-6.45	5.67	12.12
Czech return (%)	1543	0.01	1.03	-7.24	4.57	11.81
Poland return (%)	1543	0.03	1.02	-6.74	4.07	10.81
Slovakia return (%)	1543	0.03	1.08	-8.91	9.55	18.45

Source: Reuters

Table 2 includes the descriptive statistics for bond data. Volatility is measured as the difference of daily maximum and daily minimum price as a percentage of closing mid-price. Return is the changes in daily closing mid-prices.

Table 2 Descriptive statistics for bond data

	N	Mean	Std. Deviation	Minimum	Maximum	Range
Hungary volatility (%)	1305	0.59	0.65	0	5.85	8.34
Czech volatility (%)	1305	0.18	0.55	0	13.22	10.01
Poland volatility (%)	1305	0.72	0.48	0	6.84	7.55
Slovakia volatility (%)	1305	0.43	0.31	0	2.79	6.29
Hungary return (%)	1305	0.01	0.89	-18.96	3.02	12.12
Czech return (%)	1305	-0.04	1.09	-20.79	1.41	11.81
Poland return (%)	1305	-0.01	0.35	-5.26	1.13	10.81
Slovakia return (%)	1305	0.01	0.80	-22.05	8.08	18.45

Source: Reuters

5. Results

The analysis was coded in *R* software package (R Development Core Team 2016) which is a leading, open source software facility for data manipulation, calculation and graphical display. Table 3 shows the correlation matrix including the Pearson correlation coefficients related to stock market data in which the highlighted cells are the ones with significant values lower than 10%. As we can see, Hungary, Czech and Poland data show significant linear correlation while Slovakia stock index seems to be linearly independent from the others. Returns and volatility have positive correlation with other countries' respective data, while returns have negative correlation with own volatility.

Table 3 Correlation matrix for stock market data[10]

	Hungary return	Czech return	Poland return	Slovakia return	Hungary volatility	Czech volatility	Poland volatility	Slovakia volatility
Hungary return	1	.501	.522	-.007	-.148	-.146	-.155	.014
Czech return		1	.553	.016	-.129	-.210	-.163	-.026
Poland return			1	-.018	-.170	-.142	-.250	-.024
Slovakia return				1	-.006	-.012	-.031	.045
Hungary volatility					1	.471	.465	.031
Czech volatility						1	.443	.061
Poland volatility							1	.014
Slovakia volatility								1

Source: author's calculation

Bond market linear dependency was also checked with correlation for both price changes and daily volatility shown in table 4. We found that Hungarian bond price movement is significantly correlated with the bond price movements in Poland and Slovakia. Hungarian volatility is also found to be significantly correlated with Hungarian price movements and also with the other countries bond market volatilities.

These findings confirm our previous assumption regarding the relevance of using an asymmetric model for obtaining marginal distribution.

In order to evaluate the lag-lead relationship and co-movement level between each stock market index on a longer horizon, the paper will utilize a wavelet analysis. This wavelet coherence approach is applied when we want to capture interdependence through time and frequencies. The frequencies in this instance stand for the duration in days within which a movement in one variable affects the other variable through a specific time period. The dataset and wavelet coherence used in this paper are carried out solely in pairs with Hungary.

The horizontal axis stands for the time period, while the vertical axis for the frequency. The bar on the right represents the strength of the dependence between two variables. Red shows that the dependency is strong, while deep blue signifies low dependency between the variable pairs. Correspondingly, the black thick line scattered around in the red area represents strong coherency at the 5% significance level with respect to that frequency and time period.

[10] Values with p value lower than 0.1 are highlighted in the table

Table 4 Correlation matrix for bond market data[11]

	Hungary return	Czech return	Poland return	Slovakia return	Hungary volatility	Czech volatility	Poland volatility	Slovakia volatility
Hungary return	1	.012	.232	.063	-.064	-.013	-.038	-.027
Czech return		1	.027	.039	.030	-.015	-.017	.034
Poland return			1	.103	-.052	-.015	-.101	-.067
Slovakia return				1	-.008	.005	-.008	-.013
Hungary volatility					1	.124	.404	.219
Czech volatility						1	.026	.076
Poland volatility							1	.290
Slovakia volatility								1

Source: author's calculation

The stock market returns have strong interdependence in the short term at 1 day to 5 days frequency, as does stock market volatility. The interdependence between the data pairs seem to be constant over the examined period. Copula methods confirmed positive tail interdependency, which means that massive changes in return and volatility can be reflected in other national markets while the low values have no fertilization effect. According to the lagged models, we cannot identify the dominant country within the pairs.

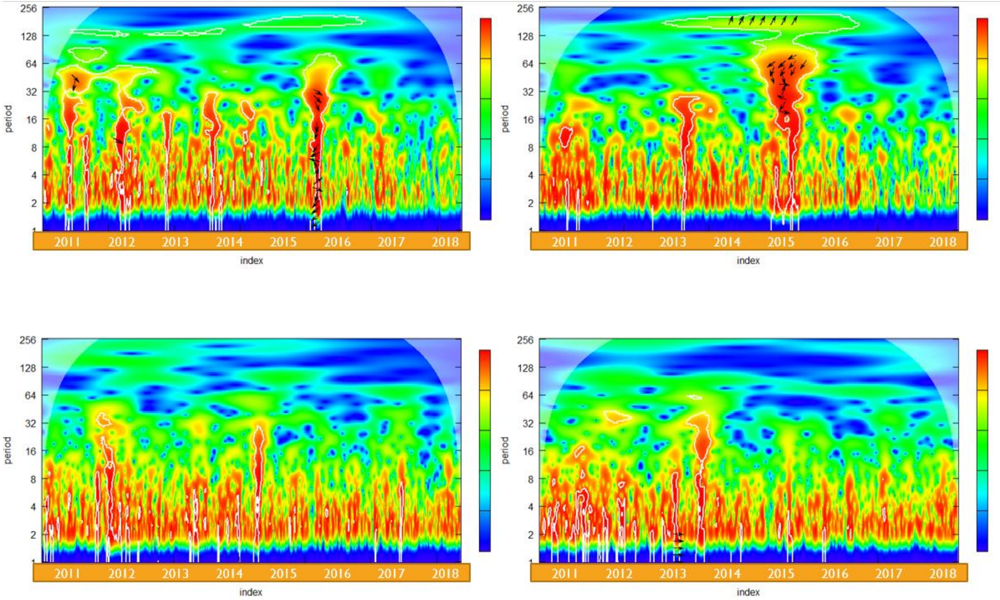
The bond market seems to be more complicated than the stock market. Czech bond data seems to be non-continuous and not as liquid as the others. As it is illustrated on figure 1, Hungary seems to have been co-moving with Poland and Slovakia in terms of bond prices until the beginning of 2017. After the first quarter of 2017, the Hungarian bond price movements became increasingly independent from Poland and Slovakia. The price changes impact can be measured for up to 64 for days as it is reflected on the upper maps of the following graph. The wavelet analysis of Hungary – Poland co-movement is illustrated on the left while Hungary – Slovakia is illustrated on the right graphs. The volatility is visualized in the bottom graphs. As we can see in spite of the independent price movement after 2017, significant volatility co-movement was detected over the whole period.

Copula methods confirmed positive tail interdependency, which means that massive changes in return and volatility can be reflected in other country's markets while the low values have no fertilization effect. Figure 2 shows the result of the Gaussian copula's ρ parameter for various lagged models. The negative values show whether the positive tail dependency has a lasting impact on the Hungarian market from effects starting on the Slovakian market and the opposite on the positive numbers. According to the lagged models, we can identify Slovakia's bond market

[11] Values with p value lower than 0.1 are highlighted in the table

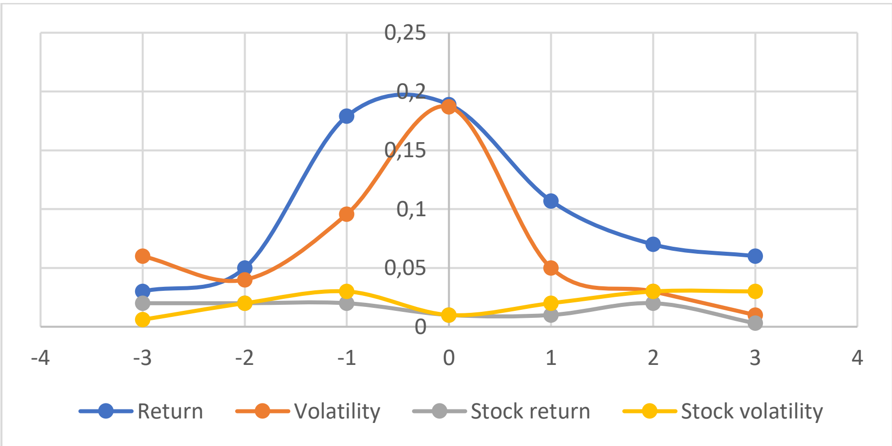
dominating the Hungarian bond market as changes on the Slovakian bond market can have protracted impact on the Hungarian market.

Figure 1 Wavelet squared coherence on bond market return (upper) and volatility (bottom) between Hungary and Poland (on the left) and Hungary and Slovakia (on the right)



Source: author's calculation

Figure 2 Coefficients from lagged Guassian copula models to detect causality between Hungary and Slovakia



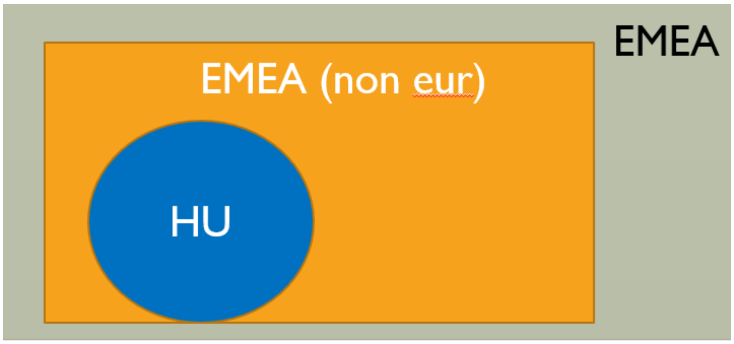
Source: author's calculation

6. Conclusion

As a result of our wavelet and copula approach, we can conclude the stock markets have been moving together with positive tail dependency but no dominant market was detected within the region under study. We can infer that stock markets are integrated to the global markets, therefore all of the countries within the region are following the same pattern and they react to global events rather than regional ones. In case of bond markets, we detected price return interdependency after the first quarter of 2017, which is likely to have been caused by the self-financing program (by the National Bank of Hungary) in long term bonds. The central bank's program aimed to make the Hungarian bond market more or less independent from international financial turmoil. As a result of the program, Hungarian monetary policy became less transparent, while the domestic banking system was captured by the state, however in the meantime, has certainly became more independent on a price level. In spite of the independent price return on bond markets, we can still detect interdependent volatility within the market which means volatility on international markets continues to affect the Hungarian market. Turbulence in the foreign bond market causes turbulence in the Hungarian market as well, so volatility can be identified as one of the certain fertilization channels.

As a result of the symmetric copula tests we can conclude the Slovakian market dominates the Hungarian market. It could be caused on the one hand, by the shared set of investors from the countries of the CEE region, on the other by the euro denominated debts in Slovakia, which allow it to enjoy the advantage of broader acceptance of its currency without FX risk to the investors. Hungary seems to be the bottleneck within the region, as Hungary is the only country offered 'junk' or not recommended sovereign debt by credit agencies. We can infer that the investors, who invest into Hungary also invest in the region, while CEE investors might not invest in Hungary due to their risk appetite or investment policy. As a result of this phenomenon if something happens to CEE investors, it certainly affects the Hungarian bond market, while Hungarian bond market investors are just a smaller proportion compared to CEE investors as you can see it on figure 3.

Figure 3 The disposition of investors within the region



Source: author's construction

References

Albulescu, C.T. – Goyeau, D. – Tiwari, A.K. (2015): Contagion and dynamic correlation of the main European stock index futures markets: a time-frequency approach. *Procedia Economics and Finance*, 20, 19–27.

Bouye, E. – Durrleman, V. – Bikeghbali, A. – Riboulet, G. – Rconcalli, T. (2000): Copulas for finance – A reading guide and some applications. Working paper, Goupe de Recherche Op´erationnelle, Credit Lyonnais.

Copeland, M. – Copeland, T. (1998): Lads, lags, and trading in global markets. *Financial Analysts Journal*, 54, 70–80.

Chui, C. K. (1992): *An Introduction to Wavelets*. San Diago: Academic Press

Dewandaru, G. – Masih, R. – Masih, A.M.M. (2015): Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets. *Physica A: Statistical Mechanics and its Application*, 419, 241–259.

Embrechts, P. – Lindskog, F. – McNeil, A. (2003): Modelling dependence with copulas and applications to risk management. In Rachev, S. (ed.): *Handbook of Heavy Tailed Distribution in Finance*. Elsevier, 329–384.

Engsted, T. - Tanggaard, C. (2001): The Danish stock and bond markets: Comovement, return predicatbility and variance decomposation, *Journal of Empirical Finance*, vol. 8 no.3, 243 - 271

Engsted, T. – Tanggaard, C. (2006): The co-movement of US and German bond markets. *International Reviwe of Financial Analysis*, 2, 2, 172-182.

Gencay, R. – Selcuk, F. – Whitcher, B. (2002): An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. London: Academic Press.

Glosten, L.R. – Jagannathan, R. – Runkle, D.E., (1993): On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48, 5, 1779–1801.

Goldstein, M. – Michael, M. (1993): The integration of world capital markets. *IMF Working Paper*, No.93/95, 1–6.

Grubel, H. (1968): International diversified portfolio: welfare gains and capital flows. *American Economic Review*, 58, 1299–1314.

In, F. – Kim, S (2013): *An Introduction to Wavelet Theory in Finance: A wavelet mulstiscale approach.* World Scientific Publishing

Janakiraman, S. – Lamba, A.S. (1998): An empirical examination of linkages between Pacific-Basin stock markets. *Journal of International Financial Markets, Institutions and Money*, 8, 155–173.

Jeong, J. (1999): Cross-border transmission of stock price volatility: evidence from the overlapping trading hours. *Global Financial Journal*, 10, 53–70.

Jiang, Y. – Nie, H. – Monginsidi, J. (2017): Co-Movement of ASEAN stock markets: New evidence from wavelet and VMD-based copula tests. *Economic Modelling*, 64, 384 –398

Kiss, G. D. (2017): Volatilitás, extrém elmozdulások és tőkepiaci fertőzések. Szeged: JATEPress Kiadó.

Lee, K. L. (2009): Convergence and interdependence between ASEAN-5 stock markets. *Mathematics and Computers in Simulation*, 79, 2957–2966.

Morlet, J. – Arens, G. – Fourgeau, E. – Giard, D. (1982): Wave propagation and sampling theory. *Geophysics,* 47, 2, 222–236

Pilajk, V. (2013): Bond markets co-movement dynamics and macroeconomic factors: Evidence from emerging and frontier markets, *Emerging Markets Review*, 17, 29–43.

R Development Core Team (2016) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna

Sanderson, J. (2010): Wavelet methods for time series with bivariate observations and irregular samping grids; PhD dissertation, University of Bristol.

Shahzad, S.J.H. – Nor, S.M. – Kumar, R.R. – Mensi, W. (2016): Interdependence and contagion among industry-level US credit markets: an application of wavelet and VMD based copula approaches. *Physica A*, 466, 310–324.

Solnik, B.H. (1974): Why not diversify internationally. *Financial Analysis Journal,* 30, 48–54.

Strang, G. – Nguyen, T. (1996): *Wavelets and Filter Banks. Wellesley*. MA: Wellesley–Cambridge Press.

Xiao, L. – Dhesi, G. (2010): Dependence structure analysis using Copula-Garch modedl: An application to UK and US stock markets, In Kovács, P. – Szép, K. – Katona, T. (eds.): *Proceeding of the Challenges for Analysis of the Economy, the Businesses and Social Progress International Scientific Conference,* 624–635.

Yan, J. (2007): Enjoy the joy of Copulas with a Package copula. *Journal of Statistical Software*, 21, 4, 1–21.