

Intraday Contagion and Tail Dependence between Stock Markets in Frankfurt, Vienna and Warsaw

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Abstract

In this paper we investigate intraday relationships between three diverse European stock markets: in Frankfurt, Vienna and Warsaw. Two of them are developed, while the last one is an emerging market. Stock exchanges in Vienna and Warsaw are competing markets in the CEE region. On the basis of 5-minute returns we analyze the tail dependence between major indices of the markets. Comparison of the dependence in the tail and in the center of the joint distribution (via spatial contagion measure) indicate strong contagion between the markets and very strong impact of German market on relations between stock exchanges in Vienna and Warsaw.

Keywords: contagion, CEE markets, risk management, tail dependence, copula

JEL codes: G01, G11, G15

1. Introduction

Globalization has enabled investors to invest on financial markets all over the world. Particularly, they can invest on a variety of stock markets, both developed and emerging, also regardless of their geographical location. This, in turn, is an opportunity to diversify investors' portfolio due to differences in behavior of stock markets in distant parts of the world or between markets on different stage of development. However, globalization also has tightened relationships between stock markets making such an international portfolio diversification a very difficult task. Hence, the study of the existence and strength of relations between stock markets is important for risk management and optimal portfolio allocation.

In the recent years large amount of financial and econometric literature has analyzed both short- and long-term linkages between prices, returns and volatility on different stock exchanges to give better description of information flow between markets and markets comovements. First papers were concentrated on linkages between developed markets (e.g. Hamao et al., 1990; Cappiello et al., 2006). In the most recent years also linkages between developed and emerging markets have been examined (Chen et al., 2002; Kim et al., 2005; Syllignakis and Kouretas, 2011), however only few of them study such relationships in Europe (Stavárek and Heryán, 2012). Moreover, results of studies of interrelationships between developed and emerging European stock markets still lack consensus.

On the basis of daily data from the period 1993 – 2002, Voronkova (2004) shows the existence of cointegration between European developed markets and stock markets in Czech Republic, Hungary and Poland. Additionally, Syriopoulos (2007) indicates that long-term linkages between emerging CEE markets (Czech Republic, Hungary, Poland and Slovakia) and developed markets (Germany and US) are stronger than among CEE countries itself. On the other hand, Černý and Koblas (2005) and Égert and Kočenda (2007) do not find long-term relations between intraday data of emerging and developed European stock markets.

More common results are observed when short-term relations are investigated. Hanousek et al. (2009) prove significant spillover effects on stock markets in Prague, Budapest and Warsaw. However, these stock markets are also significantly influenced by returns of DAX, the main index of stock exchange in Frankfurt. The impact of Frankfurt Stock Exchange is even stronger than the impact of any of the emerging markets. Similar results are evidenced by Černý and Koblas (2005). Important role of developed European markets for CEE emerging markets is also indicated by Égert and Kočenda (2007).

On the basis of intraday data, they show significant causalities between returns of CEE markets and causal relations from developed to emerging markets. Strong correlations between CEE markets and markets in euro area is confirmed by Gjika and Horvath (2013). They show that accession of CEE countries to EU increased correlations. On the other hand, Égert and Kočenda (2011) show something opposite. They find very little positive time-varying correlations among intraday returns of BUX, PX50 and WIG20. Correlations between these markets and Western European stock markets also are very weak.

The existence of high or very low correlation between stock markets is not the only factor that must be taken into account in portfolio diversification. Changes in linkages between markets during bear and bull market or during calm and turbulent periods are also of great importance. If correlation between markets increases during crisis then a loss on one of them will be accompanied by a loss on the other. This leads to the issue of contagion between stock markets. In the literature there is lack one common formal definition of contagion, but there are different approach to it. However, in general all these definitions agree that contagion occurs when interdependencies between markets in turbulent time are higher than usually, in tranquil time (see for example Forbes and Rigobon, 2002). It should be noted here that there is a difference between strong interdependency between markets and contagion. Contagion does not exists when two markets are highly correlated during both tranquil and turbulent time. It exists only when a shift in correlation is observed.

Majority of empirical works on contagion in based on data connected with various financial crises. The natural approach is to test change in the interdependence structure, usually by comparison of correlations between markets, before and after the crisis. Recently such comparisons have been done by application of various conditional correlation (CC) models. Also comovement of European stock markets have been analyzed mainly via multivariate GARCH models. Using Constant Conditional Correlation (CCC) and Smooth Transition Conditional Correlation (STCC) models, Savva and Aslanidis (2010) show that markets in Czech Republic, Hungary and Poland exhibit stronger correlations with euro area than smaller CEE markets, like Slovenia and Slovakia. On the basis of Dynamic Conditional Correlation (DCC) GARCH models Syllignakis and Kouretas (2011) show that 2007-2009 global financial crisis significantly shifted conditional correlation between developed markets (German and US) and emerging CEE markets.

However, there are considerable statistical difficulties involved in testing a shift in correlation between markets. They are caused by quite different properties of financial time series in tranquil and turbulent time. Hence, another approach to study contagion is based on analysis of the difference in behavior of the joint distribution function describing markets under study in the central part and in the tail region of its domain (see for example Durante et al., 2014).

In this paper we study contagion between three European stock markets, namely stock exchanges in Frankfurt (FSE), Vienna (VSE) and Warsaw (WSE). They are specially selected stock markets because they differ considerably, but also share some similarities. Frankfurt Stock Exchange is an example of a large developed market. It is one of the largest and the most important stock market in Europe. Its capitalization is about eighteen times greater than capitalization of Vienna Stock Exchange (VSE) and about eleven times greater than Warsaw Stock Exchange (WSE)¹. Vienna Stock Exchange, somehow smaller than FSE, is also a developed market. On the other hand, stock exchange in Warsaw is still seen as an emerging market. Despite these differences both, VSE and WSE are among the largest stock markets in Central and Eastern Europe and they are appropriate example of small important European markets. Moreover, both of VSE and WSE ensure enough liquidity to be taken into account in a global diversification issue. Hence, in the paper we analyze contagion between large and smaller stock markets, but also between developed and emerging stock markets. It will show, how similarities and differences between markets under study are reflected in contagion effects.

Analysis of contagion between the abovementioned stock markets is performed on the basis of intraday returns of the main indices of the stock markets under study from the period between March

¹ At the end of July 2015 capitalization of FSE was at the level of 1 625 718 mln € compared to 147 417mln € of capitalization of WSE and 90 932mln € capitalization of VSE. [Source: Federation of European Securities Exchanges, www.fese.eu]

22, 2013 and September 5, 2013². To study interrelationships between stock markets we apply spatial contagion measure proposed by Durante and Jaworski (2010) and conditional contagion measure.

The rest of the paper is organized as follows. In the next section we give short description of spatial contagion measure applied in the paper. We also propose conditional contagion measure to analyze the impact of one stock market to contagion between other markets. In Section 3 we present and analyze in detail the data which we use in the empirical study in Section 4. Short summary concludes the paper.

2. Spatial Contagion Measure

2.1 Contagion Measure between Two Markets

According to the description presented in the Introduction, there is a contagion between two markets if the correlation in turbulent time is stronger than in tranquil time. During crises large decreases of stock prices are observed and negative returns dominate. On the other hand, in tranquil time returns vary around zero. Hence, contagion may be understood as a difference between correlation of very low negative stock returns (in the lower tail of returns distribution) and correlation of returns from around their median (in the central part of returns distribution). This is a basis of spatial contagion measure proposed by Durante and Jaworski (2010) (see also Durante et al., 2014).

Let X and Y be a random variables that represent returns of two stock markets. Dependence between them is described by means of a copula C . For $\alpha_1, \alpha_2, \beta_1, \beta_2 \in [0,1]$ consider two following sets of \mathbb{R}^2 : the *tail* set T_{α_1, α_2} and the *central* set M_{β_1, β_2} given by the following formulas:

$$T_{\alpha_1, \alpha_2} = [-\infty, q_X(\alpha_1)] \times [-\infty, q_Y(\alpha_2)] \quad (1)$$

$$M_{\beta_1, \beta_2} = [q_X(\beta_1), q_X(1 - \beta_1)] \times [q_Y(\beta_2), q_Y(1 - \beta_2)], \quad (2)$$

where q_X and q_Y are the quintile functions associated with random variables X and Y , respectively.

The tail set T_{α_1, α_2} represents negative returns in turbulent time that are smaller than a given threshold. On the other hand, the set M_{β_1, β_2} corresponds to tranquil time and it describes returns in the central part of the joint distribution.

Following Durante and Jaworski (2010) and Durante et al. (2014) we say that there is *symmetric contagion* between X and Y at a given threshold level $\alpha \in (0,0.5)$ if Spearman correlation in the tail is greater than Spearman correlation in the central part of the distribution, i.e. if

$$\rho(X, Y | (X, Y) \in T_{\alpha, \alpha}) > \rho(X, Y | (X, Y) \in M_{\alpha, \alpha}), \quad (3)$$

where $\rho(X, Y | A)$ is a Spearman correlation between X and Y on a given set A .

In the above definition of contagion, however, the choice of the threshold α strongly influences final result. For some α formula (3) may be true, but for another α they can be false. To avoid a problem caused by arbitrary choice of threshold α Durante et al. (2014) define “symmetric contagion measure” between X and Y by the formula:

$$\gamma(X, Y) = \frac{1}{\lambda(L)} \lambda(\{\alpha \in L | \rho(X, Y | (X, Y) \in T_{\alpha, \alpha}) > \rho(X, Y | (X, Y) \in M_{\alpha, \alpha})\}), \quad (4)$$

where $L \subset [0,0.5]$ is a connected set of possible values of thresholds α , and λ is Lebesgue measure on $[0,1]$.

² We use intraday data due to very fast and significant reaction of stock markets to important public information. For example, Gurgul and Wójtowicz (2014, 2015) show that stock markets in Vienna and Warsaw react to US macroeconomic news just in first minutes after news announcements.

Spatial contagion measure defined above simply counts how many times correlation between X and Y computed in the tail set $T_{\alpha,\alpha}$ is significantly greater than correlation computed in the central part $M_{\alpha,\alpha}$ of the joint distribution of X and Y . However, it tells nothing about the size of these differences.

Analytical computation of the above contagion measure is very difficult. To overcome this difficulty and also to avoid drawbacks caused by any assumption about functional form of a copula, nonparametric empirical copulas are applied. Correctness of such approach follows from empirical copulas properties discussed by Schmid and Schmidt (2007).

The whole computation procedure of spatial contagion measure is as follows (for details see Durante et al. 2014):

1. Univariate return series are filtered via appropriate AR-GARCH models.
2. Given interval L is equally divided into a finite number n equidistant points α_i .
3. For each threshold $\alpha = \alpha_i$ from interval L bivariate data is classified into appropriate tail set $T_{\alpha,\alpha}$ and central set $M_{\alpha,\alpha}$.
4. In each set univariate empirical cumulative distribution functions are constructed and Spearman's correlations $\rho(T_{\alpha,\alpha})$ and $\rho(M_{\alpha,\alpha})$ are computed.
5. For each α null hypothesis that $\rho(T_{\alpha,\alpha}) = \rho(M_{\alpha,\alpha})$ against the $\rho(T_{\alpha,\alpha}) > \rho(M_{\alpha,\alpha})$ is tested.³
6. Contagion measure is then computed as

$$\hat{\gamma}(X, Y) = \frac{\#\{i: \rho(T_{\alpha_i, \alpha_i}) > \rho(M_{\alpha_i, \alpha_i})\}}{n}.$$

2.2 Conditional Contagion Measure

It is well known that relationships between two stock markets are also influenced by their relationships with other markets. To take this fact into account bivariate relations are frequently studied by means of multivariate models with additional exogenous variables. Hence, we propose to define conditional contagion measure between two markets X and Y dependent on the market Z when:

$$\rho(X, Y | (X, Y) \in T_{\alpha,\alpha} | Z \in T_{\alpha_0}) > \rho(X, Y | (X, Y) \in M_{\alpha,\alpha} | Z \in T_{\alpha_0}) \quad (5)$$

or

$$\rho(X, Y | (X, Y) \in T_{\alpha,\alpha} | Z \in M_{\alpha_0}) > \rho(X, Y | (X, Y) \in M_{\alpha,\alpha} | Z \in M_{\alpha_0}). \quad (6)$$

Formula (5) describes contagion between X and Y on a given level α when Z is in the lower tail T_{α_0} i.e. when negative returns of Z are observed. Analogously, formula (6) describes linkages between X and Y when Z is in its usual state.

The algorithm of computation of conditional contagion measure is similar to the algorithm for contagion measure described in the previous subsection. However, classification to the tail and central set is performed conditional on variable Z . Moreover, we test not only the significance of the difference of conditional correlations $\rho(T_{\alpha,\alpha} | Z \in T_{\alpha_0}) - \rho(M_{\alpha,\alpha} | Z \in T_{\alpha_0})$ (or $\rho(T_{\alpha,\alpha} | Z \in M_{\alpha_0}) - \rho(M_{\alpha,\alpha} | Z \in M_{\alpha_0})$), but also test the significance of the impact of variable Z on contagion between X and Y , i.e.:

$$H_0: \rho(X, Y | (X, Y) \in T_{\alpha,\alpha}) = \rho(X, Y | (X, Y) \in T_{\alpha,\alpha} | Z \in T_{\alpha_0}) \quad (7)$$

against

$$H_1: \rho(X, Y | (X, Y) \in T_{\alpha,\alpha}) < \rho(X, Y | (X, Y) \in T_{\alpha,\alpha} | Z \in T_{\alpha_0}). \quad (8)$$

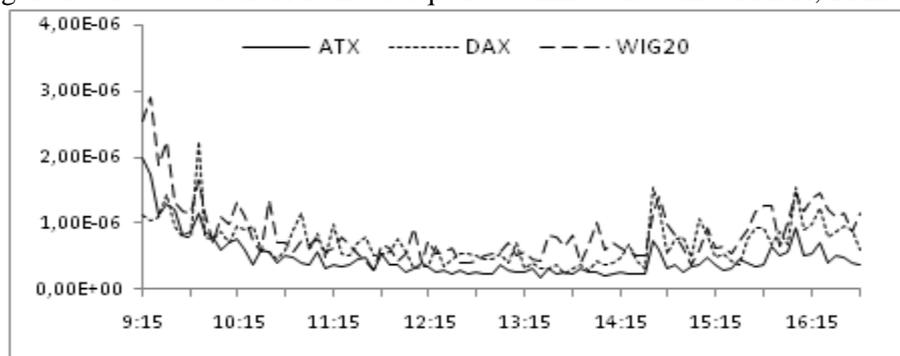
³ To verify this hypothesis we use bootstrap 95% one-sided confidence interval as in Durante et al. (2014).

3. Data

The analysis presented in this paper is based 5-minute log-returns of the main indices of stock exchanges in Frankfurt, Vienna and Warsaw, namely DAX, ATX and WIG20, respectively⁴. Data cover the period from March 22, 2013 to September 5, 2013, but we take into account only returns from days when all the markets were open. There are 111 such common trading days in our sample.

In the analysis of intraday data trading hours on the stock markets must be taken into account because the stock markets under study are open in different hours. In 2013, continuous trading started at 8:55 on VSE and at 9:00 on FSE and WSE. It ended at 17:20 (WSE), 17:30 (FSE) and at 17:35 (VSE). Moreover, on FSE and VSE there were intraday auctions from 13:00 to 13:02 and from 12:00 to 12:04, respectively. Intraday relations can be analyzed only in the periods when all three markets are open that is between 9:00 and 17:20. However, taking into account well known fact that intraday volatility increases at the beginning and at the end of trading sessions we restrict our study to shorter period between 9:15 and 17:00. Restriction of the analysis to this shorter period, however, does not remove completely periodic pattern from volatility series. Figure 1 shows U-shaped pattern observed in intraday return volatility.

Figure 1: Cross-Sectional Means of Squared 5-minute Returns of ATX, DAX and WIG20



Source: authors' calculations

To deal with periodic pattern in volatility we model conditional volatility of 5-min returns by the multiplicative components GARCH model of Engle and Sokalska (2012). In this model conditional volatility of return $r_{t,i}$ at day t and on time i is a product of a daily variance component (h_t), diurnal variance pattern (s_i) and intraday variance component ($q_{t,i}$). The daily variance component is approximated by volatility forecasts from appropriate GARCH model constructed on daily returns. Diurnal variance pattern is approximated by cross-sectional variance of all returns computed on each time i .

4. Contagion – Empirical Results

4.1 Correlations

We start the analysis by describing correlations between intraday returns under study. It will give first insight into relationships between the stock markets. Table 1 contains Spearman and Pearson correlations computed for the whole sample. All of them are significant. Hence, we can conclude that between stock markets under study significantly positive relations are observed. The strongest correlations are between both developed markets in Frankfurt and Vienna, while the weakest link is between VSE and WSE.

⁴ Data come from Bloomberg, Vienna Stock Exchange and Warsaw Stock Exchange.

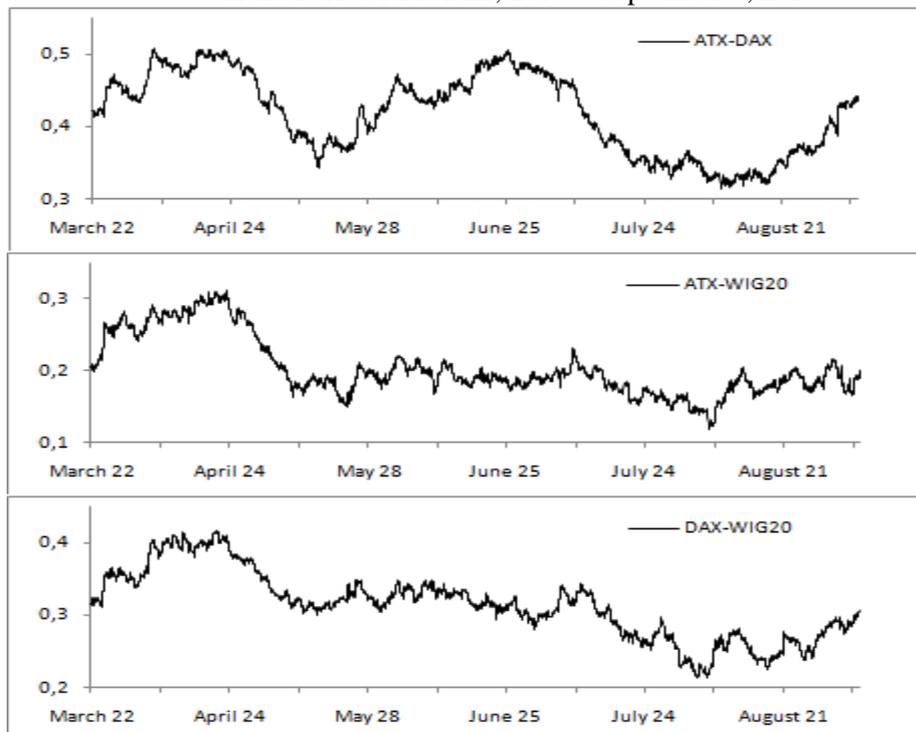
Table 1: Correlations between 5-minute Returns of ATX, DAX and WIG20
in the Period March 22, 2013 – September 5, 2013

	ATX-DAX	ATX-WIG20	DAX-WIG20
Spearman	0.36	0.20	0.28
Pearson	0.42	0.22	0.31

Source: authors' calculations

From literature it is obvious that correlation between returns is not constant, but it varies in time. To illustrate time-varying correlations between the markets we apply trivariate DCC-GARCH model of Engle (2002) with multivariate normal distribution. To model conditional variance of univariate returns we apply AR(5)-GARCH(1,1) models with t-Student distribution and with correction of diurnal pattern in volatility as described in the previous section. Figure 2 presents intraday conditional correlations between the indices. It follows that between March and September 2013 correlation between ATX and DAX varied around unconditional correlations from Table 1. On the other hand, correlation between WIG20 and the other indices decreased to reach the level of about 0.2 or 0.3 for ATX and DAX, respectively.

Figure 2: Intraday Conditional Correlations between ATX, DAX and WIG20
in the Period March 22, 2013 – September 5, 2013



Source: authors' calculations

Presented time-varying correlations between intraday returns of ATX, DAX and WIG20 give very general information about strength of relations between the indices. Computed values of both conditional and unconditional correlations indicate rather strong interdependency, particularly between stock markets in Frankfurt and Vienna. As we mentioned in the Introduction, there is a fine line between interdependence and contagion effect and even very strong correlation does not indicate contagion.

4.2 Spatial Contagion

For each pair of the indices under study we compute spatial contagion measure described in Section 2. We restrict the analysis to the interval $L = [0.05, 0.3]$ which we equally divide into 25 intervals of length 0.01. Hence, we consider 26 threshold parameters α equal to 0.05, 0.06, ..., 0.3. We

do not take into account lower α to ensure that the tail set $T_{\alpha,\alpha}$ is non-empty. On the other hand, in $T_{\alpha,\alpha}$ for α greater than 0.3 data from central part of the distribution start to dominate. Results presented in Table 2 indicate very significant contagion in each pair of the indices. It is visible particularly in the case of DAX and WIG20 where for all threshold values correlation in the tail set is significantly larger than correlation in the central part of the distribution. It means that contagion is observed irrespective of the choice of threshold α . Contagion is present also in the other pairs. Spatial contagion measure equal to 0.808 for ATX and WIG20 means that the difference between correlations in $T_{\alpha,\alpha}$ and $M_{\alpha,\alpha}$ is insignificant only in 5 out of 26 cases.

Table 2: Spatial Contagion Measure between Intraday Returns of ATX, DAX and WIG20 in the Period March 22, 2013 – September 5, 2013

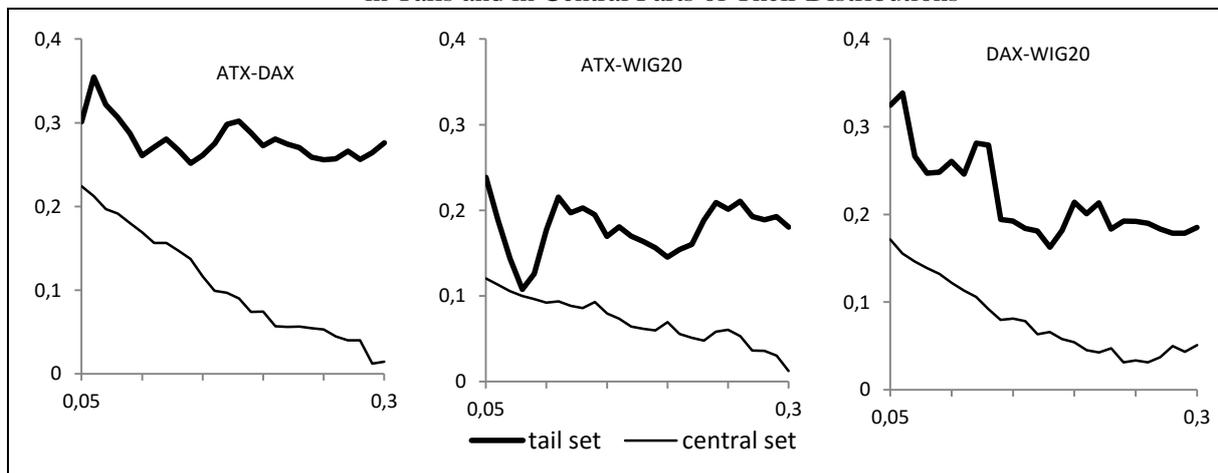
	ATX-DAX	ATX-WIG20	DAX-WIG20
spatial contagion	0.923	0.808	1

Source: authors' calculations

Computed contagion measures only count the number of significant differences between correlation in the tail and in the center of the bivariate distribution. To get more detailed information we should analyze these differences for all thresholds. Figure 3 presents correlations in $T_{\alpha,\alpha}$ and $M_{\alpha,\alpha}$ for the whole sample of α . We can see that the strongest correlation in the tail area (about 0.3) is presented between ATX and DAX. Correlation in the central part of ATX-DAX distribution decreases from 0.22 for $\alpha = 0.05$ to 0.01 for $\alpha = 0.3$. This in turn, increase the difference in correlations in the both sets from 0.08 for $\alpha = 0.05$ to 0.26 for $\alpha = 0.3$. For DAX and WIG20 the difference is almost constant and it varies around 0.14. Similar situation is for contagion between ATX and WIG20 with the exception of the smallest α . In the case of ATX and WIG20, tail correlation is significantly greater for $\alpha > 0.1$.

Comparison of results in Figure 3 with unconditional correlations in Table 1 indicates that tail correlations computed for very small threshold values are close to Spearman correlations computed for the whole samples. On the other hand, correlations in the central part are much lower than correlations presented in Table 1.

Figure 3: Correlations between ATX, DAX and WIG20 in Tails and in Central Parts of Their Distributions



Source: authors' calculations

Results from Table 2 and Figure 3 indicate the existence of very strong intraday contagion between stock markets in Frankfurt, Vienna and Warsaw. It means that these markets are strongly linked during daily turbulences and when bad news is released all three markets react in the very similar way because interrelations between them become more tighten. This is consistent with similarities in reaction of VSE and WSE to US macroeconomic news announcements (Gurgul and Wójtowicz, 2014, 2015). On the other hand, during tranquil periods returns of the indices under study tend to move almost independently.

4.3 Conditional Contagion

To illustrate how linkages between stock markets impact contagion measure between each pair of them we also estimate conditional contagion measures. Estimates results for the same set of α as in the previous subsection and for $\alpha_0 = 0.2$ are reported in Table 3. In the panel A we present conditional contagion between each pair of the markets when returns of third market are in a tail. This corresponds with formula (5). In panel B we present conditional contagion when returns of third market are around their median. This corresponds to formula (6). In parentheses we report the percentage of rejection the null hypothesis in the test (7)-(8) that conditional contagion is stronger than unconditional contagion.

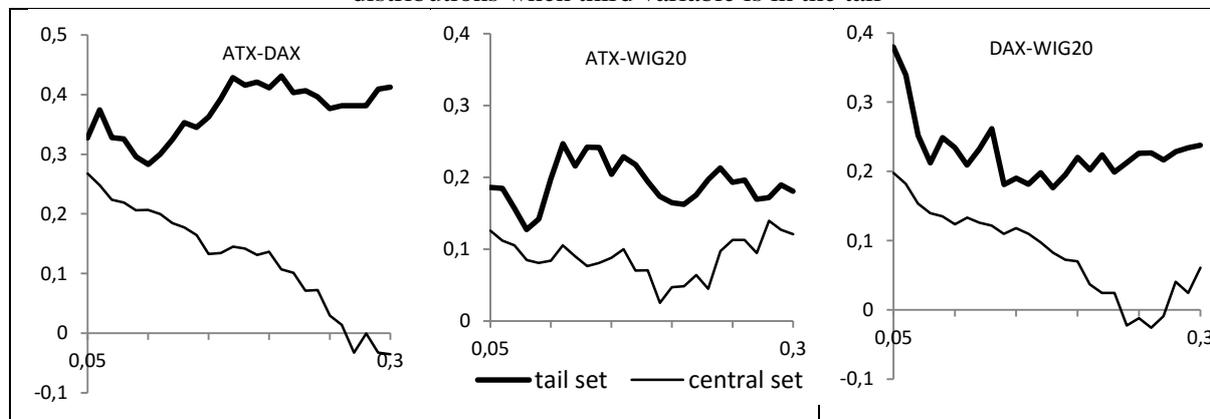
Table 3: Conditional Contagion Measure between Intraday Returns of ATX, DAX and WIG20 in the Period March 22, 2013 – September 5, 2013

Panel A: Conditional contagion measure when third variable is in the tail			
	ATX-DAX	ATX-WIG20	DAX-WIG20
spatial contagion	0.846 (0.5)	0.423 (0)	0.654 (0.077)
Panel B: Conditional contagion measure when third variable is in the center			
	ATX-DAX	ATX-WIG20	DAX-WIG20
spatial contagion	0.231 (0)	0.385 (0.077)	0.808 (0.077)

Source: authors' calculations

Conditional contagion measures in Table 3 are smaller than their unconditional counterparts in Table 2. Moreover, in three cases (ATX-WIG20 when DAX is in the tail, ATX-DAX when WIG20 is in the center and ATX-WIG20 when DAX is in the center) contagion is significant for less than half of considered threshold values α . In particular, it means the lack of conditional contagion between ATX and WIG20 when DAX is in the tail and also when DAX is in the central part of its distribution. However, results in Table 2 confirm the existence of contagion between ATX and WIG20 in general case. Those two facts mean that contagion between ATX and WIG20 strongly depends on DAX and it is only observed when DAX returns drop down dramatically. On the other hand, for DAX and WIG20 the differences between conditional correlations in tails and in the centre are significant for majority of α . It indicates that ATX does not influence contagion between those two markets. Results for the pair ATX and DAX are mixed – conditional contagion is observed only when returns of WIG20 are very low.

Figure 4: Correlations between ATX, DAX and WIG20 in tails and in central parts of their distributions when third variable is in the tail



Source: authors' calculations

When we analyze conditional correlations in tails and in central parts of distributions presented in Figure 4 we can notice that their behavior for ATX-DAX pair is different from Figure 3. Correlations in tail increases while in Figure 3 they are almost constant. They also reach higher values for larger α . Moreover, conditional correlations in the central part are higher for small threshold values and then they strongly decreases to reach even negative values for α greater than 0.25. It seems that restriction of the notion of spatial contagion between ATX and DAX to the tail of WIG20 works as a kind of a filter. However, the differences between correlations in tails and central parts of ATX-DAX is significant only for larger threshold values. It is not in line with the notion of contagion where significant differences should be mainly observed for small values of α .

5. Conclusions

In this paper we analyze and compare interrelations between stock markets in Frankfurt, Vienna and Warsaw. The analysis is performed on the basis of 5-minute data from the period March 22, 2013 – September 5, 2013. Contagion between these stock markets is examined by means of spatial contagion measure (Durante and Jaworski, 2010). However, to describe the impact of each stock market of relationships between the other markets we propose conditional contagion measure.

Results of the empirical study shows strong correlation (both conditional and unconditional) between three markets under study. The strongest correlation is observed between DAX and ATX. Application of spatial contagion measure indicates considerable contagion between all the markets. Difference between correlations in tails and in central parts of index returns distribution is significant for almost all admissible threshold values. This means that on intraday basis the stock markets under study react to bad news in a similar manner.

From the analysis of conditional contagion measure we also conclude that stock market in Frankfurt significantly impacts relationships between stock markets in Vienna and Warsaw. Restriction of the contagion analysis to given part of DAX returns distribution gives insignificant results. On the other hand, ATX does not impact contagion between DAX and WIG20 – it is significant irrespective on values of ATX returns.

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