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GRANGER CAUSALITY ANALYSIS OF THE CEE STOCK MARKETS INCLUDING NONSYNCHRONOUS TRADING EFFECTS

This paper focuses on friction in trading processes in the context of the implications of nonsynchronous trading effects, especially in the CEE stock markets. We analyze the Granger causality, and we investigate both the whole sample May 2004 – April 2012 and two equal subsamples: the 'crisis' period and the 'post-crisis' period. Our results show several causal relationships in the whole sample period, in the case of the group of the biggest CEE stock market indexes and the group of the three Baltic market indexes. Moreover, to accommodate the 'nonsynchronous trading effect II' in the Granger causality tests, we propose a version of a VAR model with a modified dynamic structure of lags for the CEE and US stock market indexes. We observe a pronounced feedback relationship for almost all of the analyzed models, both in the whole sample period and in the two subsamples. In light of our results, it seems that taking into account the 'nonsynchronous trading effect II' plays a crucial role in examining the lead-lag relationships among the world stock markets.

JEL Classification: C32, C58, G15

Keywords: CEE stock markets, market frictions, nonsynchronous trading, Granger causality

1. INTRODUCTION

An event that had significant impact on the group of Central and Eastern European (CEE) emerging markets was the accession to the European Union (EU) on May 1, 2004. Eight countries were successful in the negotiations with the EU and they all accessed the EU. These eight countries, in order of largest population size are: Poland, the Czech Republic, Hungary, the Slovak Republic, Lithuania, Latvia, Slovenia and Estonia (Southall, 2008). For this reason, these eight economies are particulary interesting in many respects. The EU enlargement creates a dynamic financial landscape, unique on a world scale (Syriopoulos, 2007).

This paper presents an analysis of some empirical problems that can be attributed to frictions in the trading processes, especially in the case of the

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eight CEE emerging stock markets. Many researchers place nonsynchronous trading in a broader class of market frictions. Some authors distinguish between two nonsynchronous trading effect problems. The first problem, called the 'nonsynchronous trading effect I', occurs when we analyze one selected domestic stock market. The second and potentially serious problem, called the 'nonsynchronous trading effect II', occurs when we investigate the relations between the equity markets in various countries. In this context, the Granger causality analysis of the indexes of the CEE emerging stock markets is a particularly important and interesting problem. It is worth stressing that the use of daily closing prices from stock exchanges in various countries is potentially highly problematic. International stock markets have different trading hours and the time series of market index returns have unequal numbers of observations. Some of the studies by-pass the non-synchronicity problem by using weekly or monthly data. In this paper, we investigate the Granger causality in the eight CEE stock markets using a daily data-matching process. In our research, we compare the empirical results for both the whole sample and two equal subsamples: 27.02.2007 – 9.03.2009 as the 'crisis' period and 10.03.2009 – 4.03.2011 as the 'post-crisis' period (each consists of 444 observations). It was necessary to appoint one date as the beginning of the 'crisis' period for all countries, therefore we suggest February 27, 2007 following Dooley and Hutchison (2009, p. 1340), and March 9, 2009 as the end of the 'crisis' period, because of the global minimum of the S&P500 index value in the whole sample, achieved on this day. The overall S&P500 index fell from 1399.04 (February 27, 2007) to 676.53 (March 9, 2009). It lost 51.64% of its previous value during the 'crisis' period. Dooley and Hutchison (2009) focused their analysis on the links between the US and a broad range of emerging stock markets over the subprime crisis sample period from February 2007 to March 2009. They analyzed three phases of the subprime crisis, and they claimed that the first phase of the crisis ran from February 27, 2007. Mun and Brooks (2012) extended Dooley's and Hutchison's analysis to a broader set of developed and emerging markets, and also extended the whole sample period to February 2010. Moreover, Frank and Hesse (2009) found that the end of February 2007 was a period when early signs of stress began to emerge in global markets prior to the time when the subprime crisis was revealed in mid-2007.

We use the bivariate VAR Granger causality model to examine interdependences between pairs of the selected CEE stock markets. However, the general VAR approach should not be used directly when the 'nonsynchronous trading effect II' is a concern, as it only allows for lagging all the independent variables in the same manner. This study contributes to the existing literature by proposing a version of the bivariate VAR model with a modified dynamic structure of lags to accommodate the 'nonsynchronous trading effect II' in the Granger causality tests. In light of our results, it seems that taking into account the 'nonsynchronous trading effect II' plays a crucial role in examining the lead-lag relationships among the world's stock markets, especially in the case of markets located in different time zones. The fundamental role of the VAR approach and Granger causality tests in the transmission mechanisms of crisis shocks confirms the importance of the analyzed economic problem. In their important paper, Forbes and Rigobon (2002) examined various crisis periods in the context of contagion. To adjust for the fact that stock markets are open during different times, as well as to control for serial correlation in stock returns and any exogenous global shocks, they utilized a VAR framework to estimate cross-market correlations. They stressed that the VAR approach is appropriate in cases when the feedback from the second country to the crisis country (i.e. the US) is expected to be small.

The remainder of this study is organized as follows. Section 2 presents a brief analysis of the 'nonsynchronous trading effect I'. In Section 3, we present the 'nonsynchronous trading effect II' and some data-matching processes. Section 4 specifies a methodological background and a brief literature review of the theoretical framework concerning the Granger causality analysis. In Section 5, we present the data and discuss the empirical results obtained. Section 6 recalls the main findings and presents the conclusions.

2. THE 'NONSYNCHRONOUS TRADING EFFECT I'

It is worth stressing that the recent empirical market microstructure literature is extensive. High–frequency financial data are important in studying a variety of issues related to the trading processes and market microstructure (Tsay, 2010). For some purposes, market microstructure is central (Campbell et al., 1997). It was reported in the literature that various frictions in the trading process that can lead to a distinction between 'true' and observed returns (e.g. Cohen et al., 1980) and some empirical phenomena can be attributed to frictions in the trading processes (e.g. Pogue, Solnik, 1974; Scholes, Williams, 1977; Hawawini, 1980; Lo, MacKinlay, 1990; Brzeszczynski et al., 2011; Olbrys, 2011; Olbrys, Majewska, 2012). As mentioned in the introduction, we can distinguish between two nonsynchronous trading effect problems. The first problem, called the 'nonsynchronous trading effect I', occurs when we analyze one selected domestic stock market. The non-trading effect induces potentially serious bias in the moments and co-moments of asset returns such as their means, variances, covariances, betas, and autocorrelation and cross-autocorrelation coefficients (e.g. Lo and MacKinlay, 1990; Campbell et al., 1997). Cohen et al. (1980) presented six empirical phenomena concerning the 'nonsynchronous trading effect I'. The most important of them are: (1) serial correlation in individual security daily returns; (2) cross-correlations between security returns and market index; (3) serial correlation in market index returns, with the smallest effect for long differencing intervals and those indexes giving the least weight to thin securities returns; this index phenomenon is called the Fisher effect[1], since Lawrence Fisher in 1966 hypothesized its probable cause. It is worth stressing that the presence of the Fisher effect in the context of the nonsynchronous trading problem is widely discussed in the literature (e.g. Perry, 1985; Atchison et al., 1987; Berglund, Liljeblom, 1988; Schwert, 1990; Olbrys, 2011; Olbrys, Majewska, 2012).

3. THE 'NONSYNCHRONOUS TRADING EFFECT II' AND DATA-MATCHING PROCESSES

The second problem concerning non-trading, called 'the nonsynchronous trading effect II', occurs when we investigate the relations between the stock markets in various countries. The national stock markets are operating in diverse time zones, with different opening and closing times, thereby making return observations nonsynchronous (Eun and Shim, 1989). These differences arise naturally from the fact that trading days in different countries are subject to different national and religious holidays, unexpected events, and so forth (Baumöhl and Výrost, 2010). Relatively many studies propose various methods to deal with the 'nonsynchronous trading effect II'. Some authors use weekly (e.g. Kadlec, Patterson, 1999) or monthly data to avoid the nonsynchronous trading problem (e.g. Kwan et al., 1995; Hanousek, Filer, 2000; Masih, Masih, 2001; Drakos, Kutan, 2005). Such solutions, however, may lead to small sample sizes and cannot capture the

[1] This is the Lawrence Fisher effect (1966), not to be confused with Irving Fisher's (1867-1947) commonly known "Fisher effect/hypothesis" considering inflation.

information transmission in shorter (e.g. daily) timeframes (Baumöhl, Výrost, 2010). Other papers attempt various daily data-matching processes. For example, Hamao et al. (1990) divide daily close-to-close returns into their close-to-open and open-to-close components. Martens and Poon (2001) use prices recorded at 4:00 p.m. London time for the US, the UK and France to study the daily dynamics of the stock index returns. In Forbes, Rigobon (2002) the stock market returns are calculated as rolling-average, two-day returns based on each country's aggregate stock market index. In many studies the following approach, also called a 'common trading window', is very popular: the data are collected for the same dates across the stock markets, removing the data for those days when any series has a missing value due to no trading (e.g. Eun, Shim, 1989; Martens, Poon, 2001; Égert, Kočenda, 2011, Olbrys, Majewska, 2012). Černy and Koblas (2008) compare the results of Granger causality and cointegration tests for different data frequencies, and to assure the comparability of the results they choose one time for each pair of tested indexes, for example 5:15 p.m. (Western and Central European Daylight Time) for a pair consisting of one US and one European index. Baumöhl and Výrost (2010) perform the Granger causality analysis on the stock market indexes from several markets and they synchronize daily data using their own data-matching procedure. Unfortunately, the majority of studies neither precisely examine, nor account for, the 'nonsynchronous trading effect II' problem of daily data.

4. THE GRANGER CAUSALITY ANALYSIS

The analysis of dynamic linkages between the stock markets has recently become one of the most active research areas in economics and finance. To measure any linkage that may exist between the stock markets, the Granger causality test may be employed. If markets are indeed linked, one should observe the Granger causality running from market to market. The Granger causality analysis is especially frequently conducted in the context of financial crises, or to investigate and support the US dominance in the international stock markets. Smith et al. (1993) found evidence of the Granger unidirectional causality running from the US to the other countries (i.e. Great Britain, West Germany, and Japan) immediately after the October 1987 world-wide crash. Kwan et al. (1995) applied the Granger causality tests to a monthly time series of nine major stock market indexes over the period January 1982 – February 1991 to examine for causal linkages, in the context of market information efficiency. Masih and Masih (2001) investigated the dynamic causal linkages amongst nine major international stock price indexes (four developed and five emerging). They pointed out that the bivariate lead-lag relationships between two stock markets, or standard Granger F -tests in a VAR framework, are useful only in capturing the short-run temporal causality. Ratanapakorn and Sharma (2002) examined the short-term and long-term relationships among the stock indexes of the US, Europe, Asia, Latin America, and Eastern Europe-Middle East index (EM) for the pre-Asian crisis and for the crisis period. The October 1987 crash of the US financial market led to the decline in the financial markets around the world, especially in Asia at the beginning of the 1990s. Consequently, in mid-1998, the East Asian crisis became a worldwide financial and economic crisis hitting emerging markets in Latin America, Middle East, Eastern Europe, and North Africa (Ratanapakorn, Sharma, 2002, p. 92). Drakos and Kutan (2005) investigated the long-run (price) and short-run (return) linkages between the Greek and Turkish stock and foreign exchange markets. They stressed that the finding of cointegration (i.e. long-run linkages) in the bivariate system implies that the Granger causal chain is in place. In other words, causality in at least one direction is guaranteed with the potential for feedback to be present. Dooley and Hutchison (2009) evaluated the transmission of the US subprime crisis, which ran from February 27, 2007, to fourteen emerging markets. In particular, they investigated how the US and Mexican markets were linked using a simple bivariate VAR model, Granger causality tests and impulse response functions.

Some researchers investigated various relationships in the case of the Visegrad Group stock markets (in Poland, the Czech Republic, Hungary, and Slovakia) using the Granger causality framework. In 2000, Hanousek and Filer employed the technique of Granger causality to examine whether secondary equity markets in four of the most advanced former communist countries exhibit the key characteristic of semi-strong efficiency, i.e. the ability to fully reflect newly-released public information in stock prices. In 2007, Syriopoulos investigated the short and long-term behaviour of major emerging Central European (Poland, the Czech Republic, Hungary, Slovakia) and developed (Germany, the US) stock markets, and assessed the impact of the European Monetary Union (EMU) on stock market linkages. In the paper dated 2008, Černy and Koblas presented cointegration and Granger causality tests in the case of the indexes from the New York, London, Frankfurt, Paris, Warsaw, Prague, and Budapest stock markets.

They used a unique high-frequency dataset. Recently, Baumöhl and Výrost (2010) performed the Granger causality analysis on stock indexes from several Asian, European, and US markets from different time zones. The results support the evidence for the US dominance in the international stock markets. As mentioned in Section 3, both Černy and Koblas (2008), and Baumöhl and Výrost (2010) stressed the importance of the nonsynchronous trading problem and they applied data-matching procedures to synchronize daily data in the case of the multivariate time series database. Bütner and Hayo (2010), in searching for the origins of financial market volatility in the case of the CEE-3 stock markets (i.e. Poland, the Czech Republic, and Hungary), uncovered some evidence of Granger causality in the foreign exchange markets. To investigate the multiscale return spillovers between the Czech and the European stock markets, Dajcman (2012) resorted to the Granger causality tests on wavelet transformed returns series for the period April 1997 – May 2010. Witkowska et al. (2012) analyzed the short and long-term international relations between stock exchanges in Central and Eastern Europe. They employed the Granger causality test for the pairs of 14 indexes from the capital markets in the CEE countries, in the period January 2000 – November 2010, but they did not mention nonsynchronous trading problems.

In the literature, the so-called 'Granger causality' is an econometric relationship which tests whether additional information from variable x helps explain y (Smith et al., 1993). A variable x is defined as a Granger-cause for another variable y, if lagged values of x used as additional regressors in a model describing y can improve the quality of modelling/forecasting. The Granger test (1969) of Granger causality is performed in the following way: we estimate a VAR-type equation and check joint significance of lagged x parameters:

$$y_t = \sum_{m=1}^{k} a_m y_{t-m} + \sum_{m=1}^{k} b_m x_{t-m} + \varepsilon_t \tag{2}$$

The null hypothesis:

$$H_0 : b_1 = b_2 = \ldots = b_k = 0 \tag{3}$$

means that x *does not* Granger-cause the y variable. The number of lags k is called the order of the VAR-type equation. The Wald's F - test for joint significance of the parameters $b_m, m = 1, \ldots, k$ is performed to test the null hypothesis (3) (Maddala, 2001). Ericsson et al. (1991, p. 15a) present an interesting classification of models for the autoregressive distributed lag[2].

Let $R_{i,t}, R_{j,t}$ be two stationary time series with zero means. The simple causal bivariate VAR model is (Granger, 1969):

$$\begin{aligned} R_{i,t} &= \sum_{m=1}^{k} a_{i,m} R_{i,t-m} + \sum_{m=1}^{k} b_{i,m} R_{j,t-m} + \varepsilon_{i,t} \\ R_{j,t} &= \sum_{m=1}^{k} a_{j,m} R_{j,t-m} + \sum_{m=1}^{k} b_{j,m} R_{i,t-m} + \varepsilon_{j,t} \end{aligned} \tag{4}$$

where $\varepsilon_{i,t}, \varepsilon_{j,t}, i \neq j$ are taken to be two uncorrelated white-noise series.

The definition of causality given above implies that $R_{j,t}$ is causing $R_{i,t}$ provided some $b_{i,m}$ is not zero. Similarly, $R_{i,t}$ is causing $R_{j,t}$ if some $b_{j,m}$ is not zero. If both of these events occur, there is said to be a feedback relationship between $R_{i,t}$ and $R_{j,t}$ (Granger, 1969).

According to Granger (1969), a time series, $R_{i,t}$, is caused by another time series, $R_{j,t}$, if the current value of $R_{i,t}$ can be better predicted from past values of $R_{i,t}$ and $R_{j,t}$, than from past values of $R_{i,t}$ alone. Essentially, Granger's definition of causality is framed in terms of predictability (Kwan et al., 1995). To determine the optimal number of lags k in a model (4), the Akaike (AIC), Schwarz (BIC) or Hannan-Quinn (HQC) information criteria are generally applied (Baumöhl, Výrost, 2010). The lowest value of the AIC, BIC or HQC indexes indicates the preferred model, that is, one with the fewest parameters that still provides an adequate fit to data. The Granger causality test is reported to work well for stationary variables. Therefore, one should first detect, e.g. based on the Augmented Dickey-Fuller test (1981), that the analyzed time series $R_{i,t}, R_{j,t}$ are stationary.

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[2] We are grateful to an anonymous referee for pointing it out.

5. DATA DESCRIPTION AND EMPIRICAL RESULTS ON THE INDEXES OF THE CEE EMERGING STOCK MARKETS

As mentioned in the introduction, eight CEE countries were successful in the negotiations with the EU and they all accessed the EU on May 1, 2004. These eight countries, in order of largest population size, are: Poland, the Czech Republic, Hungary, the Slovak Republic, Lithuania, Latvia, Slovenia, and Estonia. The raw data consists of daily closing values of major CEE stock market indexes and the New York market index – S&P500. We removed the data for those days when any series had a missing value due to no trading. Thus all the data are collected for the same dates across all of the markets and finally there are 1753 observations for each series for the period beginning May 4, 2004 and ending April 26, 2012 (eight years). We propose a 'common trading window' approach to deal with the 'nonsynchronous trading effect II'. All the analyses are conducted using the open-source computer software Gretl 1.9.9 (Adkins, 2012; Cottrell, Lucchetti, 2012).

Table 1 presents brief information about the major CEE stock market indexes in order of largest market capitalization size at the end of 2010[3].

[3] Due to the space restriction, we do not present summarized statistics for the stock exchange indexes but details are available upon request. As for the hypothesis of normally distributed observed time series of stock market indexes, our evidence is similar to Dajcman's (2012). The Doornik-Hansen (2008) test rejects the hypothesis of normally distributed observed time series of stock market indexes, both in the whole sample and two equal subsamples: the 'crisis' period and the 'post-crisis' period. In the case of all indexes, kurtosis is greater than for normally distributed time series. Almost all of the indexes are asymmetrically (left) distributed around the sample mean.

Table 1

The CEE stock market indexes used in the study

	Market	Market Capitalization, EUR billion, Dec 2010	Market Opening Time (Feb 2012)	Market Closing Time (Feb 2012)	Index	Some Details of the Index Construction
1	Warsaw	142.3	9:00 AM	5:20 PM	WIG	The WSE weighted index with relative weights based upon the capitalization of listed shares. It contains all listed companies except companies with free-float below 10%.
2	Prague	31.9	9:10 AM	4:20 PM	PX	The PSE price index of blue-chip issues, weighted by market capitalization.
3	Budapest	20.6	9:02 AM	5:00 PM	BUX	The official index of blue-chip shares listed on the BSE. It is calculated based on the actual market prices of a basket of shares. It is an index with market capitalization weighting corrected for free-float.
4	Ljubljana	7.0	9:30 AM	1:00 PM	SBI TOP	The LJSE blue-chip index and serves as the Slovene capital market benchmark index. It is a price index, weighted by free-float market capitalization.
5	Vilnius	4.2	10:00 AM	3:55 PM	OMXV	An all-share index. It reflects the current status and changes on the NASDAQ OMX Vilnius.
6	Bratislava	3.4	11:00 AM	3:30 PM	SAX	The official share index of the BSSE. It is a capital-weighted index that compares the market capitalization of a selected set of shares with the market capitalization of the same shares as of a given reference day.
7	Tallinn	1.7	10:00 AM	3:55 PM	OMXT	An all-share index. It reflects the current status and changes on the NASDAQ OMX Tallinn.
8	Riga	0.7	10:00 AM	3:55 PM	OMXR	An all-share index. It reflects the current status and changes on the NASDAQ OMX Riga.

Source: http://www.fese.be/en; http://www.nasdaqomxbaltic.com; http://www.world-exchanges.org

Note: Time is given in Western and Central European Daylight Time.

5.1. The Granger Causality Analysis of the CEE Stock Markets

We use the bivariate Granger causality model (4) to examine interdependences between pairs of selected CEE stock markets. Let $R_{i,t}, R_{j,t}$ be daily logarithmic returns on the two CEE stock market indexes at time t, for markets $i, j, i \neq j$. We use the BIC criterion to determine the optimal number of lags k in the model (4). The lowest value of the BIC index indicates the preferred model, that is, one with the fewest parameters that still provides an adequate fit to data. As mentioned in Section 4, the Granger causality test is reported to work well for stationary variables. Therefore, we first detect (based on the ADF test) that the analyzed $R_{i,t}, i = 1,\dots,8$ (cf. Table 1), and the $R_{SP,t}$ (the S&P500) series are stationary in the case of all markets, both in the whole sample 4.05.2004 – 26.04.2012 and two equal subsamples: 27.02.2007 – 9.03.2009 (the 'crisis' period), and 10.03.2009 – 4.03.2011 (the 'post-crisis' period). We apply the Augmented Dickey-Fuller test (1981) for the intercept model. We utilize maximum lag $k_{\max}$ using the following Schwert's criterion (1989):

$$k_{\max} = \mathrm{int}\{12 \cdot [(T+1)/100]^{0.25}\} \tag{5}$$

where T is the sample size, and then test down to include enough lags so that the last one is statistically significant (Adkins, 2012). Table 2 presents empirical values of the ADF τ-statistic (for the intercept model, at the 5% significance level) and suitable p-values in brackets. As a matter of fact, almost all empirical values are substantially lower than the critical value. We can observe only one empirical value almost equal to the critical value of the ADF τ - statistic in the case of the OMXV in the 'crisis' period (cf. Table 2). Then, we have to reject the null hypothesis of the presence of a unit root (i.e. the daily logarithmic returns series on the main CEE stock market indexes and the S&P500 index are stationary)[4]. MacKinnon's (1991) critical values for the rejection of the hypothesis of a unit root (for the model without trend) are: -3.437 (at the 1% level); -2.864 (at the 5% level); -2.568 (at the 10% level).

[4] The values of stock market indexes are nonstationary processes, but the first differences are stationary, thus we note that all index series are integrated of order one, I(1). Details are available upon request. We are aware of the fact that for cointegration analysis, one should have at least 30 years of data (Ratanapakorn, Sharma 2002).

Table 2

Empirical values of the ADF τ -statistic

	Index	Whole sample (1)		Crisis (2)		After crisis (3)	
		Optimal lag	τ	Optimal lag	τ	Optimal lag	τ
1	*SP*	21	-8.126 [0.000]	7	-6.559 [0.000]	17	-5.963 [0.000]
2	*WIG*	18	-9.067 [0.000]	8	-6.175 [0.000]	8	-7.234 [0.000]
3	*PX*	22	-7.668 [0.000]	8	-6.389 [0.000]	9	-7.171 [0.019]
4	*BUX*	23	-7.685 [0.000]	16	-4.183 [0.001]	13	-4.525 [0.000]
5	*SBITOP*	21	-6.530 [0.000]	15	-3.463 [0.009]	2	-10.851 [0.000]
6	*OMXV*	12	-7.452 [0.000]	12	-2.838 [0.053]	7	-5.211 [0.000]
7	*SAX*	24	-7.217 [0.000]	16	-4.366 [0.000]	6	-7.756 [0.000]
8	*OMXT*	24	-6.904 [0.000]	14	-3.931 [0.001]	11	-4.909 [0.000]
9	*OMXR*	15	-8.831 [0.000]	16	-4.436 [0.000]	16	-4.559 [0.000]

Source: authors' calculations (using *Gretl 1.9.9*)

Notes: The table is based on: (1) the whole sample period May 4, 2004 – April 26, 2012; (2) the crisis period February 27, 2007 – March 9, 2009, and (3) the after crisis period March 10, 2009 – March 4, 2011. The major CEE stock market indexes are in the same order as in Table 1. SP denotes the S&P500 index. The table presents empirical values of the ADF τ - statistic for the daily logarithmic returns series (for the intercept model, at the 5% significance level) and p-values in brackets. We utilize maximum lag using Schwert's criterion (1989) and then test down to include enough lags so that the last one is statistically significant. MacKinnon (1991) critical values for rejection of hypothesis of a unit root (for the model without trend) are: -3.437 (at the 1% level); -2.864 (at the 5% level); -2.568 (at the 10% level).

In our analysis of the Granger causality, we concentrate on selected pairs of the major CEE stock market indexes. In our opinion, the analysis of two groups of indexes is particularly well-founded: (1) the group of the biggest CEE stock market indexes: WIG, PX, BUX; (2) the group of three Baltic market indexes: OMXV, OMXT, OMXR. Table 3 provides details on the results of the causal bivariate VAR models (4). The results of the Granger causality tests of the remaining pairs of indexes are not presented in Table 3, but are available upon request.

Table 3

Results of the Granger causality tests using the model (4)

	Causal relationship $x \to y$	Whole sample (1) Optimal lag k	Whole sample (1) F	Whole sample (1)	Crisis (2) Optimal lag k	Crisis (2) F	Crisis (2)	After crisis (3) Optimal lag k	After crisis (3) F	After crisis (3)
1	$WIG \to PX$	2	6.809 [0.001]	H_1	1	7.933 [0.005]	H_1	1	3.853 [0.0503]	H_0
	$PX \to WIG$		5.116 [0.006]	H_1		5.482 [0.020]	H_1		6.328 [0.012]	H_1
2	$WIG \to BUX$	1	1.719 [0.190]	H_0	1	0.432 [0.512]	H_0	1	0.917 [0.339]	H_0
	$BUX \to WIG$		0.000 [0.992]	H_0		0.111 [0.739]	H_0		0.005 [0.943]	H_0
3	$BUX \to PX$	2	18.330 [0.000]	H_1	2	13.019 [0.000]	H_1	1	1.274 [0.260]	H_0
	$PX \to BUX$		3.772 [0.023]	H_1		7.596 [0.001]	H_1		0.059 [0.808]	H_0
4	$OMXT \to OMXV$	1	5.422 [0.020]	H_1	1	1.976 [0.161]	H_0	1	2.640 [0.105]	H_0
	$OMXV \to OMXT$		2.577 [0.109]	H_0		1.146 [0.285]	H_0		2.192 [0.140]	H_0
5	$OMXT \to OMXR$	1	11.914 [0.001]	H_1	1	0.680 [0.410]	H_0	1	6.830 [0.009]	H_1
	$OMXR \to OMXT$		0.280 [0.597]	H_0		0.026 [0.871]	H_0		0.605 [0.437]	H_0
6	$OMXV \to OMXR$	1	21.881 [0.000]	H_1	1	5.725 [0.017]	H_1	1	7.529 [0.006]	H_1
	$OMXR \to OMXV$		0.139 [0.710]	H_0		0.011 [0.916]	H_0		0.586 [0.444]	H_0

Source: authors' calculations (using *Gretl 1.9.9*)

Notes: The table is based on: (1) the whole sample period May 4, 2004 – April 26, 2012; (2) the crisis period February 27, 2007 – March 9, 2009, and (3) the after crisis period March 10, 2009 – March 4, 2011. We use the BIC criterion to determine the optimal number of lags k in the model (4). The table contains Wald's *F*-statistics and *p*-values in brackets. The model under H_0 is restricted compared to the model under H_1. The Wald's *F*-statistics is used to test H_0 versus H_1. $x \to y$ means H_1: 'x Granger-causes y'.

Several results in Table 3 are worth special notice. First, in terms of causal direction, the *F*- tests suggest that, in the whole sample period, in 7 out of 12 cases the null hypothesis of non-Granger causality is rejected at a 5% level of significance. We observe a pronounced uni-directional causal sequence in the case of the following 'Baltic' models: $OMXT \rightarrow OMXV$, $OMXT \rightarrow OMXR$, and $OMXV \rightarrow OMXR$. The latter two relationships are not surprising because the NASDAQ OMX Riga is the smallest Baltic market. Two models, $WIG \leftrightarrow PX$ and $BUX \leftrightarrow PX$, reveal bi-directional causality, i.e. exhibit a feedback relationship. Second, focusing on the results in the 'crisis period', we observe a significant uni-directional causal sequence only in the case of the model $OMXV \rightarrow OMXR$, however, the feedback relationship is observed for the same models $WIG \leftrightarrow PX$ and $BUX \leftrightarrow PX$ likewise in the entire sample. Finally, we observe only three significant uni-directional causal relationships in the 'post-crisis' period: $PX \rightarrow WIG$, $OMXT \rightarrow OMXR$, and $OMXV \rightarrow OMXR$. There is evidence for the lack of any feedback relationships in the 'post-crisis' period.

5.2. The Granger Causality Analysis in the Case of the US and CEE Markets Located in Different Time Zones

Since the CEE countries are geographically close, they are within one time zone. As a consequence, the trading hours for the CEE stock markets are about the same. As we can see in Table 1, the Warsaw Stock Exchange has the longest trading hours (from 9:00 AM to 5:20 PM). The New York Stock Exchange trades from 3:30 PM CET to 10:00 PM CET (Central European Time). Figure 1 presents the exchange trading hours (CET) and the trading overlap between the CEE and US stock markets. To simplify the analysis, we assume that the CEE and US markets open and close almost sequentially.

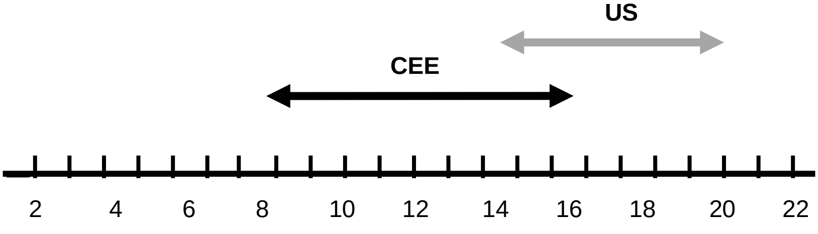

Figure 1. Exchange trading hours in the case of the CEE and US markets (CET).

Note that on a given day t, because the CEE stock markets open before the US market (cf. Figure 1), a daytime information set from the CEE market would have an influence on the US market on the same day, and a daytime information set from the US market would have an influence on the CEE markets on the next day. An information set can be seen in broad terms as the set of all information relevant for pricing an asset at a given time (Baumöhl and Výrost, 2010). Therefore, the information on the closing values of the CEE and US stock markets indexes does not belong to the same information set. To accommodate this 'nonsynchronous trading effect II' in the Granger causality tests, we proposed a version of bivariate VAR model (4) with a modified dynamic structure of lags, in the case of pairs formed by each CEE index and the S&P500 index:

$$\begin{aligned} R_{i,t} &= \sum_{m=1}^{k} a_{i,m} R_{i,t-m} + \sum_{m=1}^{k} b_{i,m} R_{SP,t-m} + \varepsilon_{i,t} \\ R_{SP,t} &= \sum_{m=1}^{k} a_{SP,m} R_{SP,t-m} + \sum_{m=0}^{k-1} b_{SP,m} R_{i,t-m} + \varepsilon_{SP,t} \end{aligned} \tag{6}$$

where: $R_{i,t}, i = 1,\ldots,8$ denote daily logarithmic returns on the appropriate CEE stock market index i at time t; $R_{SP,t}$ denotes daily logarithmic returns on the S&P500 index, and $\varepsilon_{i,t}, \varepsilon_{SP,t}, i = 1,\ldots,8$ are taken to be two uncorrelated white-noise series.

It is worth stressing that the general VAR approach should not be used directly when the 'nonsynchronous trading effect II' is a concern, as it only allows for lagging all the independent variables in the same manner.

Table 4
Results of the Granger causality tests using the modified model (6)

	Causal relationship $x \to y$	Whole sample (1)			Crisis (2)			After crisis (3)		
		Optimal lag k	F		Optimal lag k	F		Optimal lag k	F	
1	$SP \to WIG$	2	51.676 [0.003]	H_1	1	56.694 [0.000]	H_1	1	7.565 [0.006]	H_1
	$WIG \to SP$		311.93 [0.000]	H_1		183.19 [0.000]	H_1		173.92 [0.000]	H_1
2	$SP \to PX$	2	115.87 [0.000]	H_1	1	121.43 [0.000]	H_1	1	25.908 [0.000]	H_1
	$PX \to SP$		283.07 [0.000]	H_1		174.36 [0.000]	H_1		173.67 [0.000]	H_1
3	$SP \to BUX$	1	92.033 [0.000]	H_1	1	62.145 [0.000]	H_1	1	4.578 [0.033]	H_1
	$BUX \to SP$		522.19 [0.000]	H_1		195.71 [0.000]	H_1		153.16 [0.000]	H_1
4	$SP \to SBITOP$	1	276.39 [0.000]	H_1	1	123.82 [0.000]	H_1	1	24.369 [0.000]	H_1
	$SBITOP \to SP$		92.826 [0.000]	H_1		42.655 [0.000]	H_1		17.479 [0.000]	H_1
5	$SP \to OMXV$	2	92.246 [0.000]	H_1	2	43.632 [0.000]	H_1	1	21.428 [0.000]	H_1
	$OMXV \to SP$		54.797 [0.000]	H_1		17.545 [0.000]	H_1		35.942 [0.000]	H_1
6	$SP \to SAX$	1	0.427 [0.514]	H_0	2	1.793 [0.168]	H_0	1	0.767 [0.382]	H_0
	$SAX \to SP$		0.037 [0.848]	H_0		0.954 [0.386]	H_0		1.064 [0.303]	H_0
7	$SP \to OMXT$	2	114.72 [0.000]	H_1	2	54.896 [0.000]	H_1	1	35.821 [0.000]	H_1
	$OMXT \to SP$		69.712 [0.000]	H_1		26.298 [0.000]	H_1		14.604 [0.000]	H_1
8	$SP \to OMXR$	2	38.085 [0.000]	H_1	2	21.941 [0.000]	H_1	1	5.063 [0.025]	H_1
	$OMXR \to SP$		11.911 [0.000]	H_1		7.102 [0.001]	H_1		0.446 [0.504]	H_0

Source: authors' calculations (using *Gretl 1.9.9*)

Notes: The table is based on: (1) the whole sample period May 4, 2004 – April 26, 2012; (2) the crisis period February 27, 2007 – March 9, 2009, and (3) the after crisis period March 10, 2009 – March 4. 2011. The major CEE stock market indexes are in the same order as in Table 1. SP denotes the S&P500 index. We use the BIC criterion to determine the optimal number of lags k in the model (6). The table contains Wald's *F*-statistics and *p*-values in brackets. The model under H_0 is restricted compared to the model under H_1. $x \to y$ means H_1:'x Granger-causes y'.

Table 4 presents further analysis, including more details about the Granger causality in the case of pairs formed by each CEE index and the S&P500 index. We observe a pronounced feedback relationship for almost all of the analyzed models, both in the whole sample period and in two subsamples. We have no reason to reject the null hypothesis of Granger no-causality only in the case of the pairs $SP \rightarrow SAX$, $SAX \rightarrow SP$ (in all samples), and $OMXR \rightarrow SP$ (in the post-crisis sample). The evidence of many feedback relationships in Table 4 may be rather surprising but, as a matter of fact, our results are consistent with those achieved by Baumöhl and Výrost (2010). They examined the Granger causality in the case of several Asian, European, and US markets, and they used the adjusted models to reflect the 'nonsynchronous trading effect II'. They found that all of the analyzed indexes significantly Granger–cause the S&P500, while the non-adjusted Granger models suggested that none of the examined indexes had an impact on the US index. This therefore confirms that taking into account the 'nonsynchronous trading effect II' plays a crucial role in examining the lead-lag relationships among the world's stock markets. However, it is important to note that 'x Granger-causes y' does not imply that y is the effect or the result of x, as Granger 'causality' measures linear precedence and information content but does not by itself indicate causality in the common use of the term (Syriopoulos, 2007).

5.3. Contemporaneous correlations

Finally, to confirm that the use of our VAR model (6) with a modified dynamic structure of lags is well-founded, we calculate the contemporaneous correlation coefficients of daily logarithmic returns on the pairs of the S&P500 index with each CEE index (cf. Table 5). The results are consistent with those in Table 4. To wit, almost all of the cross-market correlations are statistically significant and this evidence confirms the presence of a pronounced feedback relationship for almost all of the analyzed modified VAR models (6), both in the whole sample period and in the two subsamples (cf. Table 4). We have no reason to reject the null hypothesis of the lack of contemporaneous correlation only in the case of the pairs: SP/SAX, and SP/OMXR (only in the 'post-crisis' period). Moreover, we do not observe that cross-market correlations on daily logarithmic returns are significantly higher in the crisis period than in the other periods, which is rather consistent with the literature (e.g. Ülkü, 2011).

Table 5

Contemporaneous correlations of daily logarithmic returns on pairs: (S&P500/CEE index)

Period	SP/WIG	SP/PX	SP/BUX	SP/SBITOP	SP/OMXV	SP/SAX	SP/OMXT	SP/OMXR
Whole sample	0.476 [0.000]	0.437 [0.000]	0.449 [0.000]	0.175 [0.000]	0.203 [0.000]	**0.003** **[0.894]**	0.213 [0.000]	0.092 [0.000]
Crisis	0.483 [0.000]	0.444 [0.000]	0.493 [0.000]	0.213 [0.000]	0.199 [0.000]	**0.001** **[0.978]**	0.215 [0.000]	0.132 [0.006]
After crisis	0.514 [0.000]	0.502 [0.000]	0.497 [0.000]	0.175 [0.000]	0.240 [0.000]	**-0.048** **[0.314]**	0.141 [0.003]	**0.016** **[0.739]**

Source: authors' calculations (using *Gretl 1.9.9*)

Notes: The table is based on: (1) the whole sample period May 4, 2004 – April 26, 2012; (2) the crisis period February 27, 2007 – March 9, 2009, and (3) the after crisis period March 10, 2009 – March 4, 2011. The table contains contemporaneous correlation coefficients and *p*-values in brackets. Non-significant coefficients marked in bold.

6. CONCLUSION

This study contributes to the existing literature by focusing on the friction in trading processes in the context of the implications of the nonsynchronous trading effects for the Granger causality analysis of the CEE emerging stock markets. We analyze the Granger causality on the selected pairs of major CEE stock market indexes, both in the whole sample 4.05.2004 – 26.04.2012 and two equal subsamples: 27.02.2007 – 9.03.2009 (the 'crisis' period), and 10.03.2009 – 4.03.2011 (the 'post-crisis' period). However, we observe the presence of only a few pronounced causal relationships in the whole sample period, in the case of the group of the biggest CEE stock market indexes and the group of the three Baltic market indexes. We observe only two significant feedback relationships, both in the whole sample period and in the 'crisis' period. To accommodate the 'nonsynchronous trading effect II' in the Granger causality tests, we propose a version of a VAR model with a modified dynamic structure of lags, in the case of the CEE and US stock market indexes. The evidence is that almost all of the models exhibit a pronounced feedback relationship, however, our results are consistent with the literature (e.g. Baumöhl and Výrost, 2010). In light of our results, it seems that taking into account the 'nonsynchronous trading effect II' plays a crucial role in examining the lead-lag relationships among the world's stock markets, especially in the case of markets located in different time zones. The fundamental role of the VAR approach and Granger causality tests in the transmission mechanisms of crisis shocks confirms the importance of the analyzed economic problem. The VAR framework is especially appropriate in the case when the feedback from the second country to the crisis country (e.g. the US) is expected to be small (Forbes and Rigobon, 2002). Rigobon (2003) tested for the stability of the transmission mechanisms among 36 stock markets from different time zones during the three international financial crises (Mexico 1994, Asia 1997, and Russia 1998), but he did not account for the 'nonsynchronous trading effect II' problem of daily data. He tried to deal with the answer to the question: is there a shift in the transmission of shocks during crises? In our opinion, it will be interesting to use an extended Rigobon's (2003) methodology involving nonsynchronous trading effects. Another possible direction for further investigation would be to test for structural breaks in multiple time series that are potentially impacted by financial crises. Bekaert's et al. (2002) evidence of structural breaks calls into question research which estimates the VAR-type models over the full sample period. In our opinion, an interesting research direction would be to look for structural breaks in multiple time series and then to analyze the Granger causality of the CEE emerging stock markets and the developed US and European stock markets, both in the whole sample and two equal subsamples (i.e. in the 'crisis' and 'post- crisis' periods).

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