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IMPLICATIONS OF MARKET FRICTIONS: SERIAL CORRELATIONS IN INDEXES ON THE EMERGING STOCK MARKETS IN CENTRAL AND EASTERN EUROPE

Implications of market frictions in the context of serial correlations in indexes on the Central and Eastern European (CEE) stock markets have been analysed. Market frictions, such as non-trading effects, bid/ask spreads, other transaction costs, etc., may be detected by direct measurement, or by indirect identification. Direct measurement of frictions is difficult as intraday trading data are unavailable in the case of most of the emerging CEE stock markets. Indirect identification may be conducted by detecting some empirical phenomena. One of them is evidence of serial correlations in indexes, the so-called the Fisher effect. We explore the problem of serial correlations in indexes on the eight CEE stock markets using data samples from each CEE market separately, as well as a "common trading window" approach, which is widely applied in the case of databases with multivariate time series. The evidence is that nonsynchronous trading effect II between markets may substantially disrupt the analysis of index returns on a domestic market. Using a synchronized database, one may erroneously conclude that the Fisher effect does not exist, although it is present.

Keywords: *CEE stock markets, market frictions, nonsynchronous trading, index serial correlation, market efficiency*

1. Introduction

An analysis of some empirical implications of frictions in trading processes has been performed, especially in the case of emerging stock markets. Frictions are understood as various disturbances in trading processes. Many authors place nonsynchronous trading, bid/ask spread, other transaction costs, etc., in a broad class of market

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frictions [15]. Some studies distinguish between two problematic effects of nonsynchronous trading. The first problem, called nonsynchronous trading effect I, occurs when we analyse one selected domestic stock market. The second and potentially more serious problem, called nonsynchronous trading effect II, occurs when we examine the relations between stock markets in various countries. In general, market frictions cause delays between the arrival of information and its reflection in observed stock returns, so-called price adjustment delays [35, p. 309]. This paper focuses on the implications of market frictions in the context of serial correlations in indexes on the emerging Central and Eastern European (CEE) stock markets.

Market frictions may be detected by direct measurement, or by indirect identification. Direct measurement of frictions is difficult as intraday trading data are not widely available in the case of most emerging CEE stock markets. The lack of access to intraday trading data for emerging markets in general is a fact that is both widely known and amply commented in the literature (e.g. [5, 32]). Indirect identification of the probable presence of market frictions is based on detecting some empirical phenomena (e.g. [12]). One of them is evidence of serial correlations in portfolios and indexes, the so-called Fisher effect[1]. It is worthwhile to note that the presence of frictions in trading processes confirms market illiquidity, and therefore plays a significant role in asset pricing (e.g. [5]). Furthermore, testing for serial correlations in portfolios and indexes may be an initial test of the weak-form of market efficiency. Empirical research on the theory of efficient markets has been concerned with whether prices "fully reflect" particular subsets of the available information. In tests of weak-form efficiency, the information of interest is just past price (or return) histories, and most of the results come from the random walk literature [21][2]. A lack of autocorrelations in indexes is cited as evidence for the efficient market hypothesis in its weak form, e.g. [21, 26, 35][3].

This study contributes to the existing literature by focusing on the implications of broadly defined market frictions, and their connections to serial correlations in indexes, in the case of eight Central and Eastern European stock markets[4]. The contribution is twofold.

First, we provide an indirect identification of the probable presence of market frictions on the emerging CEE stock markets, by testing for the Fisher effect in the case of

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

[2]Professor Eugene F. Fama was awarded the 2013 Nobel Prize in Economic Sciences (together with L.P. Hansen and R.J. Shiller).

[3]We are grateful to an anonymous referee for pointing out that testing for Fisher effect in a stock market index may be an initial test for the weak-form of market efficiency.

[4]These eight countries, in order of decreasing population size are: Poland, the Czech Republic, Hungary, the Slovak Republic, Lithuania, Latvia, Slovenia and Estonia.

the CEE stock market indexes. To the best of the authors' knowledge, Fisher (1966) was the first who suggested that the first order autocorrelation of the market index returns was caused by nonsynchronous trading effect I of the component securities. As for the Polish stock market, the empirical results presented in [36–38] show a pronounced Fisher effect in the case of the Warsaw Stock Exchange's (WSE) main indexes: WIG, mWIG40 and sWIG80 series. The most clear effect is observed for the sWIG80 series. The sWIG80 index comprises 80 small companies listed on the WSE. This evidence is consistent with most of the literature on frictions in trading processes, because the observed correlation is higher in those indexes that give greater weight to the securities of smaller firms. In our opinion, broad-based and comparative research concerning the whole group of emerging CEE stock markets is interesting and well-founded. For this reason, we decided to investigate the presence of the Fisher effect in the daily logarithmic returns of the CEE stock market indexes in various subsamples in the period from May 1, 2004 to April 30, 2012. Various subsamples were examined to check the robustness of the empirical results. Furthermore, following [39], we analysed two periods: the crisis period (27.02.2007–9.03.2009) and the post crisis period (10.03.2009 – 4.03.2011)[5]. We investigated the presence of the Fisher effect, not only in the major, but in all of the CEE stock market indexes. Moreover, taking into account that a single lag term may not be sufficient to correct for the bias in estimation due to market frictions on the emerging markets, we propose to study the statistical significance of serial correlation of higher orders in the daily returns of market indexes in each CEE market separately.

Second, we focus on a potentially serious problem concerning synchronized databases, which are commonly used in empirical finance research. For example, Elton et al. [19] recognized a database problem. They examined potential errors in the Center for Research in Security Prices (CRSP) database and compared the CRSP return data with Morningstar database return data. They stressed that the sources of such data for academic research are not free of errors [19, p. 2415]. Similarly, Mech [35, p. 309] found occasional errors in CRSP share data. In our research, we use our own database, not a commercial one. We explore the problem of serial correlations in indexes on the eight CEE stock markets using data from each CEE market separately, as well as a "common trading window" sample. In light of our results, it seems that applying a very popular and widely used "common trading window" approach as a data-matching procedure in the case of the group of countries investigated, may cause a substantial reduction in the number of data points, and therefore it may seriously disrupt the analysis of the daily returns of a domestic market index. As a matter of fact, it is clear that nonsynchronous trading effect II between markets induces poten-

[5]We acknowledge an anonymous referee for pointing out that it would be interesting to take into account the influence of the 2007 U.S. subprime crisis period on the Fisher effect.

tially serious biases in estimates of the serial correlation in market index returns. Using a synchronized database, one may erroneously conclude that the Fisher effect does not exist, although it is present. To the best of the authors' knowledge, no such research has been undertaken for the CEE stock market indexes.

The remainder of this study is organized as follows. Section 2 presents a brief analysis of market frictions in the context of the Fisher effect. In Section 3, we present nonsynchronous trading effect II and some data-matching processes. In Section 4, we specify the data and discuss the empirical results obtained. In Section 5, we present empirical findings regarding the Fisher effect during the 2007 U.S. subprime crisis period. Section 6 recalls the main findings and presents the conclusions.

2. Market frictions and serial correlations in indexes

Campbell et al. [11] investigated problems in the market microstructure and stressed that various frictions in the trading process can lead to a distinction between 'true" and observed returns. They focused on the fact that transaction prices differ from what they would otherwise be in a frictionless environment. As mentioned in the Introduction, market frictions may be detected by direct measurement, which is possible as intraday trading data are available. For example, Foerster and Keim [23] applied direct measurement and documented the frequency of non-trading for NYSE[6] and AMEX[7] stocks, over the period 1926–1990. Stoll [44] proposed robust empirical measures of frictions based on the bid/ask spread. The measures were computed from transaction data for NYSE/AMEX and NASDAQ stocks, and provided insights into the magnitude of trading costs, and the role of market structure.

Due to a lack of access to intraday trading data, direct measurement of frictions is difficult, or even impossible, in the case of most emerging stock markets (e.g. [5, 32]). Indirect identification of the probable presence of market frictions may be provided by detecting the existence of some empirical phenomena. It has been amply reported in the literature that some empirical phenomena can be attributed to frictions in trading processes, and can be treated as the consequences of market frictions, e.g. [3, 6, 8, 9, 12, 16, 22, 29, 33, 35–38, 40, 41].

In [12, p. 250] six empirical phenomena concerning market frictions were presented: (1) weak serial correlation in the daily returns of individual securities, (2) positive serial cross-correlations between security returns and market indexes, (3) autocorrelation between the residuals in models of a market, (4) sensitivity of beta estimates to changes in the differencing interval, the so-called beta interval effect, (5) increase

[6]NYSE – New York Stock Exchange.
[7]AMEX – American Stock Exchange.

in R^2 for the model of a market as the differencing interval is lengthened, and (6) positive serial correlation in market index returns, with the smallest effect for long differencing intervals and those indexes giving the least weight to returns on securities with low trade volumes; this phenomenon is called the Fisher effect, since L. Fisher hypothesized its probable cause in 1966 [22]. Fisher showed that the returns of stock market indexes exhibit positive autocorrelation, even when they are constructed from individual securities which do not exhibit significant autocorrelations.

The presence of the Fisher effect in the context of market frictions, and especially in relation to the problem of low trade volumes, has been discussed in the literature to a certain degree. Hawawini [29] pointed out that the presence of intertemporal cross correlations in the daily returns of securities is sufficient to explain the Fisher effect. He showed that these correlations are the major source of autocorrelation in indexes. Perry [40] stressed the problem of nonsynchronous trading in the case of the securities of small firms but he reported that non-trading was not the sole cause of serial correlation in market indexes. Berglund and Liljeblom [6] analysed the value-weighted market index on a markedly thin security market, the Helsinki Stock Exchange in Finland. *The HeSE is a specific case in the sense that its trading procedure may create additional first-order market serial correlation* [6, p. 1265]. They concluded that the Fisher effect, which is due to a lack of trading in a non-negligible number of stocks almost every day, will not contribute much to the serial correlation observed in a market. Schwert [42] analysed and compared all the major NYSE and AMEX indexes of stock prices or returns that are available monthly from 1802 to 1925 or daily from 1885 to 1962. He noticed that (…) *most of the index returns are positively autocorrelated at lag 1, which could be due to nonsynchronous trading of the individual stocks in the index (Fisher 1966)* [42, p. 415]. The empirical results presented in [36, 37] showed a pronounced Fisher effect in the case of the main indexes of the Warsaw Stock Exchange (WSE).

To detect the Fisher effect, one can study daily logarithmic returns on the analyzed stock market indexes. The whole sample could be divided into various subsamples to check the robustness of the empirical results [45, p. 30]. In the first step, the partial autocorrelation functions (PACF) should be calculated. To calculate the partial autocorrelation functions, first it should be tested, e.g. based on the DF-GLS test [18], whether the analysed series are stationary. In the next step, one should calculate the normalized sample partial autocorrelation functions for individual stationary processes in the selected samples, and then test the null hypothesis that the data generating process is $AR(0)$, using Anderson's procedure [2].

Let the stationary time series $\{x_t\}_t$, $t = 1, ..., T$, be generated by an $AR(p)$ process. Let π_k be the kth order finite sample partial autocorrelation. Anderson [2] showed that in the case of Gaussian white noise (which is equivalent to an $AR(0)$ process), π_k is asymptotically normal with:

$$E(\pi_k) = \mu_k \begin{cases} -\dfrac{1}{T} - \dfrac{k-1}{T^2} + O\left(\dfrac{1}{T^3}\right), & \text{for } k \text{ odd} \\ -\dfrac{2}{T} - \dfrac{\frac{k}{2}-2}{T^2} + O\left(\dfrac{1}{T^3}\right), & \text{for } k \text{ even} \end{cases} \tag{1}$$

$$\operatorname{Var}(\pi_k) = \sigma_k^2 = \frac{1}{T} - \frac{k+2}{T^2} + O\left(\frac{1}{T^3}\right)$$

where $k \ll T$ [31, p. 134]. The mean and variance formulae, given by (1), are used to propose a normalized partial autocorrelation, whose distribution is approximated by the $N(0, 1)$ distribution. The normalized partial autocorrelation Z_k can be constructed as:

$$Z_k = \frac{\pi_k - \mu_k}{\sigma_k} \tag{2}$$

Under the null hypothesis that the data generating process is $AR(p)$, the normalized partial autocorrelation Z_k is asymptotically $N(0, 1)$ for $k \geq p + 1$. As mentioned above, the evaluation of the first order serial correlation is carried out by testing the null hypothesis:

$$H_0 : AR(0) \tag{3}$$

If the estimate $\hat{Z}_1$ satisfies the inequality $\left|\hat{Z}_1\right| \leq 1.96$, then there is no reason to reject the null hypothesis at the 5% significance level (3).

Fisher [22] advocated testing the first-order serial correlations of the daily index. However, some researchers recommend testing for higher orders (e.g. [16]), since a single lag term may not be sufficient to correct for the bias due to market frictions, especially on emerging markets. For this reason, in Section 4 we propose to study the statistical significance of higher lags.

It is worth stressing that frictions in trading processes, especially non-trading effects, have an intricate and pervasive impact on the process of generating returns. As a consequence of this problem, suitable modifications of various econometric models are often necessary. For example, to accommodate the problem of serial correlations in market indexes, some researchers (e.g. [9, 37, 38]) included lagged values of the market factor as an additional independent variable in the regressions of market-timing models of mutual funds using Dimson's correction [16].

3. Nonsynchronous trading effect II

It is a well-known fact that international stock markets have different trading hours and the time series of market index returns have unequal numbers of observations. This is the second and a potentially serious problem concerning non-trading, called nonsynchronous trading effect II, and it occurs when we examine the relations between the stock markets in various countries. The national stock markets operate in diverse time zones with different opening and closing times, thereby making observations of returns nonsynchronous [20]. 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 [4].

Many studies attempted various methods to deal with nonsynchronous trading effect II. Some researchers use weekly (e.g. [30]) or monthly data to avoid the non-trading problem (e.g. [28]). However, the use of low frequency data leads to small samples, which is often inefficient for modeling. Other papers present various daily data-matching processes. For example, Hamao et al. [27] divided daily close-to-close returns into their close-to-open and open-to-close components. In [24], the stock market returns were calculated as rolling-average, two-day returns based on each country's aggregate stock market index. In many studies the following approach, also called 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. [20]). Baumöhl and Výrost [4] synchronized daily data using their own data-matching procedure. Unfortunately, most studies neither precisely examine nor account for the problem of nonsynchronous trading effect II for daily data.

We place the nonsynchronicity problem for daily data in the class of market frictions. In this study, we investigate the Fisher effect on the CEE stock market indexes using a daily data-matching process. To explore the problem of serial correlations in indexes on the eight CEE stock markets, we use data from each CEE market separately, as well as a common trading window sample.

4. Empirical results on the indexes of the emerging CEE stock markets

Following the collapse of communism, the countries of Central and Eastern Europe rapidly adopted the institutions associated with market economies. Formal stock markets were created in Poland and Hungary at the beginning of 1991, and in the two parts of the former Czechoslovakia in mid-1993, but their origins were very different [28, p. 624]. An event that had significant impact on the group of emerging CEE markets was the accession to the European Union (EU) on the 1st of May 2004. Eight economies were successful in their negotiations with the EU, and they all accessed the EU. These eight countries, in the order of decreasing population size are: Poland, the Czech Republic, Hungary, the Slovak Republic, Lithuania, Latvia, Slovenia and Estonia. The accession process is likely to have affected not only the development and integration of the CEE region, but also the perception of the respective emerging markets by international investors [43]. These eight emerging economies are particularly interesting in many respects. Many researchers have investigated various relationships between the three biggest Central and Eastern European markets (CEEC-3), i.e. in Poland, the Czech Republic, and Hungary, e.g. [10]. Some papers concern the Visegrad Group countries (i.e. Poland, the Czech Republic, Hungary, and Slovakia), e.g. [28], while broad-base and comparative analyses regarding a bigger group of the CEE stock markets are rather rare in the literature (e.g. [26, 39, 43]). In our analysis, we concentrate on eight CEE markets, especially in the context of market frictions.

In this study, the raw data consists of daily closing prices of the CEE stock market indexes. As noted in Section 3, to explore the problem of serial correlations in indexes on the eight CEE stock markets, we use data from each CEE market separately, as well as a common trading window sample. To create the common trading window sample, we remove the data for those days when any series has a missing value due to no trading[8]. Thus all the data are collected for the same dates across all of the markets and we obtain 1759 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 nonsynchronous trading effect II. All analyses have been conducted using the open-source Gretl 1.9.11 software [1, 14].

As mentioned in Section 2, one of the empirical phenomena on a domestic stock market concerning market frictions would be the Fisher effect. To detect the Fisher effect on the CEE stock markets in the period investigated, we study daily logarithmic returns on the CEE stock market indexes. Table 1 presents brief information about all the CEE stock market indexes analysed in order of decreasing value of market capitalization at the end of 2012.

First, we divide the whole common trading window sample (from May 4, 2004 to April 26, 2012) into six subsamples P_1–P_6 (Table 2). Next, to explore the problem of serial correlations in indexes on the eight CEE stock markets using data from each CEE market separately, we divide the whole sample period from May 1, 2004 to April 30, 2012 into suitable subsamples: P_1^i–P_6^i, $i = 1, ..., 8$, corresponding to the common window samples. All the details are presented in Table 2.

[8]The daily data-matching procedure in the presented form, called the "common window", is widely used in the literature, e.g. [8, 20, 24, 34].

Table 1. The CEE stock market indexes used in the study

Market	Market capital billion € 12.2012	Annual traded volume million € 12.2012	Market opening time 02.2012[a]	Market closing time 02.2012[a]	Index	Some details of the index construction
Warsaw	134.8	49847.67	9:00 AM	5:20 PM	WIG	The WSE weighted index with relative weights based upon the capitalization of listed shares. It contains all the listed companies except companies with a free-float below 10%.
					WIG20	The WSE blue-chip weighted index with relative weights based upon the capitalization of listed shares.
					mWIG40	The WSE index comprising 40 medium size companies listed at the WSE Main List.
					sWIG80	The WSE index comprising 80 smaller companies listed at the WSE Main List.
Prague	28.2	9967.70	9:10 AM	4:20 PM	PX	The PSE price index of blue-chip issues, weighted by market capitalization.
					PX GLOB	The PSE broad-based price index, weighted by market capitalization.
Budapest	15.7	8420.50	9:02 AM	5:00 PM	BUX	The official index of blue-chip shares listed on the BSE, calculated based on the actual market prices of a basket of shares. It is an index with market capitalization weighting corrected for free-float.
Ljubljana	4.9	302.87	9:30 AM	1:00 PM	SBI TOP	The LJSE blue-chip index serves as the benchmark index of the Slovene capital market. This price index is weighted by free-float market capitalization.
Bratislava	4.1	126.39	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.
Vilnius	3.0	129.15	10:00 AM	3:55 PM	OMXV	The all-share index. It reflects the current status and changes on the NASDAQ OMX Vilnius.
Tallinn	1.8	136.35	10:00 AM	3:55 PM	OMXT	The all-share index. It reflects the current status and changes on the NASDAQ OMX Tallinn.
Riga	0.8	16.51	10:00 AM	3:55 PM	OMXR	The all-share index. It reflects the current status and changes on the NASDAQ OMX Riga.

[a] Western and Central European daylight time.

Source: <http://www.gpw.pl/>, < http://www.fese.be/en>, <http://www.pse.cz/>, <http://bse.hu/>, <http://www.ljse.si/>, <http://www.bsse.sk/>, <http://www.nasdaqomxbaltic.com>, <http://www.world-exchanges.org>.

Table 2. Samples for the period from May 1, 2004 to April 30, 2012

Common trading window				Warsaw ($i=1$)		Prague ($i=2$)		Budapest ($i=3$)		Ljubljana ($i=4$)		Bratislava ($i=5$)		Vilnius ($i=6$)		Tallinn ($i=7$)		Riga ($i=8$)	
P_i	Period	T	P_j^i	Period	T	Period	T	Period	T	Period	T	Period	T	Period	T	Period	T	Period	T
P_1	4.05.04 26.04.12	1759	P_1^i	4.05.04 30.04.12	2012	3.05.04 30.04.12	2014	3.05.04 27.04.12	2011	3.05.04 30.04.12	1999	3.05.04 30.04.12	1966	3.05.04 30.04.12	1979	3.05.04 30.04.12	2021	3.05.04 27.04.12	2004
P_2	5.05.05 26.04.12	1538	P_2^i	2.05.05 30.04.12	1759	2.05.05 30.04.12	1762	2.05.05 27.04.12	1758	3.05.05 30.04.12	1745	2.05.05 30.04.12	1724	2.05.05 30.04.12	1723	2.05.05 30.04.12	1763	2.05.05 27.04.12	1748
P_3	4.05.06 26.04.12	1324	P_3^i	2.05.06 30.04.12	1507	2.05.06 30.04.12	1509	2.05.06 27.04.12	1504	3.05.06 30.04.12	1496	2.05.06 30.04.12	1482	2.05.06 30.04.12	1476	2.05.06 30.04.12	1509	2.05.06 27.04.12	1495
P_4	9.05.07 26.04.12	1113	P_4^i	2.05.07 30.04.12	1256	2.05.07 30.04.12	1258	2.05.07 27.04.12	1254	3.05.07 30.04.12	1250	2.05.07 30.04.12	1242	2.05.07 30.04.12	1232	2.05.07 30.04.12	1255	2.05.07 27.04.12	1245
P_5	6.05.08 26.04.12	894	P_5^i	5.05.08 30.04.12	1006	2.05.08 30.04.12	1007	5.05.08 27.04.12	1005	5.05.08 30.04.12	1002	2.05.08 30.04.12	997	6.05.08 30.04.12	989	2.05.08 30.04.12	1003	6.05.08 27.04.12	994
P_6	5.05.09 26.04.12	672	P_6^i	4.05.09 30.04.12	757	4.05.09 30.04.12	756	4.05.09 27.04.12	756	4.05.09 30.04.12	753	4.05.09 30.04.12	751	4.05.09 30.04.12	746	4.05.09 30.04.12	754	5.05.09 27.04.12	748

The whole "common trading window" sample (from May 4, 2004 to April 26, 2012) is divided into six subsamples. The whole sample period from May 1, 2004 to April 30, 2012 is divided into suitable subsamples, corresponding to the "common trading window" samples, to analyse the data from each CEE market separately. T is the number of data points.

It is important to note that the daily data-matching procedure caused a substantial reduction in the number of data points. For example, in the case of the Estonian stock market (Tallinn), the number of data points in the whole sample period fell from 2021 (P_1^7) to 1759 (P_1), thus it lost almost 13% of the original number of data points as a result of the common trading window procedure. Likewise, we observe a considerable reduction in the number of data points in the case of the other markets.

To better specify the time periods used in the common trading window samples in Table 2, we consider (in Table 3) some particular dates, e.g. for the P_4 sample and suitable samples $P_4^i, i = 1, ..., 8$.

Table 3. Explanation of the choice of the initial date (9.05.2007) in the common trading window sample P_4 (cf. Table 2) and suitable samples $P_4^i, i = 1, ..., 8$

Date	Common trading window	Warsaw ($i = 1$)	Prague ($i = 2$)	Budapest ($i = 3$)	Ljubljana ($i = 4$)	Bratislava ($i = 5$)	Vilnius ($i = 6$)	Tallinn ($i = 7$)	Riga ($i = 8$)
1.05.2007	–	–	–	–	–	–	–	–	–
2.05.2007	–	+	+	+	–	+	+	+	+
3.05.2007	–	–	+	+	+	+	+	+	+
4.05.2007	–	+	+	+	+	+	+	+	–
5.05.2007	–	–	–	–	–	–	–	–	–
6.05.2007	–	–	–	–	–	–	–	–	–
7.05.2007	–	+	+	+	+	+	–	+	+
8.05.2007	–	+	–	+	+	–	+	+	+
9.05.2007	+	+	+	+	+	+	+	+	+

The table presents the choice of the initial date in the common trading window sample P_4 and suitable samples P_4^i, i = 1, ..., 8. + denotes that the series has a value, – denotes that the series has a missing value due to no trading. As we can see, the first common date is 9.05.2007.

To calculate the partial autocorrelation functions (PACF), we should first detect (e.g. based on the DF-GLS test) whether the analysed series are stationary. Using daily data, we use a maximum lag equal to five, in order to control for any within-week variation in trading patterns [10, 24] and then remove lags until the last one is statistically significant [1]. The empirical values of the DF-GLS τ-statistics (we test at the 5% significance level) are presented in Table 4. Cook and Manning's [13, p. 271] critical values of the DF-GLS τ-statistics (for the intercept model) for the rejection of the hypothesis of a unit root lie between –2.02 (for T = 250) and –1.94 (for T = 2500). All of the empirical values presented in Table 4 are substantially lower than the critical value for the intercept model. The details are given in Table 4. Finally, we can conclude that the unit-root hypothesis can be rejected in all cases.

In the next step, we calculate the normalized sample partial autocorrelation functions for the individual stationary processes for all the samples, and we test the null hypothesis (3), using Anderson's [2] procedure. Table 5 provides details on the normalized PACFs for the analysed series in the case of the CEE market indexes, for the common trading window samples. Tables 6, 7 present the normalized PACFs for the analysed series, with the data from each CEE market analysed separately. The samples are described in detail in Table 2.

Table 4. Empirical values of the DF-GLS τ-statistics

Common trading window		P_j^i	Warsaw ($i = 1$)	Prague ($i = 2$)	Budapest ($i = 3$)	Ljubljana ($i = 4$)	Bratislava ($i = 5$)	Vilnius ($i = 6$)	Tallinn ($i = 7$)	Riga ($i = 8$)
P_i	τ interval		τ interval	τ interval	τ					
P_1	[–30.99; –4.29]	P_1^i	[–12.06; –4.76]	[–7.60; –5.26]	–15.15	–12.21	–2.02	–8.89	–6.89	–17.04
P_2	[–37.79; –7.72]	P_2^i	[–30.88; –9.02]	[–10.40; –10.03]	–16.91	–28.09	–1.98	–10.28	–13.48	–5.54
P_3	[–26.42; –6.52]	P_3^i	[–12.61; –2.98]	[–16.48; –16.43]	–6.74	–2.99	–2.49	–12.88	–14.82	–8.26
P_4	[–24.28; –4.74]	P_4^i	[–5.69; –4.32]	[–26.99; –15.39]	–14.56	–13.08	–4.91	–12.03	–11.64	–8.70
P_5	[–30.94; –4.09]	P_5^i	[–23.94; –8.15]	[–11.09; –10.15]	–9.14	–2.85	–21.64	–7.84	–11.79	–11.84
P_6	[–24.07; –2.71]	P_6^i	[–6.47; –4.39]	[–2.47; –1.99]	–6.92	–2.64	–29.87	–6.88	–3.24	–4.67

The table presents empirical values of the DF-GLS τ-statistics (we test at the 5% significance level) for the six subsamples based on the common trading window sample, as well as the empirical values of the DF-GLS τ-statistics for each CEE market data sample separately. Due to the restrictions on table size, in the cases of Warsaw (four indexes) and Prague (two indexes) the ranges of the DF-GLS τ-statistics are presented. The CEE stock markets are in the same order as in Table 1. The samples are based on Table 2. Cook and Manning's [13] critical values of the DF-GLS τ-statistics (for the intercept model) for the rejection of the hypothesis of a unit root lie between –2.02 (for $T = 250$) and –1.94 (for $T = 2500$).

Source: Authors' calculations using the Gretl 1.9.11 software.

Table 5. Normalized PACF estimators for the CEE market indexes (the common trading window samples)

P_i	WIG	WIG20	mWIG40	sWIG80	PX	PX GLOB	BUX	SBI TOP	SAX	OMXV	OMXT	OMXR
P_1	1.611	–0.312	**5.812**	**7.517**	0.687	0.830	0.956	**4.776**	0.003	**5.099**	**4.805**	–1.689
P_2	1.435	–0.363	**5.286**	**6.648**	0.701	0.795	0.724	**4.265**	–1.187	**4.724**	**4.536**	–1.482
P_3	1.525	–0.242	**4.913**	**6.738**	0.596	0.694	0.760	**3.648**	–1.550	**4.162**	**4.137**	**–2.122**
P_4	1.336	–0.284	**4.326**	**5.586**	0.307	0.414	0.317	**3.144**	–1.410	**3.862**	**3.133**	**–2.078**
P_5	1.444	0.022	**4.373**	**5.703**	0.429	0.549	0.231	1.534	–1.218	**3.538**	**2.639**	–1.665
P_6	0.777	–0.751	**3.731**	**5.295**	–0.380	–0.455	–0.574	0.673	–1.642	**3.190**	**2.112**	–1.468

The table is based on six subsamples of the common trading window sample (cf. Table 2). The CEE stock market indexes are in the same order as in Table 1. Absolute normalized estimates (2) greater than the critical value for the 5% significant level, 1.96, are marked in bold [2, 31].

Source: Authors' calculations using the Gretl 1.9.11 software.

Table 6. Normalized PACF estimators for the CEE market indexes in Warsaw, Prague and Budapest

P_j^i	Warsaw ($i = 1$)				Prague ($i = 2$)		Budapest ($i = 3$)
	WIG	WIG20	mWIG40	sWIG80	PX	PX GLOB	BUX
P_1	**4.3945**	1.8807	**9.1662**	**10.6565**	**3.0852**	**3.2334**	**3.2984**
P_2	**4.1082**	1.7491	**8.5031**	**9.6238**	**2.9269**	**3.0403**	**3.0579**
P_3	**3.9156**	1.6423	**7.8830**	**9.2470**	**2.5610**	**2.6738**	**2.9878**
P_4	**3.4701**	1.3766	**7.2454**	**8.3666**	**2.2157**	**2.3329**	**2.4073**
P_5	**3.7068**	1.8962	**7.2867**	**8.6812**	**2.3325**	**2.4342**	**2.1937**
P_6	**2.4100**	0.6595	**5.9333**	**7.3475**	**1.0062**	**0.9897**	**–0.3685**

Table 7. Normalized PACF estimators for the CEE market indexes in Ljubljana, Bratislava, Vilnius, Tallinn and Riga

P_j^i	Ljubljana ($i = 4$)	Bratislava ($i = 5$)	Vilnius ($i = 6$)	Tallinn ($i = 7$)	Riga ($i = 8$)
	SBI TOP	SAX	OMXV	OMXT	OMXR
P_1	**8.5013**	–1.0601	**6.7895**	**6.6536**	–1.4068
P_2	**7.7503**	**–2.4776**	**6.2102**	**6.3736**	–1.1142
P_3	**6.8052**	**–2.4767**	**5.5025**	**5.8779**	–1.5494
P_4	**5.9398**	**–2.2263**	**4.9731**	**4.9726**	–1.4412
P_5	**3.4681**	**–2.0301**	**4.5389**	**4.2342**	–1.4681
P_6	**2.0822**	**–2.5281**	**3.8053**	**2.9832**	–2.1722

Tables 6, 7 are based on separate subsamples for each CEE market (cf. Table 2). Each CEE market data subsample has been analysed separately. The CEE stock market indexes are in the same order as in Table 1. Absolute normalized estimates (2) greater than the critical value for the 5% significant level, 1.96, marked in bold [2, 31].

Source: Authors' calculations using the Gretl 1.9.11 software.

The empirical results presented in Table 5 (the common trading window approach) show a pronounced Fisher effect only in the case of the following series: the mWIG40 and sWIG80 (Warsaw), the SBI TOP (Ljubljana) – in four samples (P_1–P_4), the OMXV (Vilnius), and the OMXT (Tallinn). We have no reason to reject the null hypothesis (3) in the case of the other series. However, these results are rather controversial and they clearly show that nonsynchronous trading effect II induces potentially serious biases in estimates of the serial correlation in market index returns and may disrupt the analysis of daily returns for domestic market indexes. In light of the results presented in Table 5, one may erroneously conclude that the Fisher effect does not exist, although it is present. Tables 6, 7 present further analysis concerning the normalized sample partial autocorrelation functions for the individually analysed series in each subperiod. We observe a pronounced Fisher effect in the case of almost all the series, except for the WIG20 index (the Warsaw Stock Exchange blue-chip index, cf. Table 6). It is worthwhile to note that the results for the Polish stock market are in accord with previous findings by Olbrys [36–38]. Furthermore, only the results for the Latvian stock market in Riga are different, but this is not surprising because it is the smallest CEE stock market (cf. Table 1). To sum up, the results for the other markets are novel and, to the best of the authors' knowledge, have not been discussed in the literature.

As mentioned in Section 2, some researchers recommend analysing higher orders of daily serial correlation in market index returns and they argue that a single lag term may not be sufficient to correct for the bias due to market friction (e.g. [16]). In our opinion, the bias due to thin trading may appear on emerging markets in particular. For this reason, we study the statistical significance of higher orders of the normalized PACF estimators. We propose a maximal lag of $k = 5$, because of the use of daily data [10, 24]. The details are presented in Tables 8, 9.

Table 8. Higher order serial correlation in market index daily returns for individually analysed subsamples from CEE market in Warsaw, Prague and Budapest (significance of the normalized PACF estimators)

Sample	Lag $-k$	Warsaw ($i = 1$)				Prague ($i = 2$)		Budapest ($i = 3$)
		WIG	WIG20	mWIG40	sWIG80	PX	PX GLOB	BUX
P_1^i	$k = 2$	–	– –	+	+	– –	– –	– –
	$k = 3$	+	+	++	++	–	–	–
	$k = 4$	+	–	+	–	+	+	++
	$k = 5$	+	–	+	+	++	+	+
P_2^i	$k = 2$	–	– –	+	+	– –	– –	– –
	$k = 3$	+	+	++	++	–	–	–
	$k = 4$	+	–	+	–	+	+	++
	$k = 5$	+	–	+	+	+	+	+
P_3^i	$k = 2$	–	– –	+	+	– –	– –	– –
	$k = 3$	+	+	++	++	–	–	–
	$k = 4$	+	–	+	+	+	+	++
	$k = 5$	–	–	+	–	+	+	+
P_4^i	$k = 2$	– –	– –	–	–	– –	– –	– –
	$k = 3$	+	+	++	++	–	–	–
	$k = 4$	+	–	+	+	+	+	++
	$k = 5$	+	–	+	–	+	+	+
P_5^i	$k = 2$	– –	– –	–	–	– –	– –	– –
	$k = 3$	+	+	+	+	–	–	–
	$k = 4$	+	–	+	+	+	+	++
	$k = 5$	–	–	+	–	+	+	+
P_6^i	$k = 2$	– –	– –	–	–	– –	– –	–
	$k = 3$	–	–	–	–	–	–	–
	$k = 4$	–	–	–	–	+	+	+
	$k = 5$	–	–	+	–	–	+	+

Table 9. Higher order daily serial correlation in market index returns for individually analysed subsamples from each CEE market in Ljubljana, Bratislava, Vilnius, Tallinn and Riga (significance of the normalized PACF estimators)

Sample	Lag $-k$	Ljubljana ($i = 4$)	Bratislava ($i = 5$)	Vilnius ($i = 6$)	Tallinn ($i = 7$)	Riga ($i = 8$)
		SBI TOP	SAX	OMXV	OMXT	OMXR
P_1^i	$k = 2$	– –	++	+	++	+
	$k = 3$	–	–	+	++	–
	$k = 4$	–	–	+	+	–
	$k = 5$	+	+	–	++	+
P_2^i	$k = 2$	– –	+	+	+	+
	$k = 3$	–	– –	+	++	–
	$k = 4$	–	–	+	–	–
	$k = 5$	+	–	–	++	+
P_3^i	$k = 2$	– –	+	+	+	+
	$k = 3$	–	–	+	++	+
	$k = 4$	–	–	+	–	–
	$k = 5$	+	–	–	++	+
P_4^i	$k = 2$	– –	+	+	+	+
	$k = 3$	–	–	+	+	–
	$k = 4$	–	–	+	–	–
	$k = 5$	+	–	–	++	–
P_5^i	$k = 2$	–	+	+	+	+
	$k = 3$	+	–	+	+	–
	$k = 4$	–	–	+	–	–
	$k = 5$	+	–	–	++	–
P_6^i	$k = 2$	–	+	+	–	+
	$k = 3$	–	–	+	+	–
	$k = 4$	–	–	+	+	–
	$k = 5$	++	–	–	+	–

Tables 8, 9 are based on separate subsamples from each CEE market (cf. Table 2). The CEE stock market indexes are in the same order as in Table 1. The significance of the normalized PACF estimators [2] is denoted as follows: – negative, – – significantly negative at the 5% level, + positive, ++ significantly positive at the 5% level. Lags up to $k = 5$.

Source: Authors' calculations using the Gretl 1.9.11 software.

Several of the results presented in Tables 8, 9 are important and worth special notice, especially in the case of the three biggest CEE stock markets in Warsaw, Prague and Budapest.

As for the Polish stock market, the positive, statistically significant lag –3 normalized PACF estimator of the indexes that cover medium (mWIG40) and small (sWIG80) size companies listed on the WSE draws special attention. Furthermore, we observe negative, statistically significant lag –2 normalized PACF estimators in the case of the WSE blue-chip index WIG20 for all the subsamples, while, as noted above, we do not observe the Fisher effect in the case of the WIG20. This is some very interesting evidence and the results for the index based on large firms may confirm the hypothesis that non-trading is not the only source of serial correlation in market portfolios (cf. [30, 40]). Another interesting piece of evidence is that from the case of the Czech stock market. Both the PX and PX GLOB indexes reveal negative, statistically significant lag –2 normalized PACF estimators for all the subsamples. As a consequence of this problem, suitable modifications of various models, including the market variable, would possibly be necessary for the Czech market. As pointed out earlier, to accommodate the problem of market frictions, suitable lagged values of the market factor may be included as an additional independent variable in the regressions based on the model for a market index. Similarly, in the case of the Hungarian stock market, we observe negative, statistically significant lag –2 normalized PACF estimators for the subsamples from P_1^3 to P_5^3, and the conclusions about additional independent lagged variables in models of the market index may be similar. The results for the three Baltic stock markets in Vilnius, Tallinn and Riga, as well as for the Slovak and the Slovenian markets in Bratislava and Ljubljana, show statistically significant normalized PACF estimators of various orders. These few statistically significant results for the normalized PACF estimators seem to be rather incidental.

5. Fisher effect on the CEE stock markets in the 2007 U.S. subprime crisis period

Additionally, in our research we compare the empirical results for two subsamples of equal size: 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), to conduct a sensitivity analysis. As it was necessary to appoint one date as the beginning of the crisis period in all the countries, we suggest February 27, 2007 following [17, 25, 39]. Similarly, we advocate March 9, 2009 as the end of the crisis period because the global minimum value of the S&P500 index was achieved on this day (cf. [39]). Table 10 provides details on the normalized PACFs in the analysed series, for the common trading window subsamples: crisis and after crisis as well as for each CEE market analysed separately.

The empirical results reported in Table 10 confirm the following conclusions: (1) the daily data-matching procedure caused a substantial reduction in the number of data points; (2) using a synchronized database, one may conclude that the Fisher effect does not exist, although it is present in the case of most indexes, in both subsamples: crisis and after crisis; (3) the results regarding the Fisher effect are rather robust to the choice of sample. Only in the case of the BUX (Budapest), the normalized PACF estimator is significant in just one of the periods, the crisis period. In the other cases the PACF estimator is either insignificant in both periods or significant in both periods.

Table 10. Normalized PACF estimators for the CEE market indexes

Index	Common trading window				Each CEE market data sample analysed separately			
	Crisis		After crisis		Crisis		After crisis	
	T	PACF	T	PACF	T	PACF	T	PACF
WIG	444	0,2696	444	0,4240	506	1,6239	503	1,9275
WIG20		–0,4366		–0,3478		0,4169		1,0030
mWIG40		1,6270		0,8447		3,6973		3,1355
sWIG80		2,2063		2,5530		4,0695		4,0893
PX		–0,2526		0,2358	509	1,1057	500	0,9285
PX GLOB		–0,0814		0,0603		1,2618		0,7267
BUX		0,5064		–1,1279	502	2,9909	504	–0,3088
SBI TOP		2,6630		3,1556	504	4,8633	501	4,8402
SAX		–0,5592		0,2464	498	–0,5505	498	–0,3803
OMXV		1,7771		2,5108	491	2,6435	493	4,0273
OMXT		1,5953		1,8067	508	3,6365	498	2,0415
OMXR		–1,7495		–1,2379	503	–0,1465	494	–1,7473

The table is based on two subsamples of equal size: 27.02.2007–9.03.2009 as the crisis period, and 10.03.2009–4.03.2011 as the post crisis period. The CEE stock market indexes are in the same order as in Table 1. Absolute normalized estimates (2) greater than the critical value for the 5% significant level, 1.96, are marked in bold [2, 31].

Source: Authors' calculations using the Gretl 1.9.11 software.

6. Conclusions

Using each CEE stock market data sample separately, as well as a common trading window sample, we examine one of the empirical phenomena of domestic stock markets concerning market frictions, the so-called Fisher effect, in the case of the CEE stock market indexes. To check the robustness of the empirical results, we investigate various subsamples in the whole period investigated, May 2004–April 2012, as well as analysing two subsamples of equal size: the crisis period (27.02.2007–9.03.2009) and the post crisis period (10.03.2009–4.03.2011). The evidence is that nonsynchronous trading effect II between markets may induce potentially serious biases in estimates of serial correlation in market index returns and may disrupt the analysis of daily returns for domestic market indexes. Using a synchronized database, the result of the common trading window data-matching procedure, one may erroneously conclude that the Fisher effect does not exist, although it is present in the case of almost all the CEE market indexes. The presence of serial correlation in market index returns indirectly confirms that the emerging CEE stock markets are not frictionless. This evidence is consistent with the hypothesis that market frictions cause autocorrelation between index returns by delaying price adjustment [35], and it confirms that prices do not always fully reflect all the available information. Hanousek and Filer [28] present strong evidence that the Visegrad Group markets are not yet semi-strong efficient, while our research shows that more of the CEE stock markets are probably not informational efficient, even in the weak form. This evidence is consistent with results presented by Guidi et al. [26]. Their autocorrelation analysis for the period 1999–2009 indicates that the returns of selected CEE indexes are not random walks, especially after accession to the EU. However, our conclusions regarding market efficiency must be viewed as tentative. Therefore, more extensive tests must be conducted before we can draw any more definitive conclusions.

Moreover, our results confirm the statistical significance of higher lags of the normalized partial autocorrelation functions in the case of the biggest CEE stock markets in Warsaw, Prague and Budapest. In our opinion, as a consequence of this problem, suitable modifications of various models, including the market variable, would possibly be necessary on these markets.

Finally, we agree with Baumöhl and Výrost [4] comments that the use of a wide range of time-series models could be questionable if non-synchronocities are not accounted for, especially because the current implementations of these models in most econometric software inherently assume synchronous data.

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