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Stock Market Integration and the Speed of Information Transmission

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Abstract
Using a unique dataset covering two years of high frequency data on the indices from markets in the U. S., London, Frankfurt, Paris, Warsaw, Prague, and Budapest, we perform cointegration and Granger causality tests with data of different frequencies (from 5 minutes to 1 day). The aim is to describe the time structure in which markets react to the information revealed in prices on other markets. The results suggest that the speed of information transmission is very fast. In all cases the strongest reaction occurs within 1 hour. Therefore, the use of daily data may be misleading when analyzing the issues of stock market integration and information transmission between markets.

1. Introduction

The increasing globalization of the world economy should obviously have an impact on the behavior of national stock markets. The relaxation of all types of economic barriers and developments in information technologies are, among other things, expected to induce stronger stock market integration as opposed to stock market fragmentation. With integrated stock markets, information originating from one market should be important to other markets. This assumption has motivated an intensive area of empirical research on the transmission of information across equity markets.

Using a rough criterion, this research can be divided into two areas. The first area studies stock market integration and focuses on statistical relationships between the indices from different markets, typically using cointegration or Granger causality analysis, e.g., (Huang, Fok, 2001), (Seabra, 2001), (Dickinson, 2000), (Bracker et al., 1999), (Chelley-Steeley et al., 1998), (Richards, 1996), (Chou et al., 1994). The second area focuses on the effect of macroeconomic releases from different countries on different markets. It studies the impact of the releases on market returns, volatility, and trading volumes. Papers from this area include, for example, (Andersen et al., 2003), (Connolly, Wang, 2003), (Wongswan, 2003), and (Ehrmann, Fratzscher, 2002).

In this paper we address the same problem of stock market integration as defined by the first area of research, but employ the high-frequency data characteristic of the second research area. Cointegration and Granger causality tests between stock market indices have hitherto been performed using data with daily or even less frequent observations, perhaps because high-frequency[1] data on indices from most

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stock markets have not been easily available historically. Studies of stock market reactions to macroeconomic releases typically employ high-frequency index data only from markets in the U.S. and London, using FTSE 100 futures as a proxy for the spot index. Nevertheless, these studies suggest that markets react to macroeconomic releases very quickly, faster than within one hour. Therefore, there are good reasons to believe that the stock market reaction to the information revealed in prices on other stock markets should also be very fast. The use of daily data in cointegration and Granger causality tests could then be misleading.[2]

If the reaction of prices in Market A to information revealed by prices in Market B occurs faster than within one day, then we should not detect cointegration or Granger causality with daily data, i.e., the markets should appear informationally efficient. In this case informational efficiency means that today's expectation of tomorrow's return in Market A, conditional on the available information, equals today's return in Market A. Cointegration and Granger causality would imply, however, that we could improve the expectation of tomorrow's return in Market A using the information about today's return in Market B. On the other hand, when using data of a frequency close to the speed of information transmission between the two markets, we should detect cointegration and Granger causality. By further increasing the data frequency, cointegration and Granger causality should disappear once the data are collected at intervals much lower than the time needed for information transmission between the two markets. With such high-frequency data, the markets would appear to be completely independent.

The arguments presented above suggest that data frequency should play an important role for cointegration and Granger causality tests among indices from different stock markets. Therefore, we perform cointegration and Granger causality tests with data of different frequencies. We use a unique dataset covering two years of high-frequency data on the indices from the markets in the U. S., London, Frankfurt, Paris, Warsaw, Prague, and Budapest. This allows us to vary the data frequency from five minutes to one day. Our aim is to uncover the time structure of the reaction of prices on one market to the information revealed in prices on other markets. We are particularly interested in the speed at which the information is transmitted between the markets.[3]

We are aware that we cannot directly address the nature of the information transmission. Our tests cannot distinguish if the information revealed by the prices in one market is transmitted directly to the prices in another market or if the two markets react to some other relevant information about economic fundamentals (e.g., macroeconomic releases) in a similar manner but at slightly different speeds. In other words, we do not address the question of contagion between markets versus reaction to economic fundamentals.

[1] The term "frequency" is actually used incorrectly in this area of research. When we say daily frequency of the data, we mean, in fact, a daily period. With higher frequencies, like hourly or 30-minute frequencies, we mean data collected hourly or at 30-minute intervals.

[2] In general, even if markets react relatively quickly to any specific information, analysis based on daily data can make sense, because information is coming throughout the day and the change in the daily closing price can be viewed as its aggregation. However, Granger causality and cointegration analysis with daily data should not be used to decide about the presence or absence of stock market integration.

[3] Egert and Kočenda (2005) employ the same dataset to investigate only the highest five-minute frequency data using a wide range of econometric techniques.

TABLE 1 Daily Time Periods of Available Data on Individual Indices

Index	Time period	
	from	to
S&P 500	15:30	22:10
DJIA	15:30	22:00
FTSE 100	9:00	17:25
DAX 30	9:00	20:10, from Nov. 2003 only to 17:40
CAC 40	9:05	17:25
WIG 20	10:05	15:55
PX 50	9:30	15:55
BUX	9:00	16:25

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

TABLE 2 Statistics on Logarithms of Indices and Five-minute Logarithmic Returns

Index	Obs.	Mean	Std. Dev.	Min.	Max.
	Logarithms of indices				
S&P 500	40 007	7.01	0.063	6.87	7.11
DJIA	39 133	9.22	0.050	9.09	9.30
FTSE 100	50 484	8.42	0.060	8.28	8.53
DAX 30	55 868	8.26	0.093	8.01	8.42
CAC 40	50 959	8.20	0.078	8.01	8.34
WIG 20	35 053	7.44	0.123	7.08	7.66
PX 50	38 296	6.70	0.244	6.27	7.15
BUX	44 295	9.36	0.243	8.95	9.84
	Logarithmic five-minute returns				
S&P 500	39 499	3.40E-6	7.22E-4	-0.010	0.008
DJIA	38 590	3.15E-6	7.47E-4	-0.012	0.011
FTSE 100	49 874	-2.94E-6	5.37E-4	-0.014	0.007
DAX 30	55 363	3.60E-6	9.17E-4	-0.023	0.016
CAC 40	50 441	2.17E-6	7.33E-4	-0.008	0.010
WIG 20	34 546	7.80E-7	1.29E-3	-0.012	0.019
PX 50	37 451	1.56E-5	7.41E-4	-0.020	0.019
BUX	43 798	5.91E-6	1.06E-3	-0.014	0.011

2. Data

The data employed in this paper were provided free of charge by Bloomberg, Prague. We use five-minute interval data on the following stock market indices: S&P 500 and Dow Jones Industrial Average (U. S.), FTSE 100 (London), DAX 30 (Frankfurt), CAC 40 (Paris), WIG 20 (Warsaw), PX 50 (Prague), and BUX (Budapest). It is not possible to obtain historical five-minute interval data for all of these indices. The data are stored in the Bloomberg database only for the most recent months. Therefore, the data were downloaded 24 times over 24 months so that a time span starting on June 2, 2003, at 13:30 and ending on June 6, 2005, at 23:55 Western and Central European Daylight Time was covered.[4]

Table 1 shows the time periods for which the data are mostly available each trading day for each individual index. *Table 2* shows basic summary statistics on

[4] Western and Central European Daylight Time is equal to GMT+1:00, except when it observes daylight saving time, when it is equal to GMT+2:00.

the natural logarithms of the indices and on the associated logarithmic five-minute returns (five-minute logarithmic differences).[5]

3. Methodology

To test for Granger causality and cointegration, we use the standard methodology proposed by Granger (1969, 1986) and Engle and Granger (1987) as described, for example, in (Enders, 1995). All tests are performed on natural logarithms of the indices' time series using simple OLS estimation procedures.[6]

3.1 Granger Causality and Cointegration Tests

In order to test for Granger causality among stock market indices x_t and y_t, we estimate the equation

$$\Delta \ln y_t = c + \sum_{i=1}^{K} \alpha_i \Delta \ln y_{t-i} + \sum_{i=1}^{K} \beta_i \Delta \ln x_{t-i} + \varepsilon_t \quad (1)$$

and perform an F test for joint insignificance of the coefficients β_i, $i=1...K$. The null hypothesis claims that x_t does not Granger cause y_t. For each pair of stock market indices, we can perform two Granger causality tests so that we can decide whether x_t Granger causes y_t, or y_t Granger causes x_t, or both, or neither. The selection process of the proper number of lags K is described in the end of this section.

When testing for cointegration of the pair of stock market indices x_t and y_t, we have to first determine if the logarithms of both indices are integrated of the order 1, denoted as $I(1)$.[7] This means that the levels of the series' logarithms must be non--stationary (contain a unit root) and the differences must already be stationary. To test for stationarity, we employ the standard augmented Dickey-Fuller test (ADF test). For levels we estimate equation (2) and for differences equation (3):

$$\ln y_t = c + \beta t + \delta \ln y_{t-1} + \sum_{i=1}^{K} \alpha_i \Delta \ln y_{t-i} + \varepsilon_t \quad (2)$$

$$\Delta \ln y_t = c + \delta \Delta \ln y_{t-1} + \sum_{i=1}^{K} \alpha_i \Delta^2 \ln y_{t-i} + \varepsilon_t \quad (3)$$

We allow the levels to contain a constant term and a linear time trend, whereas for the differences we include only a constant term in the estimated equation. Under the null hypothesis of the presence of a unit root (non-stationarity), the test statistic defined as the t-ratio of $(\delta - 1)$ equals zero. To test this hypothesis, we compare the test statistic to the finite sample critical values tabulated by Cheung and Lai (1995).

[5] More information about the composition as well as other characteristics of the investigated indices can be retrieved on the appropriate stock markets' web pages.

[6] The results do not change significantly when OLS with a correction for heteroscedasticity is employed. Even though the investigated data are of high frequency, as described in Subsection 4.2, the test regressions only employ high-frequency lags but are in fact estimated with daily data. Therefore, the absence of any strong conditional heteroscedasticity is not that surprising.

[7] It should be mentioned that simple random walk like stochastic time series models of a stock price (and thus also of a stock market index) imply that the logarithms of the stock price contain a unit root and its differences (logarithmic returns) are stationary. This result is also predominantly confirmed in many previous studies.

If the logarithms of both series x_t and y_t are found to be $I(1)$, then we proceed to the test of cointegration. We estimate a simple linear relationship between the two time series defined by equations (4) or (5):

$$\ln y_t = c + \alpha \ln x_t + \varepsilon_t \tag{4}$$

$$\ln x_t = c + \alpha \ln y_t + \varepsilon_t \tag{5}$$

Then we apply the ADF test to the estimated residuals e_t from each of the two equations (4) or (5). This means that we estimate the equation

$$e_t = \delta e_{t-1} + \sum_{i=1}^{K} \alpha_i \Delta e_{t-i} + \varepsilon_t \tag{6}$$

In this case we do not even allow for a constant in equation (6) because e_t is a series of regressions' residuals. Further, we proceed as with the ADF test applied to levels and differences of the logarithms of stock market indices, but employ the finite sample critical values tabulated by MacKinnon (1991). If the time series of the residuals e_t is tested as stationary, then we claim that the stock market indices x_t and y_t are cointegrated.

Cointegration between the indices x_t and y_t indicates the presence of a long run equilibrium relationship represented by equation (4) or (5). If one index deviates from this relationship in a period t, then it tends to return to it in subsequent periods. As a result, none of the indices should depart too far from this equilibrium. This idea is mathematically expressed with an error correction model that can be estimated using the following equations:

$$\Delta \ln y_t = c_1 + \delta_1 e_{t-1} + \sum_{i=1}^{K} \alpha_{1i} \Delta \ln y_{t-i} + \sum_{i=1}^{K} \beta_{1i} \Delta \ln x_{t-i} + \varepsilon_t \tag{7}$$

$$\Delta \ln x_t = c_2 + \delta_2 e_{t-1} + \sum_{i=1}^{K} \alpha_{2i} \Delta \ln y_{t-i} + \sum_{i=1}^{K} \beta_{2i} \Delta \ln x_{t-i} + \varepsilon_t \tag{8}$$

where e_t are the estimated residuals from equations (4) or (5). If the indices x_t and y_t are found cointegrated, then at least one of the coefficients δ_1 and δ_2 should appear significant in the estimated equations (7) and (8) and its sign should be such that the deviation from the long-run equilibrium in period t - 1 (e_{t-1} is used as a proxy for this deviation) will be corrected in the following period t.

In the tests described above, sums of lagged differences are included in the estimated equations (1), (2), (3), (6), (7), and (8). The lagged differences control for potential serial autocorrelation in residuals. To select the highest lag K, we use a modification of the non parametric method presented by Campbell and Perron (1991), and Ng and Perron (1995). The number of lags K is initially set at the maximum value of eight and the statistical significance of the coefficient on the highest lag is checked using a simple t-test. If it is insignificant at the 10% level, the number of lags is reduced by one and the procedure is repeated until statistical significance of the coefficient by the highest lag is achieved. If lagged differences for two variables are included (as in equations (1), (7), and (8), then we include the same number of lagged differences for both of them. Therefore, K is set when at least one of the coefficients on the highest lag is significant at the 10% level of significance.

TABLE 3 Maximum Number of Lags Available in Granger Causality and Cointegration Tests for Each Pair of Indices and Different Data Frequencies

Indices pair	Frequency							
	5 min	10 min	20 min	30 min	40 min	50 min	1 hour	1 day
DJIA and S&P	8	8	8	8	8	6	5	8
S&P and FTSE	8	8	4	2	1	1	0	8
S&P and DAX	8	8	4	2	1	1	0	8
FTSE and DAX	8	8	8	8	8	6	5	8
FTSE and CAC	8	8	8	8	8	6	5	8
DAX and CAC	8	8	8	8	8	6	5	8
DAX and WIG	8	8	8	8	7	5	4	8
DAX and PX	8	8	8	8	8	6	5	8
DAX and BUX	8	8	8	8	8	6	5	8
WIG and PX	8	8	8	8	7	5	4	8
WIG and BUX	8	8	8	8	7	5	4	8
PX and BUX	8	8	8	8	8	6	5	8

3.2 Tests with Different Data Frequencies

The major goal of this paper is to compare the results of Granger causality and cointegration tests for different data frequencies. Specifically, we perform the tests with the stock market index data of the following frequencies: 5 minutes, 10 minutes, 20 minutes, 30 minutes, 40 minutes, 50 minutes, 1 hour, and 1 day. To assure comparability of the results with different data frequencies, we proceed in the following way. For each pair of the tested indices we choose one time and select the available daily observations only for this particular time. The chosen times are 21:50 for a pair of U. S. indices, 15:40 for a pair of European indices, and 17:15 for a pair consisting of one U. S. and one European index. All the times are expressed in Western and Central European Daylight Time. With such "daily" time series, we use different lags for the tests with different frequencies. For example, when performing Granger causality tests on five-minute interval data we employ five-minute lags in equation (1), with ten-minute interval data we employ ten-minute lags, etc. With daily data frequency, we do not control for any potential Monday effects and take Friday as the preceding day. The times 21:50, 15:40, and 17:15 are chosen so that enough lags on all frequencies are available for both indices in the pair. Simultaneously, we avoid the closing times of any of the markets to prevent some potential special properties of the closing time index values from influencing the results. Nevertheless, the maximum number of lags allowed in the estimated equations is lower than eight as the frequencies approach one hour (see *Table 3*).

Depending on each individual pair of indices, the number of observations employed in the tests ranges between 408 and 498 for frequencies up to one hour, with a typical value around 470. For the tests with daily frequency the number of observations ranges between 313 and 483.

4. Results

The results of all Granger causality and cointegration tests are given in *Appendix*, *Tables A1* and *A2*. The results of the estimation of all error correction models will be provided upon request. We performed Granger causality and cointegration tests with different frequencies of the following twelve pairs of stock market indices: S&P 500 and DJIA, S&P 500 and FTSE 100, S&P 500 and DAX 30, FTSE 100 and DAX 30, FTSE 100 and CAC 40, DAX 30 and CAC 40, DAX 30 and WIG 20, DAX 30 and PX 50, DAX 30 and BUX, WIG 20 and PX 50, WIG 20 and BUX, and PX 50 and BUX.

The DJIA and S&P 500 cover stock markets in the same country. Thus, Granger causality or cointegration relationships should occur only at very high frequencies, because the transmission of information should be very fast. Unfortunately, the two indices do not measure the performance of two non-intersecting sets of stocks. In fact, the DJIA can be viewed as a "subset" of the S&P 500. All 30 DJIA index components are among the 500 stocks whose prices are used to compute the value of the S&P 500 index (at least throughout the time span investigated in this paper). For example, in August 2004, the weight of the 30 DJIA index components in the S&P 500 index was around 35 %. This weight can change slightly over time due to the S&P 500 index weighting scheme. While the DJIA is calculated on a price-weighted basis, the S&P 500 components are weighted proportionally to the market capitalization of the corresponding companies. Therefore, it is not possible to compute that part of the S&P 500 index measuring the remaining 470 stocks not included in the DJIA, unless we know the exact market capitalization of all the S&P 500 components at any point in time. The "overlap" of the two indices could cause a slight bias in the results of this paper. The bias should lead to not detecting any Granger causality, because no time series will ever Granger cause itself. In the case of cointegration, the bias should lead to finding a cointegration relationship because any time series is trivially cointegrated with itself, as the residuals from the regressions (4) or (5) equal zero. Neither of the two biases should be too serious, however, because about two-thirds of the S&P 500 index is calculated using the prices of the 470 stocks not included in the DJIA. Nevertheless, it should be mentioned that any of the 470 companies whose stocks are not included in the DJIA index has a much lower market capitalization than any of the 30 companies whose stocks are included in both indices. Thus, when using DJIA and S&P 500 indices in Granger causality and cointegration analysis in this paper, we in fact investigate the transmission of information revealed in prices of large (represented by the DJIA) and relatively small U.S. companies (represented by the S&P 500).

The second and third pairs investigate the relationships between the U. S. S&P 500 index and the two major European indices of the markets in London (FTSE 100) and Frankfurt (DAX 30). The next three pairs include three European indices: FTSE 100, DAX 30, and CAC 40 of the stock market in Paris. The next three pairs study the relationships between the DAX 30 and three indices from relatively small and still emerging Eastern European markets in Warsaw (WIG 20), Prague (PX 50), and Budapest (BUX).[8] The last three pairs include the three emerging markets indices WIG 20, PX 50, and BUX.

Whenever possible, we allow for a maximum of eight lags of the logarithmic differences in all the performed tests. However, the number of available lags is lower

[8] The choice of the DAX 30 index in the pairs with the three Eastern European markets' indices was motivated by Germany's prominent role among international trade counterparties of the Eastern European countries. An alternative choice could be the FTSE 100 index; however, the number of overlapping observations with this index is much lower.

TABLE 4 Results of Granger Causality Tests with Different Data Frequencies

GC →	Frequency							
	5 min	10 min	20 min	30 min	40 min	50 min	1 hour	1 day
S&P→DJIA	░			░	░			
DJIA→S&P	█							
S&P→FTSE	█	░						
FTSE→S&P								
S&P→DAX	▓			▓	░			
DAX→S&P		▓						
FTSE→DAX			▓	█	░		░	
DAX→FTSE	█		█			█	░	
FTSE→CAC				█	▓		░	
CAC→FTSE	▓		▓	▓		▓	▓	▓
DAX→CAC		░		▓	█	█	▓	░
CAC→DAX		▓		▓		▓	▓	░
DAX→WIG	█	▓		▓	█	█	█	
WIG→DAX	▓				░			░
DAX→PX					▓	▓	█	
PX→DAX								
DAX→BUX	█				░	█	▓	
BUX→DAX					░			
WIG→PX				▓	░		▓	
PX→WIG	░			█	░		█	▓
WIG→BUX	░						░	
BUX→WIG		▓				▓	▓	
PX→BUX					░			▓
BUX→PX		░	█	█	█	█	█	░

Notes: The symbols stand for Granger causality at the ░ 10%, ▓ 5%, and █ 1% significance level. With hourly frequency and the pairs of the S&P 500 index with the FTSE 100 and DAX 30 indices, not enough lags are available to perform Granger causality tests.

for data frequencies close to one hour. The maximum number of available lags in Granger causality and cointegration tests for different frequencies with each pair of indices is given in *Table 3*. The problem of a low number of available lags becomes the most serious in the case of the following two pairs: S&P 500 with FTSE 100 and S&P 500 with DAX 30. Here, the number of available lags drops to two for 30-minute frequencies and to one for 40- and 50-minute frequencies. With hourly data the tests cannot be performed at all because zero lags are available. Therefore, the results of the tests for these two pairs of indices cannot be viewed as fully comparable to results with the other pairs.

We should also be careful when comparing the test results from daily data to the results from data of other frequencies. Due to numerous holidays the number of available observations is lower with daily data than with other frequencies. Moreover, we do not control for any possible Monday effects and regard Fridays as directly preceding Mondays.[9]

4.1 Granger Causality

The results of Granger causality tests are given in *Table A1* in *Appendix*. They show a rich structure of Granger causality relationships. *Table 4* summarizes these results for each pair of indices and each data frequency.

[9] If Monday dummies are included in the regressions with daily data, the results of the tests do not change, even though the dummies are significant in most cases.

First, let us consider Granger causality between the two U.S. stock market indices: S&P 500 and DJIA. This pair can serve as a benchmark because the two indices are from markets in the same country. In line with this fact we detect the strongest result only with the highest five-minute frequency where the DJIA index Granger causes the S&P 500 index at the 1% significance level and vice versa; the S&P 500 Granger causes the DJIA but only at the 10% significance level. This means that the two indices either react very quickly to each other, or react to information relevant for the U.S. stock markets almost equally fast and in a similar manner. Moreover, the direction of Granger causality goes from the DJIA index to the S&P 500 index. This suggests that the prices of stocks of relatively small U. S. companies (represented by the S&P 500 index) react very quickly to the price changes of stocks of large U. S. companies (represented by the DJIA index). Additionally, our results also suggest that the S&P 500 Granger causes the DJIA with 30-minute and 40-minute data frequency but only at the 10% significance level. This result is, therefore, relatively unimportant compared to the result obtained with five-minute data frequency.

Second, we consider Granger causality between the S&P 500 index and the two major European indices, the FTSE 100 and DAX 30. Here, we see a slightly different pattern than with the two U. S. indices above. The S&P 500 Granger causes the FTSE 100 at the 1% significance level with five-minute data frequency and at the 10% significance level also with ten-minute data frequency. With the DAX 30 index, the pattern of Granger causality results is a bit richer. The S&P 500 Granger causes the DAX 30 at the 5% significance level with 5- and 30-minute data frequency and additionally with 40-minute data frequency at the 10% significance level. The opposite Granger causality relationship is detected only once. The DAX 30 index Granger causes the S&P 500 with ten-minute data frequency at the 5% significance level. Therefore, we conclude that the two major European stock markets react to information from the stock markets in the U.S. within approximately 30 to 40 minutes after this information is reflected in the S&P 500 index. However, the first and strongest reaction occurs very quickly, approximately within the first ten minutes. The evidence for an opposite reaction of the S&P 500 index to information revealed in the European indices is weak.

Third, we analyze Granger causality results among the three European stock market indices, the FTSE 100, DAX 30, and CAC 40. In this group a very rich Granger causality pattern is detected with frequencies ranging from five minutes to one day. Numerous Granger causality relationships in both directions and among all three pairs of indices are found with data frequencies between 20 minutes and one hour. With the highest five-minute data frequency, only two Granger causality relationships are present: the DAX 30 Granger causes the FTSE 100 at the 1% significance level and the CAC 40 Granger causes the FTSE 100 at the 5% significance level. With daily data frequency, Granger causality relationships are detected only at the 5% and 10% levels of significance. The CAC 40 index Granger causes the FTSE 100 index at the 5% level of significance, and both directions of Granger causality are found between the DAX 30 and CAC 40 indices but only at the 10% significance level. We conclude that the three European markets react to the information revealed on these markets approximately within one hour, with the strongest reaction occurring after 20 minutes. The fastest is the reaction of the FTSE 100 index whose first reaction to the DAX 30 and CAC 40 indices seems to occur within five minutes.

Fourth, we look at the results of Granger causality between the Frankfurt DAX 30 and the three indices from the relatively small Eastern European stock markets in Warsaw (WIG 20), Prague (PX 50), and Budapest (BUX). We find evidence that the DAX 30 index Granger causes all three Eastern European stock market indices. There is little evidence of an opposite relationship. With five-minute data frequency, the DAX 30 index Granger causes the WIG 20 and BUX indices at the 1% significance level. With this data frequency, the opposite Granger causality relationship is also detected between the DAX 30 and WIG 20 indices, but only at the 5% level of significance. Additionally the DAX 30 Granger causes the WIG 20 with 10-minute and 30-minute data frequency at the 5% significance level. With 40-minute, 50-minute, and one-hour data frequencies, the DAX 30 Granger causes all three Eastern European stock market indices at different levels of significance with the strongest result for the WIG 20 index, where Granger causality is detected at the 1% significance level using all the three data frequencies.

The opposite Granger causality relationship is quite rare. The WIG 20 and BUX Granger cause the DAX 30 with 40-minute data frequency but only at the 10% significance level and the WIG 20 index Granger causes the DAX 30 index also with daily data frequency but again only at the 10% level of significance. As already mentioned, while the WIG 20 Granger causes the DAX 30 with the highest 5-minute data frequency at the 5% level of significance, the opposite Granger causality relationship is detected at the 1% significance level. We conclude that the three small markets react to information revealed by the market in Frankfurt and not vice versa. The stock market in Prague seems to react more slowly than the markets in Warsaw and Budapest. However, in all three cases the information is predominantly transmitted after 40 minutes to one hour. Thus, the reaction speed of these markets is slightly slower but comparable to that between the major European markets. This finding partly contradicts the results of various studies that investigate informational efficiency and various types of information transmission in the emerging Eastern European markets, e.g., (Hanousek, Filer, 2000) or (Podpiera, 2000, 2001). These studies find typically little evidence for informational efficiency of these markets and are in this sense particularly skeptical about the stock market in Prague.

Finally, we consider Granger causality among the indices from the three markets in Warsaw, Prague, and Budapest (WIG 20, PX 50, and BUX).[10] With the WIG 20 and PX 50 pair we detect Granger causality with 5-, 30-, 40-minute, 1-hour, and 1-day data frequencies. However, the result with the 5-minute data frequency is weak. The PX 50 index Granger causes the WIG 20 index with 5-minute data frequency only at the 10% significance level. With 30-minute and 1-hour data frequencies, the PX 50 index Granger causes the WIG 20 index at the 1% significance level, while the opposite Granger causality relationship is detected at the 5% level of significance. With 40-minute data frequency both directions of Granger causality appear but only at the 10% significance level. Additionally, the PX 50 is found to Granger cause the WIG 20 with daily data at the 5% significance level. Thus, the Granger causality pattern between the WIG 20 and PX 50 indices is somewhat chaotic.

Much more interesting are the results with the WIG 20 and BUX pair and

[10] An overview of the general developments and the specific features of the Warsaw, Prague, and Budapest stock markets is available in (Egert, Kočenda, 2005), for example.

particularly with the PX 50 and BUX pair. The BUX index is found to predominantly Granger cause the WIG 20 and PX 50 indices and not vice versa. With all the data frequencies ranging from 20 minutes to 1 hour, the BUX index Granger causes the PX 50 index at the 1% level of significance. Additionally, the same result is found with 10-minute and daily data frequencies, but only at the 10% significance level. The opposite Granger causality relationship is detected only with 40-minute and daily data frequencies and only at the 10% and 5% levels of significance, respectively. With the WIG 20 and BUX pair of indices, the dominance of the BUX is not so obvious. However, here also the BUX index Granger causes the WIG 20 index with 10-minute, 50-minute, and 1-hour data frequencies at the 5% significance level, while the WIG 20 index Granger causes the BUX index only with 5-minute and 1-hour data frequencies and only at the 10% level of significance. Therefore, we conclude that among the three Eastern European stock markets, the Budapest market is the clear leader. The markets in Warsaw and Prague react to it within 1 hour. Particularly strong is the reaction of the stock market in Prague. Admittedly, these conclusions are rather daring. It might be the case that the market in Prague reacts to the same information as the market in Budapest but with a delay, particularly as a slower reaction to changes in the DAX index was detected with the Prague market.

4.2 Order of Integration

The results of the order of integration tests are presented in *Table A2* in *Appendix A*. Note that for different pairs of indices we use different observations. Therefore, the results for one index could differ depending on the other index included in the pair. In line with the previous empirical research and with the theoretical stochastic models of stock prices, most of the indices are found to be $I(1)$ at any frequency and using any significance level in the tests. However, with some indices and some data frequencies (particularly with daily data frequency), we find systematic deviations from this rule. Namely, the FTSE 100, DAX 30, CAC 40, and WIG 20 indices are in some cases found to be stationary already in levels, i.e. $I(0)$. The individual cases are listed below.

The FTSE 100 index appears to be $I(0)$ with 40-minute and daily data frequencies at the 10% significance level when paired with other European indices (daily observations at 15:40). With daily data frequency, the FTSE 100 is also found to be $I(0)$ even at the 5% significance level when used in a pair with the U. S. S&P 500 index (daily observations at 17:15). The DAX 30 with daily data frequency is found to be $I(0)$ at the 5% significance level when paired with any other index. The CAC 40 is tested as $I(0)$ with daily data frequency at the 10% significance level when paired with other European indices. Finally, the WIG 20 index is found to be $I(0)$ with daily data frequency at the 5% significance level when paired with the DAX 30 and the other Easter European indices. Here we do not have any explanation for these surprising results other than the limitations of the econometric techniques used rather than some fundamental pattern.

4.3 Cointegration

The results of cointegration tests for different pairs of indices and different data frequencies are given in *Table A2*. Cointegration of two time series represents a strong relationship. It implies the existence of a long-run equilibrium, towards which the two time series tend to converge. It also implies that the two time series must share a common stochastic trend. Moreover, cointegration tests are based on the ADF test, which is known to have low power. This means that even if the two time series are cointegrated in reality, the ADF test is quite likely not to detect this relationship. Therefore, it is not surprising that cointegration is detected only rarely in the data. Additionally, to test for cointegration the two time series must be $I(1)$. Thus, the above--mentioned indices' time series that were tested as $I(0)$ cannot be considered as cointegrated with any other index, even if the residuals from the cointegrating equation (4) or (5) were found to be stationary. Regarding this limitation, we detect cointegration only with two pairs of stock market indices, the FTSE 100 and CAC 40 and the PX 50 and BUX. With these two pairs (particularly with the PX 50 and BUX pair), the pattern of detected Granger causality relationships was also very rich.

For the FTSE 100 and CAC 40 pair, cointegration is detected with 30-minute, 50-minute, and 1-hour data frequencies. The error correction models suggest that the CAC 40 index reacts in all cases to the deviations from long-run equilibrium. For the PX 50 and BUX pair, cointegration is detected with data frequencies ranging from 30 minutes to 1 hour. In all these cases the error correction models show the reaction of both indices to the deviations from long-run equilibrium. However, the detected reaction of the PX 50 index is stronger, confirming the dominance of the BUX index already revealed in the Granger causality tests.

The rare appearance of cointegration relationships contrasts with the findings of other studies that have often suggested the presence of cointegration with closing time daily data of various pairs of stock market indices.[11] However, the use of closing time daily data in cointegration tests is quite misleading. Such data are not simultaneous as the closing times of different markets typically differ.

5. Conclusion

Using a dataset covering two years of high-frequency data, we investigate the issue of stock market integration from a novel perspective. We perform cointegration and Granger causality tests with data of different frequencies. Our aim is to describe the time structure in which markets react to the information revealed in prices on other markets. Particularly, we want to detect the speed of information transmission between the different markets. We employ the indices from stock markets in the U. S. (S&P 500 and Dow Jones Industrial Average), London (FTSE 100), Frankfurt (DAX 30), Paris (CAC 40), Warsaw (WIG 20), Prague (PX 50), and Budapest (BUX). The tests are performed for twelve different pairs of indices using data of 5-, 10-, 20-, 30-, 40-, 50-minute, 1-hour, and daily frequencies.

The results suggest that the markets react very quickly to the information revealed in the prices from other markets. In all cases the strongest reaction occurs within one hour, with the first reaction detected often after only five minutes. The U.S. markets seem to be an important source of information for the markets in London and Frankfurt, which react to such information within approximately 30 to 40 minutes, with the strongest reaction occurring within the first ten minutes. The three major European markets in London, Frankfurt, and Paris react to the information revealed in

[11] E.g., (Huang, Fok, 2001), (Seabra, 2001), (Dickinson, 2000), (Bracker et al., 1999),Chelley-Steeley et al., 1998),(Richards, 1996), or (Chou et al., (1994)

these markets within one hour, while the strongest reaction is detected after 20 minutes. The fastest is the reaction of the FTSE 100 index. The three small Eastern European markets in Warsaw, Prague, and Budapest react to the information revealed in the market in Frankfurt predominantly after 40 minutes to one hour. The slowest seems to be the reaction of the stock market in Prague. The stock market in Budapest appears to be a clear leader among the three Eastern European markets. The markets in Warsaw and Prague react to it within one hour, with the reaction of the stock market in Prague being particularly strong.

We are aware that when interpreting the results, we have neglected the differences in institutional arrangements of each of the stock markets. On the other hand, the aim of each stock market is to have a fast, efficient, and transparent trading system that helps to quickly reveal undistorted stock prices. Thus, when investigating information transmission, slight differences in institutional arrangements on the different markets should not matter too much.[12]

[12] To get a detailed description of the trading systems on each of the markets and for each of the stocks included in the investigated indices would be almost impossible. Some of the indices might contain stocks that are traded using different systems on the same market. Moreover, the U.S. S&P 500 and DJIA indices contain stocks that are traded on different markets.

Appendix

TABLE A1 Results of Granger Causality Tests

Data frequency	$\ln x_t$ GC $\ln y_t$				$\ln y_t$ GC $\ln x_t$			
	Obs.	*K*	R^2	*P*-value	Obs.	*K*	R^2	*P*-value
				x_t = S&P 500; y_t = DJIA				
5 minutes	488	3	0.028	*0.090*	487	3	0.040	*0.005*
10 minutes	488	8	0.055	*0.517*	487	8	0.058	*0.468*
20 minutes	487	6	0.036	*0.361*	486	6	0.036	*0.267*
30 minutes	488	7	0.057	*0.085*	486	6	0.055	*0.587*
40 minutes	488	4	0.040	*0.088*	487	4	0.042	*0.375*
50 minutes	486	3	0.021	*0.302*	485	3	0.023	*0.276*
1 hour	488	4	0.020	*0.309*	486	4	0.022	*0.649*
1 day	428	2	0.008	*0.263*	427	2	0.010	*0.208*
				x_t = S&P 500; y_t = FTSE 100				
5 minutes	474	1	0.031	*0.001*	473	6	0.029	*0.519*
10 minutes	473	3	0.016	*0.097*	470	8	0.029	*0.303*
20 minutes	474	1	0.005	*0.114*	474	1	0.001	*0.663*
30 minutes	471	2	0.019	*0.522*	471	1	0.014	*0.988*
40 minutes	470	1	0.000	*0.763*	471	1	0.009	*0.721*
50 minutes	470	1	0.001	*0.628*	475	1	0.008	*0.831*
1 hour								
1 day	430	1	0.009	*0.549*	432	1	0.013	*0.739*
				x_t = S&P 500; y_t = DAX 30				
5 minutes	480	1	0.023	*0.013*	480	1	0.009	*0.406*
10 minutes	476	8	0.038	*0.567*	476	8	0.043	*0.034*
20 minutes	480	1	0.004	*0.216*	480	1	0.001	*0.855*
30 minutes	477	1	0.014	*0.035*	477	1	0.013	*0.840*
40 minutes	476	1	0.006	*0.099*	481	1	0.009	*0.521*
50 minutes	476	1	0.001	*0.598*	481	1	0.006	*0.977*
1 hour								
1 day	332	8	0.048	*0.451*	323	8	0.070	*0.173*
				x_t = FTSE 100; y_t = DAX 30				
5 minutes	488	4	0.040	*0.489*	488	5	0.064	*0.007*
10 minutes	488	7	0.059	*0.266*	488	2	0.037	*0.116*
20 minutes	485	7	0.068	*0.044*	485	7	0.073	*0.002*
30 minutes	487	8	0.079	*0.002*	487	8	0.061	*0.107*
40 minutes	486	6	0.052	*0.057*	486	6	0.035	*0.598*
50 minutes	487	1	0.005	*0.154*	486	3	0.028	*0.004*
1 hour	487	4	0.045	*0.094*	487	4	0.033	*0.100*
1 day	404	6	0.029	*0.485*	397	6	0.038	*0.106*
				x_t = FTSE 100; y_t = CAC 40				
5 minutes	490	4	0.051	*0.233*	490	5	0.057	*0.028*
10 minutes	489	8	0.059	*0.162*	490	4	0.049	*0.235*
20 minutes	488	7	0.054	*0.203*	488	7	0.062	*0.030*
30 minutes	485	8	0.067	*0.006*	485	8	0.076	*0.011*
40 minutes	485	6	0.049	*0.016*	485	6	0.047	*0.128*
50 minutes	488	3	0.010	*0.397*	485	6	0.049	*0.010*
1 hour	486	4	0.034	*0.079*	486	4	0.037	*0.040*
1 day	455	2	0.021	*0.139*	447	2	0.029	*0.030*
				x_t = DAX 30; y_t = CAC 40				
5 minutes	497	8	0.076	*0.151*	497	7	0.051	*0.326*
10 minutes	498	6	0.055	*0.060*	498	6	0.061	*0.048*
20 minutes	493	7	0.055	*0.122*	496	4	0.047	*0.122*
30 minutes	492	8	0.055	*0.045*	492	8	0.069	*0.013*
40 minutes	497	1	0.029	*0.006*	491	7	0.054	*0.157*
50 minutes	494	4	0.036	*0.004*	494	4	0.030	*0.018*
1 hour	494	3	0.034	*0.039*	493	4	0.053	*0.023*
1 day	465	4	0.013	*0.076*	440	8	0.048	*0.052*

TABLE A1 Results of Granger Causality Tests *(continued)*

Data frequency	$\ln x_t$ GC $\ln y_t$				$\ln y_t$ GC $\ln x_t$			
	Obs.	K	R^2	P-value	Obs.	K	R^2	P-value
x_t = DAX 30; y_t = WIG 20								
5 minutes	483	7	0.120	*0.003*	483	6	0.068	*0.019*
10 minutes	482	6	0.045	*0.013*	482	5	0.042	*0.631*
20 minutes	478	6	0.038	*0.595*	482	2	0.030	*0.617*
30 minutes	481	2	0.024	*0.014*	480	8	0.046	*0.545*
40 minutes	481	2	0.038	*0.002*	479	7	0.061	*0.085*
50 minutes	481	1	0.034	*0.000*	485	5	0.020	*0.694*
1 hour	481	1	0.029	*0.001*	485	4	0.033	*0.974*
1 day	395	4	0.034	*0.128*	391	5	0.039	*0.055*
x_t = DAX 30; y_t = PX 50								
5 minutes	465	7	0.061	*0.501*	465	8	0.052	*0.804*
10 minutes	464	8	0.064	*0.532*	469	7	0.047	*0.931*
20 minutes	469	6	0.068	*0.593*	478	2	0.031	*0.616*
30 minutes	463	8	0.054	*0.180*	467	8	0.039	*0.884*
40 minutes	454	8	0.059	*0.034*	458	7	0.051	*0.689*
50 minutes	471	4	0.036	*0.042*	417	6	0.027	*0.657*
1 hour	464	5	0.070	*0.004*	472	4	0.044	*0.299*
1 day	347	8	0.047	*0.530*	369	7	0.023	*0.485*
x_t = DAX 30; y_t = BUX								
5 minutes	481	1	0.015	*0.008*	481	4	0.046	*0.362*
10 minutes	481	7	0.028	*0.465*	481	5	0.045	*0.389*
20 minutes	481	1	0.026	*0.368*	486	2	0.026	*0.646*
30 minutes	481	1	0.019	*0.148*	484	8	0.042	*0.680*
40 minutes	478	8	0.039	*0.096*	486	1	0.025	*0.077*
50 minutes	471	7	0.083	*0.001*	476	7	0.044	*0.105*
1 hour	479	4	0.044	*0.020*	484	4	0.045	*0.250*
1 day	344	8	0.054	*0.198*	456	1	0.004	*0.609*
x_t = WIG 20; y_t = PX 50								
5 minutes	458	7	0.059	*0.649*	458	8	0.074	*0.073*
10 minutes	455	8	0.064	*0.525*	461	7	0.031	*0.441*
20 minutes	460	6	0.071	*0.371*	466	5	0.031	*0.293*
30 minutes	454	8	0.064	*0.047*	467	3	0.036	*0.007*
40 minutes	448	7	0.049	*0.097*	472	2	0.025	*0.065*
50 minutes	456	5	0.029	*0.251*	468	4	0.019	*0.229*
1 hour	457	4	0.046	*0.040*	470	3	0.036	*0.009*
1 day	318	7	0.068	*0.117*	315	7	0.058	*0.029*
x_t = WIG 20; y_t = BUX								
5 minutes	474	7	0.042	*0.052*	474	7	0.090	*0.713*
10 minutes	474	2	0.013	*0.432*	474	3	0.027	*0.025*
20 minutes	470	8	0.044	*0.428*	471	5	0.021	*0.887*
30 minutes	470	8	0.050	*0.481*	473	1	0.006	*0.214*
40 minutes	470	6	0.026	*0.220*	472	2	0.015	*0.514*
50 minutes	471	5	0.050	*0.127*	473	1	0.014	*0.014*
1 hour	470	4	0.043	*0.053*	472	1	0.015	*0.034*
1 day	431	1	0.001	*0.522*	428	1	0.005	*0.480*
x_t = PX 50; y_t = BUX								
5 minutes	475	1	0.002	*0.316*	460	7	0.059	*0.906*
10 minutes	469	2	0.016	*0.179*	459	8	0.081	*0.061*
20 minutes	474	1	0.025	*0.579*	461	8	0.171	*0.000*
30 minutes	464	7	0.036	*0.756*	456	8	0.114	*0.000*
40 minutes	452	7	0.033	*0.075*	449	8	0.082	*0.002*
50 minutes	458	5	0.025	*0.891*	408	6	0.085	*0.000*
1 hour	460	4	0.018	*0.881*	457	5	0.092	*0.000*
1 day	313	7	0.063	*0.045*	313	7	0.089	*0.052*

Notes: Obs. stands for the number of observations and K for the number of lagged differences used in the Granger causality tests. R^2 stands for that of the unrestricted equations. The reported P-values indicate the F-tests' significance levels at which the null hypothesis of no Granger causality can be rejected.

TABLE A2 Results of Cointegration and the Order of Integration Tests

Data frequency	ADF tests on residuals from						ADF tests on levels and differences			
	$\ln y_t = c + \alpha \ln x_t + \varepsilon_t$			$\ln x_t = c + \alpha \ln y_t + \varepsilon_t$			$\ln x_t$	$\Delta \ln x_t$	$\ln y_t$	$\Delta \ln y_t$
	Obs.	K	P-value	Obs.	K	P-value	P-value	P-value	P-value	P-value
				x_t = S&P 500; y_t = DJIA						
5 minutes	487	7	*0.802*	487	7	*0.941*	0.982	0.000	0.841	0.000
10 minutes	487	4	*0.824*	487	4	*0.945*	0.977	0.000	0.858	0.000
20 minutes	486	6	*0.961*	486	6	*0.993*	0.985	0.000	0.970	0.000
30 minutes	487	4	*0.865*	487	4	*0.971*	0.958	0.000	0.864	0.000
40 minutes	487	5	*0.836*	487	5	*0.974*	0.938	0.000	0.725	0.000
50 minutes	485	3	*0.978*	485	3	*0.993*	0.995	0.000	0.986	0.000
1 hour	487	0	*0.998*	487	0	*0.999*	0.995	0.000	0.993	0.000
1 day	467	0	*0.784*	467	0	*0.954*	0.256	0.000	0.361	0.000
				x_t = S&P 500; y_t = FTSE 100						
5 minutes	474	3	*0.999*	474	3	*0.996*	0.994	0.000	0.999	0.000
10 minutes	470	6	*0.980*	473	3	*0.991*	0.998	0.000	0.999	0.000
20 minutes	475	0	*0.896*	475	0	*0.883*	0.976	0.000	0.999	0.000
30 minutes	475	0	*0.803*	475	0	*0.787*	0.755	0.000	0.951	0.000
40 minutes	474	0	*0.906*	474	0	*0.693*	0.702	0.000	0.888	0.028
50 minutes	471	0	*0.965*	471	0	*0.858*	0.564	0.000	0.823	0.000
1 hour										
1 day	317	6	*0.993*	317	6	*0.979*	0.419	0.000	0.037	0.000
				x_t = S&P 500; y_t = DAX 30						
5 minutes	480	4	*0.990*	480	4	*0.973*	0.994	0.000	0.998	0.000
10 minutes	476	7	*0.944*	476	7	*0.939*	0.998	0.000	0.997	0.000
20 minutes	476	3	*0.954*	481	0	*0.872*	0.976	0.000	1.000	0.000
30 minutes	477	1	*0.857*	481	0	*0.743*	0.755	0.000	0.992	0.000
40 minutes	480	0	*0.897*	480	0	*0.684*	0.702	0.000	0.977	0.000
50 minutes	477	0	*0.371*	476	1	*0.285*	0.564	0.000	0.959	0.003
1 hour										
1 day	384	4	*0.056*	384	4	*0.181*	0.419	0.000	0.044	0.000
				x_t = FTSE 100; y_t = DAX 30						
5 minutes	488	7	*0.997*	488	7	*0.898*	0.997	0.000	1.000	0.000
10 minutes	488	1	*0.989*	488	2	*0.827*	0.642	0.000	1.000	0.000
20 minutes	487	4	*0.937*	487	4	*0.659*	0.220	0.000	0.990	0.000
30 minutes	488	1	*0.915*	488	1	*0.515*	0.217	0.000	0.977	0.000
40 minutes	488	1	*0.642*	488	1	*0.363*	0.096	0.000	0.977	0.000
50 minutes	487	1	*0.410*	487	1	*0.156*	0.225	0.000	0.996	0.000
1 hour	488	0	*0.427*	488	0	*0.281*	0.906	0.000	0.998	0.000
1 day	460	1	*0.014*	460	1	*0.127*	0.087	0.000	0.043	0.000
				x_t = FTSE 100; y_t = CAC 40						
5 minutes	490	5	*0.970*	490	5	*0.778*	0.997	0.000	1.000	0.000
10 minutes	490	2	*0.872*	490	5	*0.415*	0.642	0.000	1.000	0.000
20 minutes	489	4	*0.910*	489	4	*0.364*	0.220	0.000	0.998	0.000
30 minutes	489	3	*0.587*	489	3	*0.075*	0.217	0.000	0.972	0.000
40 minutes	489	2	*0.030*	489	2	*0.005*	0.096	0.000	0.941	0.000
50 minutes	489	1	*0.006*	489	1	*0.001*	0.225	0.000	0.981	0.000
1 hour	484	5	*0.009*	484	5	*0.003*	0.906	0.000	0.992	0.000
1 day	475	0	*0.069*	475	0	*0.139*	0.087	0.000	0.060	0.000
				x_t = DAX 30; y_t = CAC 40						
5 minutes	498	5	*1.000*	498	5	*1.000*	1.000	0.000	1.000	0.000
10 minutes	497	8	*1.000*	497	8	*1.000*	1.000	0.000	1.000	0.000
20 minutes	493	8	*0.995*	493	8	*0.987*	0.990	0.000	0.998	0.000
30 minutes	498	0	*1.000*	494	7	*0.999*	0.977	0.000	0.972	0.000
40 minutes	497	1	*1.000*	491	7	*0.999*	0.977	0.000	0.941	0.000
50 minutes	496	1	*1.000*	498	0	*0.999*	0.996	0.000	0.981	0.000
1 hour	498	0	*0.998*	494	3	*0.997*	0.998	0.000	0.992	0.000
1 day	483	1	*0.254*	483	1	*0.084*	0.043	0.000	0.060	0.000

TABLE A2 Results of Cointegration and the Order of Integration Tests *(continued)*

Data frequency	ADF tests on residuals from						ADF tests on levels and differences			
	$\ln y_t = c + \alpha \ln x_t + \varepsilon_t$			$\ln x_t = c + \alpha \ln y_t + \varepsilon_t$			$\ln x_t$	$\Delta \ln x_t$	$\ln y_t$	$\Delta \ln y_t$
	Obs.	*K*	*P*-value	Obs.	*K*	*P*-value	*P*-value	*P*-value	*P*-value	*P*-value
x_t = DAX 30; y_t = WIG 20										
5 minutes	483	2	*0.999*	483	3	*1.000*	1.000	0.000	0.999	0.000
10 minutes	482	6	*1.000*	482	6	*1.000*	1.000	0.000	0.998	0.000
20 minutes	481	3	*0.653*	481	3	*0.842*	0.990	0.000	0.605	0.000
30 minutes	481	2	*0.893*	481	2	*0.875*	0.977	0.000	0.866	0.000
40 minutes	482	1	*0.852*	479	7	*0.941*	0.977	0.000	0.347	0.000
50 minutes	481	1	*0.885*	481	1	*0.908*	0.996	0.000	0.483	0.000
1 hour	480	3	*0.840*	480	3	*0.891*	0.998	0.000	0.402	0.000
1 day	365	6	*0.239*	365	6	*0.346*	0.043	0.000	0.033	0.000
x_t = DAX 30; y_t = PX 50										
5 minutes	462	8	*0.999*	462	8	*1.000*	1.000	0.000	0.999	0.000
10 minutes	466	7	*0.999*	466	7	*1.000*	1.000	0.000	0.997	0.000
20 minutes	472	4	*0.997*	472	4	*0.999*	0.990	0.000	0.974	0.002
30 minutes	463	8	*0.985*	463	8	*0.986*	0.977	0.000	0.855	0.000
40 minutes	455	7	*0.960*	455	7	*0.846*	0.977	0.000	0.864	0.000
50 minutes	412	6	*0.988*	412	6	*0.872*	0.996	0.000	0.740	0.000
1 hour	464	5	*0.999*	479	0	*0.998*	0.998	0.000	0.580	0.000
1 day	463	0	*0.175*	463	0	*0.019*	0.043	0.000	0.577	0.000
x_t = DAX 30; y_t = BUX										
5 minutes	481	5	*0.998*	481	5	*1.000*	1.000	0.000	0.561	0.000
10 minutes	481	7	*0.989*	481	7	*0.999*	1.000	0.000	0.932	0.000
20 minutes	481	3	*0.822*	481	3	*0.969*	0.990	0.000	0.935	0.000
30 minutes	479	8	*0.791*	478	8	*0.936*	0.977	0.000	0.520	0.000
40 minutes	481	1	*0.945*	478	7	*0.965*	0.977	0.000	0.932	0.000
50 minutes	480	1	*0.961*	478	5	*0.978*	0.996	0.000	0.767	0.000
1 hour	479	4	*0.972*	479	4	*0.985*	0.998	0.000	0.859	0.000
1 day	463	0	*0.427*	463	0	*0.046*	0.043	0.000	0.692	0.000
x_t = WIG 20; y_t = PX 50										
5 minutes	458	7	*0.998*	458	7	*0.997*	0.999	0.000	0.999	0.000
10 minutes	460	6	*0.992*	460	6	*0.995*	0.998	0.000	0.997	0.000
20 minutes	472	0	*0.668*	463	5	*0.577*	0.605	0.000	0.974	0.002
30 minutes	470	0	*0.834*	470	0	*0.901*	0.866	0.000	0.855	0.000
40 minutes	472	0	*0.468*	472	0	*0.446*	0.347	0.000	0.864	0.000
50 minutes	475	0	*0.399*	475	0	*0.474*	0.483	0.000	0.740	0.000
1 hour	471	0	*0.512*	471	0	*0.510*	0.402	0.000	0.580	0.000
1 day	449	0	*0.118*	449	0	*0.011*	0.033	0.000	0.577	0.000
x_t = WIG 20; y_t = BUX										
5 minutes	474	7	*0.994*	474	7	*0.996*	0.999	0.000	0.561	0.000
10 minutes	474	0	*0.986*	474	0	*0.993*	0.998	0.000	0.932	0.000
20 minutes	471	5	*0.246*	471	5	*0.316*	0.605	0.000	0.935	0.000
30 minutes	471	5	*0.604*	471	5	*0.865*	0.866	0.000	0.520	0.000
40 minutes	472	2	*0.216*	472	2	*0.335*	0.347	0.000	0.932	0.000
50 minutes	474	0	*0.339*	474	0	*0.515*	0.483	0.000	0.767	0.000
1 hour	473	0	*0.562*	473	0	*0.619*	0.402	0.000	0.859	0.000
1 day	447	0	*0.142*	447	0	*0.007*	0.033	0.000	0.692	0.000
x_t = PX 50; y_t = BUX										
5 minutes	461	6	*0.987*	461	6	*0.989*	0.999	0.000	0.561	0.000
10 minutes	474	0	*0.904*	474	0	*0.897*	0.997	0.000	0.932	0.000
20 minutes	465	6	*0.321*	465	6	*0.319*	0.974	0.002	0.935	0.000
30 minutes	456	8	*0.099*	456	8	*0.098*	0.855	0.000	0.520	0.000
40 minutes	462	6	*0.023*	462	6	*0.025*	0.864	0.000	0.932	0.000
50 minutes	457	5	*0.003*	457	5	*0.003*	0.740	0.000	0.767	0.000
1 hour	459	4	*0.002*	459	4	*0.001*	0.580	0.000	0.859	0.000
1 day	325	6	*0.347*	325	6	*0.333*	0.577	0.000	0.692	0.000

Notes: *Obs.* stands for the number of observations and *K* for the number of lagged differences used in the ADF tests. The reported *P*-values indicate the ADF tests' significance levels at which the null hypothesis of non--stationarity can be rejected. Finite sample critical values are from Cheung and Lai (1995) for the ADF tests with the levels and differences of indices' logarithms and from MacKinnon (1991) for the ADF tests with the residuals. *P*-values other than 0.01, 0.05, and 0.10 are computed using a logistic interpolation. Such *P*-values are fine for testing at the common significance levels of 10 %, 5 %, and 1 %, but rather speculative outside this range.

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